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1° LEVEL OF AUTOMATION: THE EFFECTIVENESS OF ADAPTIVE CRUISE CONTROL ON DRIVING AND VISUAL BEHAVIOUR

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ABSTRACT

This doctoral dissertation is a key point of multidisciplinarity, able to synthesize and unite some of the key notions of civil and industrial engineering research.

The research activities, carried out at the DICAM Department of the University of Bologna during a three-year PhD program, have allowed the analysis of the driver assistance systems, called Advanced Driver Assistance Systems (ADAS) in relation to road safety. The study is structured according to several evaluation steps, related to definite on-site tests that have been carried out with different samples of users, according to their driving experience with the ACC. The evaluation steps concern:

- The testing mode and the choice of suitable instrumentation to detect the driver's behaviour in relation to the ACC.
- The analysis modes and outputs to be obtained, i.e.:
  - Distribution of attention and inattention;
  - Mental workload;
  - The Perception-Reaction Time (PRT), the Time To Collision (TTC) and the Time Headway (TH).

The main purpose is to assess the interaction between vehicle drivers and ADAS, highlighting the inattention and variation of the workloads they induce regarding the driving task. The research project considered the use of highly innovative technologies for data recording and analysis, such as a system for monitoring visual behavior (ASL Mobile Eye-XG - ME), a powerful GPS that allowed to record the kinematic data of the vehicle (Racelogic Video V-BOX) and a tool for reading brain activity (Electroencephalographic System - EEG). In addition, the use of experimental testing has increased knowledge of the relationship between the driver and the surrounding road environment. Just during the analytical phase, a second and important research objective was born: the creation of a graphical interface that would allow exceeding the frame count limit, making faster and more effective the labeling of the driver's points of view.

The results show the parameters considered suitable for road safety in the road context. Through a complete and exhaustive picture of the vehicle-driver interaction, it has been possible to highlight the main sources of criticalities related to the user and the vehicle, in order

to concretely reduce the accident rate. In addition, the use of mathematical-computational methodologies for the analysis of experimental data has allowed the optimization and verification of analytical processes with neural networks that have made an effective comparison between the manual and automatic methodology.

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ACRONYMS

ADAS: Advanced Driver Assistance Systems

ACC: Adaptive Cruise Control

PRT: Perception-Reaction Time

V-BOX: Racelogic Video V-BOX

ME: ASL Mobile Eye-XG

EEG: Electroencephalographic System

DA: Driving Automation

CG: Common Ground

SA: Situational Awareness

TTC: Time To Collision

LOA: Level of automation

KEYWORDS

Advanced Driver Assistance Systems
Adaptive Cruise Control
Visual Behaviour
Driving Behaviour
Road Safety
Mental Workload
Human factor

1. INTRODUCTION

1.1. Motivation

The aim of this doctoral thesis is to highlight the impact of new Advanced Driver Assistance Systems (ADAS) on road safety. The study, specifically, focuses on the evaluation of the interaction between the user, investigating his subjective and objective behavior, and the vehicle, equipped with innovative mechanisms, the basis of the emerging development of autonomous driving.

The importance of this research is linked to how automation is changing the usual driving style, introducing new tasks and areas of visual interest. Considering these systems as the first step towards total automation of the vehicle, it is necessary to evaluate their influence on user behavior, in order to avoid possible misunderstandings in the transition from autonomous to manual control.

In the first level of automation, in fact, the role of the driver is still fundamental; the vehicle has systems that serve as an aid to driving while assuming the driver's alert reaction to possible accidental maneuvers that the ADAS cannot manage. In this sense, the Situational Awareness (SA) of the driver is fundamental as it implies real-time knowledge of driving scenarios, considering driving maneuvers in traffic such as directional change, overtaking, lane change, reversing and parking. The SA means therefore to realize what happens in the surrounding environment also in relation to the presence of certain infrastructural elements which are: roundabouts, traffic lights intersections, pedestrian crossings, bicycle crossings, interchanges, rectifiers, and curves. Over the years, a theory of situational awareness has been developed, describing three levels:

- Level 1 - Perception of elements in the environment: simple recognition of objects, events, people, systems, environmental factors and their states (positions, conditions, methods, actions);
- Level 2 - Understanding the current situation: development of a general framework of the environment of interest;
- Level 3 - Projection of the future state: the ability to understand how stored information can affect future conditions of the entire environment.

When driving behaviour does not reflect one of these levels, there is the 'lack of SA'. It is considered one of the main causes of road accidents attributed to the human error occurring in the Common Ground (CG) between man and vehicle (Faure et al., 2016). Driving Automation (DA) in fact promotes a constant increase of the functionalities related to the CG to make the exchange man-machine faster and clearer, avoiding errors (Huber et al., 2010; Vanderhaegen et al., 2006). Therefore, the CG allows continuous and timely feedback to the driver to reduce cognitive stress and highlight the 'transition moment' (MT) between autonomous and manual driving (Eriksson et al., 2017). By increasing the levels of knowledge of the CG, it will be possible to outline a framework of optimal driver comfort, in full compliance with road rules (Banks et al., 2014).

These conditions lead to major changes in traffic flow. The driver assistance system that highlights this variation is the Adaptive Cruise Control (ACC). This ADAS represents the evolution of Cruise Control; it allows to establish of a precise distance from the previous vehicle modulating the cruise speed and decreasing the possibility of collision accidents (Lin et al., 2008). The ACC, in fact, by limiting sudden braking, acts on the control of the engine and introduces two other important advantages: the reduction of emissions of harmful substances and the deterioration of the road surface (Zhang et al., 2018). In addition to the environmental impact, the use of ACC has also led to a real change in driving behaviour. According to Stanton (2009), about 75% of accidents are related to human error. For this reason, manufacturers' cars design the ACC to control maneuvers on the road, establishing a different reaction time for humans and machines (Wang et al., 2019). The study of this factor is fundamental in relation to the visual behavior of the user and his workload. The term workload refers to the mental load to which an individual is subjected, in order to perform an action. It is a fundamental parameter in the field of road safety since it allows to estimate how the infrastructure engages the human mind. Therefore, depending on the cognitive load it is possible to estimate the level of performance of drivers.

Low workload levels correspond to low-performance levels, where inattention prevails. The level of performance increases with the growth of the mental load required, until a maximum peak level is reached, then decreases drastically. The probability of error increases as the level of performance exhibited decreases. It is necessary, therefore, that the mental load is neither too high, not to exceed the reaction-decision ability of the driver, nor too low, not to cause inattention. For these reasons, the risk of road accidents is greater in geometric elements or specific tasks to which workloads compete or very low or very high (Kantowitz et al., 2000; Cuenen et al., 2015; Lyu et al., 2017).

1.2. Original Contribute

The research discusses the study of ADAS-driver-road interaction by proposing a highly innovative experimentation in terms of samples and tools. Firstly, a high number of users (48 males), with different knowledge of ADAS, were involved. This allows to analyse the ADAS's effectiveness and diversified impact, connected with the levels of attention and workload, to compare the condition of inexperience with wide period of use (Deery et al., 1999; Donmez, Boyle e Lee, 2010; Dickie et al., 2009; Rajaonah et al., 2006). Secondly, the three instruments, i.e. the Mobile Eye Tracker (ME), the Video V-Box Pro and the electrode brain helmet (EEG), highlight the factors of interaction between the ADAS, drivers and street. In addition, the administration of questionnaires, provided to analyse deeply the perception of the system both before and after using it (Dickie et al., 2009). In this way, it was possible to obtain specific information about risks' driver from a subjective and objective point of view. According to Summala (1988), in fact, analysing this dual awareness, it is fundamental to implement the 'zero-risk model'. Drivers monitor the subjective and objective risks continuously, to find a balance while driving, without the interference of the fear (Rudin-Brown et al., 2014). The users, indeed, must have an emotional comfort that reduces the complexities and the uncertainties of the system to obtain an optimal ergonomic design (Cahour et al., 2009).

These aspects are combined with the road test. This choice rises in a panorama where the simulator turns out to be more used because it removes the problems connected with the boundary conditions, such as traffic, weather and real risks of driving (Ariën et al., 2013, Lin et al., 2008). On site, in fact, the interactions between road, vehicle and driver are numerous and they allow to extrapolate the real behavior and the workload of drivers (Luo et al., 2010). For example, to consider the driver's attention using ACC, it was possible to analyse the movement of the pupil, that is the 'point of fixation' of the user in the driving scene, extrapolated thanks to the use of the ME (Bucchi et al., 2012; Dondi et al., 2011). These different 'point of fixation' make a comparison between the two states of the system (on/off). When the system is active, in fact, the car accelerates in relation to the relative speed of the previous vehicle, creating a traffic wave according to the car following model; consequently, the driver focuses his attention on the various traffic components (Chandler et al., 1958). If all vehicles were equipped with active ACC, the propagation of these waves would be constant and homogeneous, as shown by the data of the Video V-Box. This tool, in fact, allows to evaluate the kinematic features of the vehicle, connected with the driving behaviours. In this way, the trend of speed and acceleration of the vehicle are commensurate with the workload.

According to Brookhuis' studies (2010), when drivers are subject to high workloads, they tend to decrease driving speed (Milleville-Pennel et al., 2015; Engström et al., 2005; Reimer et al., 2012). These changes arise with also the brain's activity tracking with the EEG. This technique is one of the main methods to follow the workload's waves. Using special electrodes, placed on top of the head, the EEG provides direct access to brain activities. It highlights a limited cost and invasiveness and obtains an objective assessment of cognitive phenomena (Aricò et al., 2016; Aricò et al., 2018; Di Flumeri et al., 2018; Acerra et al., 2019).

1.3. Thesis approach

The research analyses user behavior in relation to the use of the Adaptive Cruise Control system and evaluates how this instrument influenced the driver's reaction. For the analysis, the user and the vehicles were equipped with an innovative instrument suitable for the experiment. A combined approach was adopted between the various factors described below and analysed in the following order:

- Visual Behavior Analysis: the elements that drivers observe while driving has been identified and categorized, in order to evaluate the attention and inattention percentages of each user, both with the system on or off. For this purpose, Eye-tracking technology was used i.e. the Mobile Eye Tracker XG tool, which allows tracking of eye movement.
- Driving Behavior Analysis: the driving behavior was examined through the processing of vehicle kinematic data, recorded by the Video V-Box. It also extrapolated the trend of speed, acceleration and consequently the Reaction-Perception Time (PRT). This factor is based on non-invasive observations because is important to obtain reaction time estimates representative of performance in real situations.
- Workload analysis: the measurement was performed directly on the drivers by calculating the mental workload (Workload index) to which they are subjected while driving. The data is derived from the records of the brain helmet (EEG) and the analysis of the self-assessment questionnaires, completed by each participant in the test.

In the field of level of automation (LOA), the reduction of direct control of the vehicle by the driver makes it pass from actor to spectator in driving, even in dangerous situations. However, this step should not be interpreted as replacing the role of the driver, but as active cooperation between the two entities because the automation is not able to act autonomously yet, especially considering all the variables present in the driving environment (Banche et al., 2014). The mechanisms linked to the operation of ADAS are therefore the first elements to be examined to verify whether the 'Distributed Cognition' is valid for safety purposes. The ADAS, in fact, were born with the intention of mitigating accidents, reducing the overall severity of the collisions, injuries and deaths. Seacrist's studies (2020) have suggested that the use of ADAS can prevent up to 57% of accidents and injuries. In addition, considering the level of attention, it was possible to highlight a sharp growing of about 80% for distracted drivers (Lee et al., 2002; Fleming et al., 2019). By increasing the levels of CG, it will be possible to outline a framework of optimal comfort of the driver, in full compliance with road rules (Banks et al., 2014).

1.4. Experimental tests

The on-site test was carried out with an experimental sample, instructed to drive a not owned car. The test was performed from 9 am to 5 pm. Each user remained busy for about 2 hours from the start to the end of the test. Fifty-two drivers have been involved in the study: 26 with no previous experience of ACC (Mean-age = 40,84 years; Range: 35÷55; SD = 5.57) and 26 ACC users (Mean-age = 45.81 years; Range: 35÷50; SD = 6.02), who have been using the systems at least for 3 months (mean number of hours of experience with ACC = 3.31 hours ± 1.81, range: 1 ÷ 5). The average driving experience was 22 years (SD = 6.89) for ACC non-users and 27.81 years (SD = 6.02) for ACC users. They were selected in order to have a homogeneous experimental group in terms of age, sex, and driving expertise. Everyone had normal vision and none of them wore eyeglasses or lenses, to avoid artifacts in eye-movement monitoring. They had a valid driving license and none of them had previous driving experience on the road segment considered in this study. Everyone was paid and they did not know anything about the aims of the study to avoid any bias in their behaviour.

The experiment was conducted following the principles outlined in the Declaration of Helsinki of 1975, as revised in 2000. The study was approved by the Ethical Committee of the University of Bologna. Informed consent and authorization to use the video graphical material were obtained from each subject on paper, after the explanation of the study.

Before carrying out the test, informative material was sent to the participants to make them aware of:

- The test modalities and test purposes;
- The equipment that they would wear during the test, with a description of their operation and on-site calibration methodology;

- The description of the test track so that they knew the features;
- The test mode driving, in which it was specified that they could drive freely, respecting the Highway Code;
- The description of the driver assistance systems that they would have tried, with a description of the operation, activation/deactivation of the systems, with the enclosed use manuals for each vehicle.

To carry out the test, a vehicle equipped with Adaptive Cruise Control, was hired, namely a Volkswagen Passat SW model with a diesel engine, equipped with an automatic transmission (Figure 1.1).

Figure 1.1. Volkswagen Passat SW with ACC.

In order to test the operation of the ACC system, a BMW Series 1 model was chosen to carry out trials during the test phase, considering them as cars to follow (Figure 1.2).

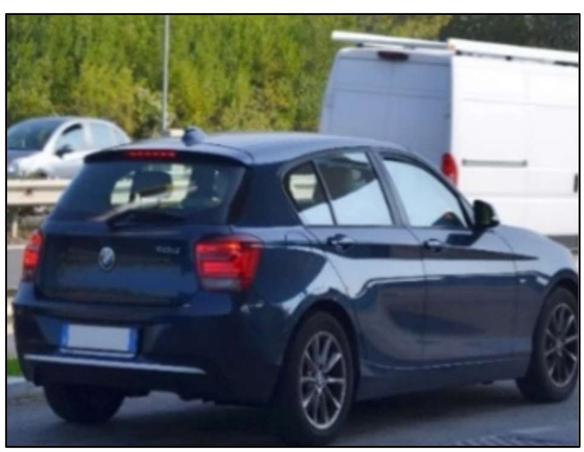


Figure 1.2. Prey vehicles.

Each user has completed 2 laps of the route, considering each lap for these purposes:

- Lap 1: the adaptation to the vehicle and the ACC system;
- Lap 2: the definite test with system start-up on the outward or return section, randomly between users. In the test phase, both with an on and off system, the driver was asked to follow the previous vehicle (called ‘prey’). The presence of the latter has the purpose of simulating a series of ‘events’ on the course, or sudden braking, in order to obtain the activation of the system in the test vehicle (if system ON) or the braking reaction of the driver (in case of system OFF). Half experimental sample drove with the ON system on the forward section and the other half on the return section, in order to avoid bias experimental. The order of ACC ON and OFF conditions had been randomized among the subjects, in order to avoid any order effect.

During the first lap, the driver was free to try the ACC system. The data recorded during the second lap were considered for the analysis. According to Rudin-Brown et al. (2004), the event type was selected as the most probable one coherently with the ACC mode of operation, as well as the safest to be acted, without introducing any risk for the actors, for the experimental subjects and the traffic in general. Users were in the vehicles with operators checking the correct conduct of the test.

The activation of the ACC, was indicated by the operator on board but managed manually by the participant of the test, it was possible through the use of steering wheel controls with the following procedure (Figure 1.3):

a) Press the ‘O/I’ button on the steering wheel to turn on the system;
b) Press the ‘MODE’ button on the steering wheel to switch the ACC to speed limiter;
c) Select the "Automatic Distance Controller" option;
d) Press the distance setting button and adjust the "VERY LONG" distance level (when the vehicle is in motion, the ACC ON symbol appears on the panel, white, with or without a vehicle depending on the presence of a vehicle in front);
e) Press the SET button: the green symbol appears on the instrument panel;
f) Select the + and – to impose the speed(choice of 90 km / h).

Figure 1.3. ACC system control buttons on the left side of the steering wheel.

Once the system is switched ON, various indicators are displayed on the dashboard according to the reciprocal position with the vehicle in front. While driving, the system is able to activate only if the driver of the vehicle does not press either the brake or the accelerator. In this case, the vehicle, in a completely autonomous way, keeps the motion at a speed lower, than the maximum speed selected and automatically adjusts the distance to the vehicle in front based on that indicated. The dashboard interface (Fig 1.4) shows on the top left the green icon that shows the activation of the system. In particular, the stylized figure of the vehicle with the speedometer confirms the activation of the system; whereas, the three blue lines (7.14 and 21 m respectively) allow the definition of a distance from the previous vehicle set at 21 km.

Figure 1.4. Dashboard of the car with ACC On.

In this way, once the desired cruising speed is reached, it is possible to see speed decreases due to an approach to the previous vehicle.

1.4.1. The circuit

The subjects had to drive along the Tangenziale of Bologna (Italy), a bypass road, coplanar with the urban section of the A14 highway. It is a primary road, mainly straight with wide radius curves, with two lanes in each direction (excluding the emergency lane); it has a speed limit of 90 km/h. This road has been chosen because it has the right requirements for the application of the Adaptive Cruise Control as it allows a speed higher than 60 km/h and it has a multi-lane carriageway in each direction with horizontal signs in a good maintenance state. These characteristics allowed participants to drive as safely as they would normally do in their car, with naturalistic behaviour (Figure 1.5).

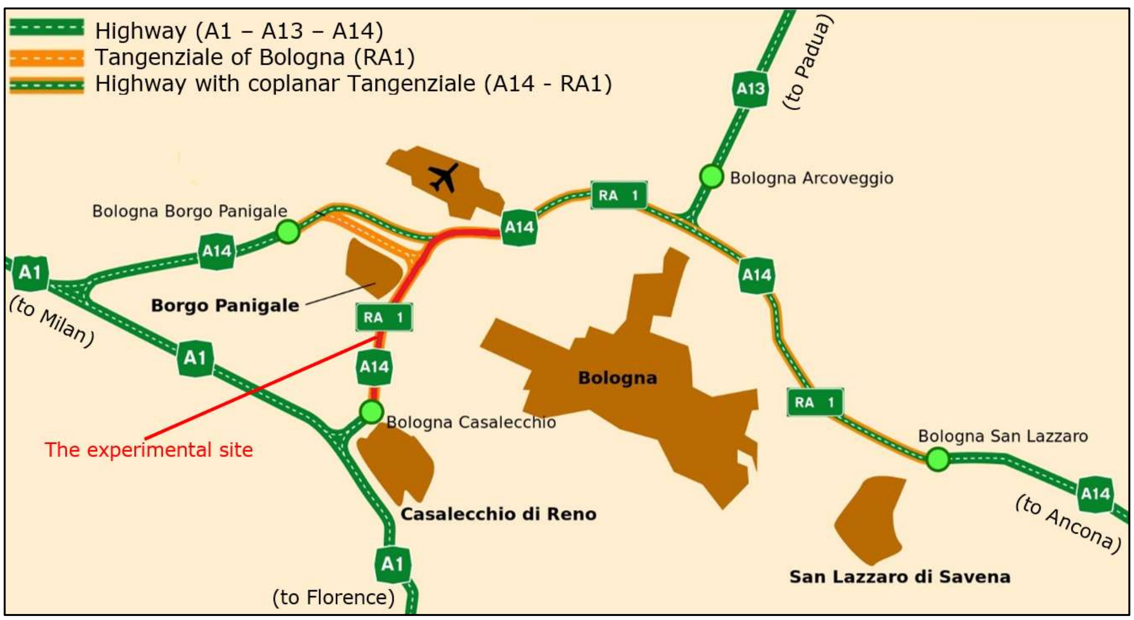


Figure 1.5. Itinerary of the Experimentation.

1.4.2. Instruments and aims

Drivers and vehicles were instructed to use innovative equipment that enabled the analysis of:

- The Visual Behavior of the users, that is the identification of the elements of the infrastructure and of the road environment that most attract the attention of drivers. For this purpose, Eye Tracking technology was used, in particular the tool the Eye Tracker ASL Mobile Eye-XG (ME), which allows the driver's gaze to be continuously observed while driving.

- The Driving Behavior, such as the driving style of the road users along the road layout. To this end, the results obtained from the VIDEO V-BOX PRO device are processed, which allows continuous monitoring of certain kinematic vehicle parameters.
- The physical and mental Workload, which can be objective, i.e. perceived by the drivers throughout continuous monitoring of the driver's brain activity, evaluated with the brain electrode helmet (EEG), or subjective assessed through various questionnaires such as the NASA-TLX.

1.5. Objectives of the research

The objectives of the thesis concern the evaluation of road-vehicle-driver interactions. In fact, initially, it was possible to define an actual output of how the driver can respond to the demands of the new driver assistance system, considering the various maneuvers he is forced to perform on the road. It was then possible to define some important questions:

- How is the driver’s visual behaviour with the use of ADAS?

- How do the kinematic parameters of the vehicle change?

- How is the brain activity described?

Parameters such as speed and acceleration, allowed to define some important parameters such as Time To Collision(TTC), Time Headway (TH), and Perception-Reaction Time (PRT). Others, such as eye fixations, evaluated attention and distraction while driving. However, having to manually count the frames related to the various categories, a great limit for the conduct of analysis in time contexts appropriate has been. For this reason, an innovative interface, introduced by neural networks, has been devised to allow frames to be evaluated automatically, assigning them to the categories of interest.

2. THE FIRST LEVEL OF AUTOMATION

2.1. Advanced Driver Assistance Systems

Advanced driver assistance systems, commonly called ADAS, are born with the aim of supporting the users in the driving process in order to increase road safety and reduce the risks deriving from critical situations such as, for example, heavy traffic or queues.

They detect the environment surrounding throughout various types of sensors such as radars, video cameras, and ultrasound devices. Some systems, in addition to alerting the driver, can intervene in the driving of the vehicle by considering the longitudinal and transverse direction, or by accelerating, braking, and steering independently, within certain limits. In fact, the driver must constantly monitor the system and be ready, at all times, to take full control of the driving (Figure 2.1).

Figure 2.1.Visual Representation of ADAS.

European Parliament in December 2017 approved by a majority the mandatory installation of some advanced driver assistance systems on all newly registered cars. Some ADAS, therefore, will soon be mandatory on all new cars. Specifically, devices such as Automatic Emergency Braking (following the detection of pedestrians), the Lane Keeping System, and Adaptive Cruise Control (speed regulator) will be standard.

With the aim of drastically reducing the victims of road accidents, caused by human errors in 90% of the cases, these technologies will become indispensable for the homologation purposes of the vehicle, just like the ABS, which prevents the wheels from locking while braking, and the Control Electronic Stability Program (ESP), which became mandatory starting from the 1st of November in 2014.

2.1.1. <u>Types of ADAS</u>

The main Advanced Driver Assistance Systems can be cataloged according to the Euro NCAP 2018 classification in three main categories:

- Lane control systems;
- Speed regulation systems;
- Systems that improve visibility.

2.1.1.1. Lane Control System

Lane control systems alert the driver if the lane line is approaching or crossed without using the direction indicator (arrow). They are very useful for preventing sleep strokes and distractions often caused by infotainment systems and smartphones.

The main variants of this type of system, available on vehicles on the market, are Lane Departure Warning (LWD) and Lane-Keeping Assist (LKA).

Lane Departure Warning (LDW) is a system that warns the driver when the car gets too close to the boundary strip of the driving lane (Figure 2.2). Especially in long-distance journeys, the driver can unintentionally get too close to the line that defines his lane, remaining unaware of the potential danger until it is too late to remedy: the wheels may be on the grass or the gravel side of the road or, in extreme cases, the car can move on the trajectory of the arriving vehicles. The sudden awareness by the driver could generate a panic response, resulting in a loss of control of the car and a subsequent accident. The warning is given through an audible signal or vibration of the steering wheel. It is, therefore, a system that requires the driver to take corrective action to not cross the road markings. Generally, this system works only at high speeds and does not activate if the driver uses the direction indicators. Its operation can be compromised by the poor visibility of the horizontal strips in case of heavy rain, fog, mud, snow or poor maintenance. In this case, some technologies warn the driver of the impossibility of assisting him.

Lane-Keeping Assist (LKA) is an alarm system designed to help the vehicle maintain the lane without accidents. However, while warning systems require the driver to take corrective action, Lane Keep Assist automatically generates a counter-steering that returns the car to its lane (Figure 2.3). When the car is close to the lane boundary strip, the system actively brings it back to the correct trajectory, by applying a slight braking force on a single wheel or direct input on the steering, in the event of electric power steering.

A video camera mounted on the interior rear-view mirror "reads" the demarcation strips in front of the vehicle, combining this information with speed and trajectory to calculate the time and distance that precede the crossing of the lane limit. If the value of one or more of these parameters is lower than the limit value, Lane-Keeping Assist intervenes by applying a slight correction to the steering. The corrective maneuver is intentionally slight and can be easily countered, so as not to relieve the driver of the responsibility to consciously drive his car. However, since the driver does not have to use Lane Keep Assist as a replacement for driving, some systems deactivate if they detect that he is maintaining passive driving.

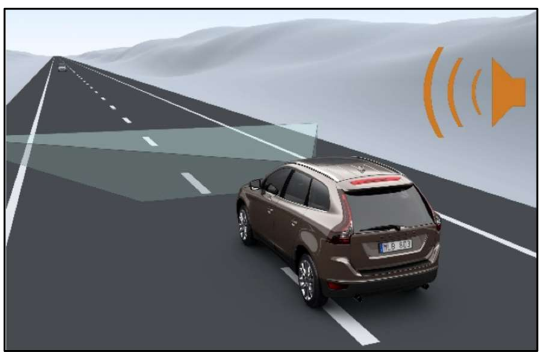


Figure 2.2. Lane Departure Warning.

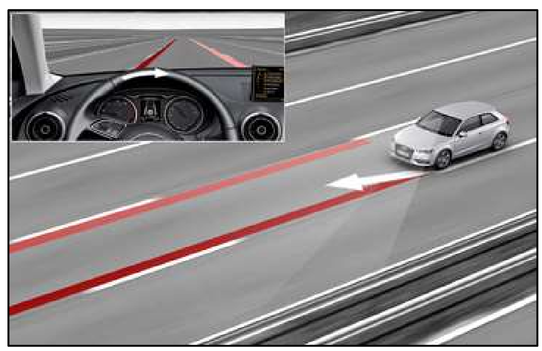


Figure 2.3. Lane-Keeping Assist.

2.1.1.2. Speed Regulation Systems

Speed regulation systems help the driver to adjust the speed of the vehicle according to environmental and traffic conditions. The main variants of this type of system, available on the vehicles on the market, are:

- Speed Alarm Systems or Intelligent Speed Assistance, for compliance with speed limits;
- Autonomous emergency braking systems, to avoid rear-end collisions;
- Speed regulation system according to the safety distance.

Speed Alarm Systems or Intelligent Speed Assistance (ISA) help the driver contain speed within the specified limits (Figure 2.4). Excessive speed is one of the main causes of accidents. Speed limits are intended to promote the safe use of the road network, keeping traffic speeds below the maximum allowed in various circumstances, and protecting both passengers and other road users. Excessive speed can be unintentional: if the driver is tired or distracted, he can easily exceed the permitted speed without realizing it; in other cases, he may miss the reading of a signal that invites you to moderate speed, for example by entering a residential area. Some speed alarm systems display the current speed limit so that the driver is always aware of the maximum speed allowed on that stretch of road. The speed limit can be determined by software that analyzes the images provided by a video camera and recognizes vertical signs, or by particularly accurate satellite navigation. Some systems emit an acoustic signal that warns the driver of exceeding the permitted speed. Currently, these are systems that can also be deactivated and require a response from the driver to the warning.

Figure 2.4. Intelligent Speed Assistance (ISA).

Emergency braking systems help the driver to avoid accidents caused by late braking or insufficient braking force, with the aim of reducing the collision speed in the event of an impact with another vehicle (Figure 2.5).

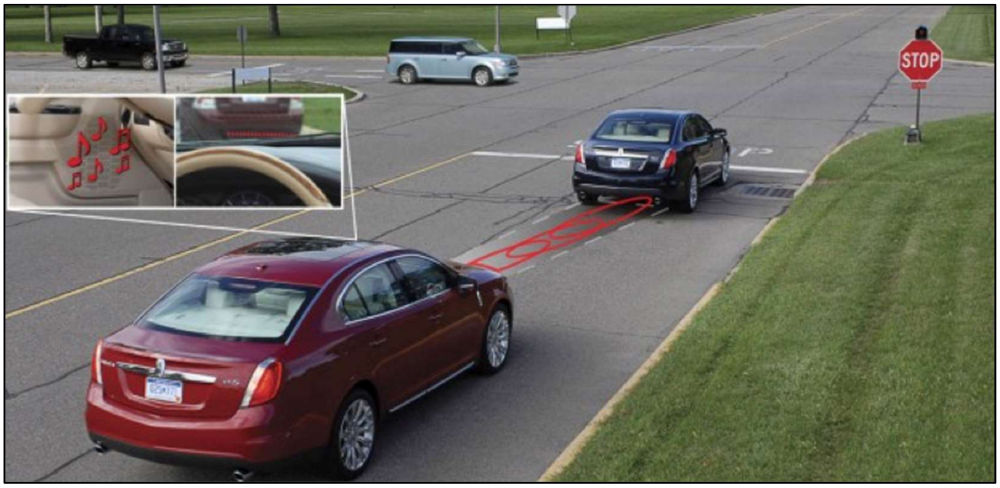


Figure 2.5. Emergency Braking System.

These systems belong to the Autonomous Emergency Braking category (automatic emergency braking systems):

- Autonomous: the system acts independently from the driver to avoid or mitigate the impact;
- Emergency: the system intervenes only in a critical situation;
- Braking: the system tries to avoid impact by operating the brakes.

AEB systems improve safety in two ways: firstly, they help to avoid impact by identifying critical situations in time and alerting the driver; secondly, they reduce the gravity of unavoidable accidents, reducing the speed of the collision and, in some cases, predisposing the car and seat belts to impact.

Their operation is based on optical sensors, cameras, or LIDAR able to identify obstacles in front of the vehicle. At first, the AEB generally warns the driver of the possible imminent impact and then, if the driver does not react to the warning, the system intervenes autonomously applying total or partial braking.

Cruise Control is an electronic system that allows automatic adjustment of the speed of a vehicle or another vehicle. The driver selects the desired speed, and it is maintained, compatibly with the trim conditions of the car itself. There are two types: Cruise Control and Adaptive Cruise Control. The first only maintains the speed set by the driver. The driver can choose to increase or decrease the set speed, for example, if he decides to overtake another car, press the accelerator and increase the speed that will return to the one previously set only when the acceleration stops. Unlike cruise control, the Adaptive Cruise Control (ACC) system recognizes previous vehicles along the driving path and their speed and consequently intervenes independently in the management of the engine and brakes in order to maintain the right safety distance (Figure 2.6).

Figure 2.6. Adaptive Cruise Control.

2.1.1.3. Systems that Improve Visibility

The systems that improve visibility help the driver in those driving situations that are not very visible from the passenger compartment, due to particular traffic or road conditions. The main variants of this type of system, available on the vehicles on the market, are:

- Adaptive headlights, to increase visibility in corners;
- Blind corner warning systems, for visibility in overtaking maneuvers;
- Parking assistance systems.

Most driving maneuvers are based on what the driver can see. In daylight, in clear weather conditions, the visibility of the road ahead is generally adequate. Night driving, on the other hand, can be challenging. The adaptive headlights rotate the light beam around the curves of the road, giving the driver a better view of the area in front (Figure 2.7). They vary the lighting according to the course of the road, the speed of travel, traffic and environmental conditions. They guarantee maximum brightness without, however, disturbing the vision of the drivers of the vehicles coming from the opposite or preceding direction of travel.

Figure 2.7. Adaptive Headlights.

The blind corner is that portion of space behind the moving vehicle that has a particular characteristic: when another car is occupying that area at the moment of overtaking, it is not visible either with the interior mirror or with the rear-view mirrors (Figure 2.8).

Systems are now available that can monitor the blind angle, helping the driver to change lanes in safe conditions and alerting him through an acoustic or luminous signal in the event that a vehicle not visible through the mirrors is arriving. The system is able to recognize static objects present along the road such as safety barriers, poles or parked vehicles: in these cases, it does not trigger the signal. The system is active from 5 to 180 km/h and assists the driver in facilitating driving especially in city traffic and on multi-lane roads.

Figure 2.8. Blind angle warning system.

Parking assistance systems use ultrasonic sensors which, by means of acoustic signals, warn the driver of the distance between the vehicle and adjacent obstacles during the maneuver (Figure 2.9).

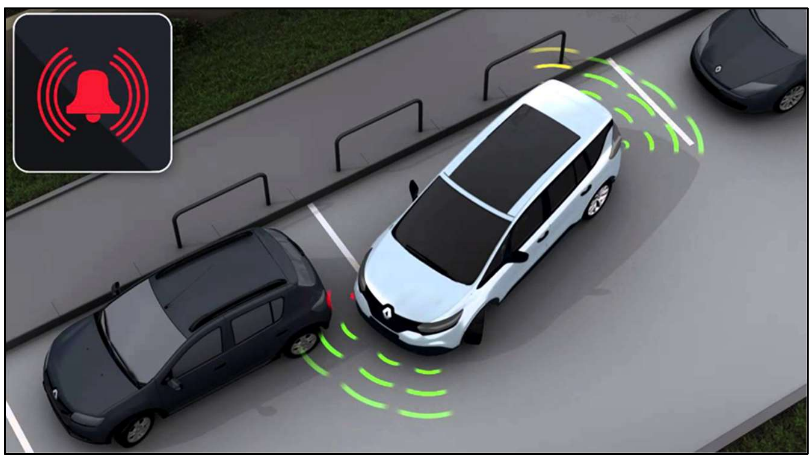


Figure 2.9. Parking assistance system.

2.1.2. Adaptive Cruise Control

Adaptive Cruise Control (ACC) is one of the main technologies of Advanced Driver Assistance Systems (ADAS) among the first level of automation, which tried to reproduce human driving. This technology allows for establishing a set distance from the previous vehicle, by modulating cruising speed and limiting abrupt braking (Lin et al., 2008; Hajek et al., 2013; Piccinini et al., 2015). The ACC detects the surrounding environment through sensors, radar, cameras and ultrasonic devices thus controlling traffic situations and modulating the engine and powertrain

(Morando et al., 2016). When the chosen distance falls below the safety threshold, the system automatically intervenes in the management of the engine and brakes to reduce the speed of travel, when the road is free again the ACC returns the vehicle to the set cruising speed. It has been calculated that, when combined with an anti-collision warning system, the ACC can reduce the number of sudden stops on motorways by 67% and rear-end collisions by 73%.

The ACC, while maintaining the speed set by the driver, is also able to adapt it to traffic conditions, by accelerating or decelerating automatically. In fact, the system records the environment in front of the vehicle so that, if the driver gets too close to the vehicle in front, the system slightly decelerates to ensure compliance with the safety distance. This distance can also be adapted to the driving behavior of the individual.

With the term "adaptive" the main characteristic of the system is expressed, which is able to adapt the speed to traffic conditions, accelerating or decelerating automatically thanks to the reception of information on the environment outside the vehicle through frontal RADAR or LIDAR sensors, appropriately Weighted. The standard ACC can be activated at speeds between approximately 30 km/h and about 200 km/h.

The ACC Stop & Go variant, in addition to keeping the safety distance from the car in front constant, reduces the vehicle speed up to the stop in case of queues. The car then restarts automatically thanks to the system or the driver who puts the accelerator pedal into action.

The first version of the commercial ACC system was presented in 2000 and allowed implementation only for sections on the motorway and along the highways, the second version, presented in 2004, extended its use also to state roads. The future ACC generation will be different from the current one for the even more powerful analysis software.

Today, the ACC system can be based on LIDAR or RADAR technologies; the first uses a laser instrument, while the second uses radio waves to control the environment surrounding the vehicle. The RADAR system was preferable because it worked even in adverse weather conditions, such as in the presence of fog or of completely dirty frontal vehicle sensors. The RADAR system uses a sensor placed on the front of the vehicle that emits a continuous series of electromagnetic waves and evaluates the time between the emission of the wave and its return; in this way, the on-board electronics can assess the presence and distance of obstacles in front of the vehicle. Finally, it should be pointed out that the driver can decide at any time to resume manual driving control, by using the brake pedal or pressing the deactivation button on the steering wheel while using the ACC.

Nowadays, many drivers use the ACC while driving because of its comfortability. In particular, they used the system for 95% of off-urban roads and 99% of motorways. These percentages fluctuate with the traffic conditions and tend to increase on roads with high-speed limits and in case of long journeys (Huber et al., 2010; De Winter et al, 2014).

Level 1 leads to partial automation in which the system assists the driver by relieving the tasks related to the driving process. The application of autonomous taxonomies suggests that in this level of automation the users should control the task of driving with the mind, having hands and feet free (Stanton et al., 2009; Banks et al., 2014). This condition should not be interpreted as replacing the role of the driver by machine but as active cooperation between the two entities (Weyer et al., 2015). In fact, the systems are not able to act autonomously, thus the role of the driver is still essential: he can decide to activate the system or take control of the vehicle at any time, by pushing on the accelerator or braking button (Biassoni et al., 2016; Seacrist et al., 2020).

Despite the fact that the ACC was born to improve road safety, mitigating accidents and reducing the overall severity of collisions, injuries and deaths, it introduces new accidental causes. For instance, the system could lose the previous vehicle in curves or not detect small vehicles, such as motorcycles; it also presents problems for the identification of stationary vehicles, especially in city contexts and low visibility due to rain and fog (Kaber et al., 2001; Christoffersen et al., 2002; Inagaki, 2003; Klein et al., 2004; Weick et al., 2005; Harbluk et al., 2007; Beller et al., 2013). So, the study of the interaction between this system and the driver's behaviour, specifically how this innovative cooperation could influence the attention and the mental workload of drivers, is very important.

Since car driving is a dynamic control activity in a continuously changing environment, attention and mental workload are related to driving performance and road safety (Ryu & Myung, 2005). They are closely linked to the accident rate for both very high and extremely low values. Under extreme mental workload, drivers may exhibit delayed information processing, or even not respond at all to incoming information, because the amount of information exceeds their capacity to process it. In contrast, when the mental workload is lower than the proper level, i.e. drivers feel under-engaged, they become bored, they could even experience mind-wandering episodes and thus also tend to make driving mistakes (Engström et al., 2005; Brookhuis & De Waard, 2010; Reimer et al., 2012; Milleville-Pennel et al., 2015; Aricò et al., 2016; Di Flumeri et al., 2018; Young et al., 2002).

Thus, the ability of a mental workload measure to evaluate drivers' effort correctly and continuously might be valuable in strengthening road safety, improving the usability of ACC, and designing appropriate adaptive automation strategies (Ryu & Myung, 2005).

Several research studies about the evaluation of the influence of the ACC on the drivers' mental workload and attention have been carried on, but many of them have been developed in a simulator and didn't include a multimodal approach.

Nilsson (1996), for example, has investigated the safety effects of ACC in critical traffic situations through a simulator study, which has involved twenty drivers. Only performance-based measures (braking behaviour) and subjective assessments (NASA-TLX) have been used in order to evaluate the influence of ACC when the user has been stuck from a braking leading vehicle. The obtained results have shown that ACC didn't change the difficult of the driving task, because all the subjects have performed the task relatively well, but has increased the reaction times. These results have been confirmed also by Bianchi Piccinini et al. (2012) and Takada et al. (2015), that have estimated the subjects' mental workload by only physiological measures (electrocardiograms and respiration).

Vollrath et al. (2011) have conducted a simulator study to evaluate the ACC influence on driving behaviour. The have selected a sample group of twenty-two participants that drove on a highway and on a motorway in two different conditions (with and without ACC). Using only performance-based measures (maximum velocity, driver reaction time), they have found that with ACC delayed driver reactions in critical situations, as a narrow curve or a fog bank, have occurred.

Schakel et al. (2017) have developed a naturalistic driving study consisting of eight drivers that have driven their car with ACC for five weeks. They have monitored only performance-based measures (spacing, headway, speed, acceleration, lane use, and the number of lane changes) and they have found lower reaction times in the ACC ON condition. These results have been confirmed also by the driving simulator study developed by Xiong (2012), Fleming et al. (2019), Törnros et al. (2002) and Lee et al. (2002).

In a driving simulator study, Hoedemaeker et al. (1998) have involved thirty-eight users, that drove on a motorway with ACC and manually, and they have found that all went faster in the first case because they trusted the performance of the system.

In different simulator studies, Stanton et al. (1997, 2000, 2005, 2002, 2007) have used performance-based measures to study the influence of ACC in terms of drivers' distraction. They have found that the use of ACC has decreased the driver's situation awareness and attentional resources. Cho et al. (2006), by psychological measures (locus of control, trust, workload, stress, etc.), have explained that this decrease was due to the shift of their attention away from driving.

Rudin-Brown et al. (2004) have studied, in test-track research, the behavioral adaptation induced by the ACC in drivers. They have considered eighteen drivers that have followed a lead vehicle with and without ACC. By performance-based measures, they have shown that with ACC the drivers' behavioral adaptation has increased because they were more focused on the secondary task and so the response time to a hazard condition has increased. These results have been confirmed also by the driving simulator study developed by Ma et al. (2005), Dey et al. (2016), Wang et al. (2022).

De Winter et al. (2014) have investigated by subjective assessments (NASA_TLX) the effects of ACC on drivers' workload and situation awareness. They have found that this last deteriorated using ACC compared to manual driving.

2.1.3. Data collection

The data collected aims to understand how ADAS influences the behavior of drivers while driving. Although the purpose of the ADAS is to have a positive effect on road safety, it was found that they can have negative effects on driver behavior. The introduction of such systems, in fact, could lead to situations in which the attention of drivers is diverted from traffic as induced to perform secondary activities that can distract the attention from driving. As a result, a driver may not notice a sudden danger and may not be ready to react promptly. Therefore, the impacts on the safety of these technologies often do not meet the expected benefits, because drivers change their behavior while driving. This behavior change is called Behavioral Adaptation (BA). To analyze in depth the Behavioral Adaptation of drivers towards driver assistance systems, it is necessary to take into consideration various factors such as the role of secondary driving tasks, Situational Awareness (SA) and their acceptance by users.

It has been possible to define also a multimodal approach that integrates results coming from different techniques: workload subjective assessment (NASA-TLX and personal questionnaires), workload physiological measures (brain activity through Electroencephalographic Technique and visual behavior through Eye Tracking device), and performance-based measures (car parameters through the Video Vbox Pro device mounted on the vehicle).

Thanks to this multimodal approach, it was possible to:

- understand the ACC effects on the drivers' primary task, in order to evaluate how ACC use can have an impact on their workload and attention. They have been assessed, in particular, for ACC experienced and inexperienced users, to evaluate the influence of the previous ACC knowledge.
- compare the different measures used, in order to provide evidence of the complementarity of the obtained results.

3. THE IMPACT OF ACC ON VISUAL BEHAVIOUR

3.1. Introduction

Visual behavior is a useful analysis methodology to identify user areas of interest. In the road context, in fact, specific elements can be perceived even at a distance, considering specific contexts of brightness or positioning. In addition to infrastructure elements, drivers can also be attracted to specific mechanisms within vehicles, especially with the new introduction of the Advanced Driver Assistance Systems (ADAS). Many studies, in fact, have reported variations in the driver's gaze in relation to the layout characteristics of the dashboard or, simply, of the points of insertion of the controls of the new systems. Visual behaviour, in this way, becomes one of the main focuses of road safety analysis, evaluated in relation to the introduction of ADAS. In particular, eye tracking allows you to identify the areas of interest of the driver, defining them close to attention or inattention (Ghasemi et al., 2022; Acerra et al., 2019; Lantieri et al., 2021; Ghasemi et al., 2020; Vignali et al., 2019).

3.1.1. Eye Tracking

Eye tracking is a process that monitors eye movements to determine where a subject is looking, what they are observing, and how long their gaze lingers over a certain point in space. It is a technique that records the dilation and contraction of the pupils, thus realizing the eye tracking that is the path taken by the eye during vision (Figure 3.1).

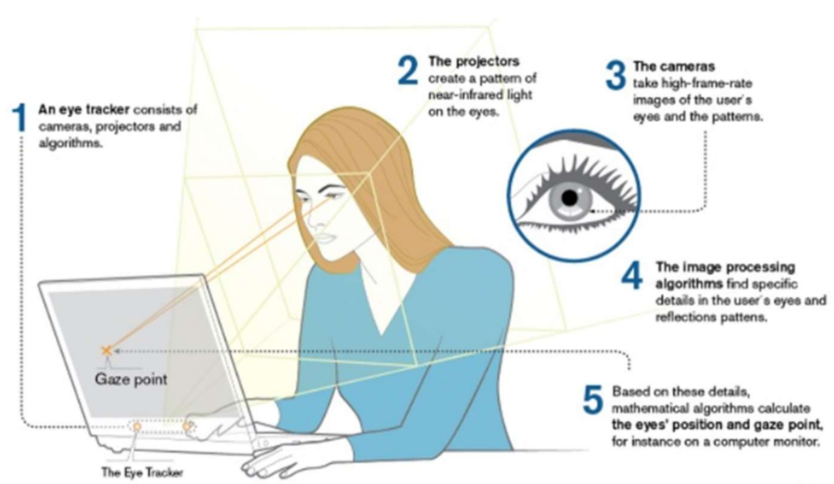


Figure 3.1. The Eye Tracking Technology.

It was born for clinical purposes, with the aim of understanding how the mechanisms of human vision work. The eyes move at least 3 or 4 times per second, when we observe something, following a seemingly random order. A displacement lasts a tenth of a second, while fixations last from 2 to 4 tenths of a second.

In 1879, Louis Emile Javal noted that, when reading a text, people focus on some words, while others move more quickly. Edmund Huey later created an instrument capable of tracing the movement of the eyes in reading. This device consisted of a kind of contact lens, equipped with a hole for the pupil, which was connected to an aluminum pointer, capable of moving according to the movement of the eyes. With this tool, which can be considered an early eye tracker, Huey was able to study what words the reader was dwelling on.

Later developments in eye tracking came with Charles H. Judd, who developed a non-intrusive eye tracking device, unlike Huey's. Judd's instrument recorded the movements of the eyes on the film, allowing a more detailed study of the pupil's actual position. Guy Thomas Buswell, on the other hand, analyzed eye movements in reading, considering the different ages and different levels of education of people. Buswell's studies were fundamental to the development of eye tracking in literacy, which is still of great importance today. These theories were published in the book "How people look a picture: a study of psychology".

In 1931, Earl, James, and Carl Taylor created the Ophthalmologist and Metronoscope, which were used to record eye movement during reading, helping people read more effectively. Through these studies, they were able to understand that reading was not only a regular movement of words, as Luis Javal had proposed, but, on the contrary, a reader scans more words, stops to better understand them and performs a scan again. Breaks are called fixations and scans are called saccharides.

In 1967, Yarbus used the eye tracker on a group of people, asking them to observe a familiar scene for three minutes, and asking them several questions, in order to understand the eye tracking strategy.

In the 1970s and 1980s, there was considerable development of this technology in marketing, in order to measure the effectiveness of ads in magazines. This allowed to determine which parts of the page are viewed most and for how long (Khan et al., 2019).

In 1990, the Gallup Applied Science eye tracking system was used by NFL analyst Joe Theismann and fans to determine which parts of the game were lost to the observer.

Since 2001, Tobii Technology has developed eye tracking technology, which allows disabled users to control eye trackers using only their eyes.

In 2009, Pernice and Nielsen confirmed the use of this technology to analyze what people see accurately, what draws their attention or what they ignore, reporting these deductions in their book, entitled "Eyetracking Web Usability" (Botero, 2019). The search for eye tracking is continuing to study eye movement and the link between the eyes and mind in reading and many other fields.

3.1.1.1. Fields of application of eye tracking

Eye Tracking studies visual behaviour to understand cognitive and emotional processes, providing theoretical and conceptual approaches. This is a highly developed technique because it is not invasive in obtaining information on vision and brain functions; it is used in different fields, such as in neuromarketing, in the processes of literacy and autism spectrum disorder, in psychology, in understanding human behaviour, and in medicine. An example is reported by Chamorro who in 2012 stated that saccharide movements can be used as biological markers of neurological and psychiatric diseases (Botero, 2019).

The first field, in which eye tracking is used, is represented by the literacy process. This research began in the second half of the twentieth century, focusing on the study of fixations and saccharides, considering the complex coordination between lexicon, semantics and coding of words.

The second field is related to the study of cognitive processes, such as attention and memory. Attention is the process by which information, both from the environment and from the person himself, is filtered and selected. Memory, on the other hand, is a complex process through which images are encoded, recorded and retrieved.

The third field is the diagnosis of neurological and psychiatric pathologies. In this case, the use of the eye tracker has the purpose of supporting diagnoses, such as autism spectrum disorder, Williams syndrome, schizophrenia and Alzheimer’s.

The fourth field, finally, is the study of the interaction between person and machine (usability), as in the use of mobile phones, computers and TV (Botero, 2019).

These applications, which are combined with those linked to the subsidy for the control of wheelchairs, prostheses and rehabilitation applications, define their high versatility and effectiveness.

3.1.1.2. The eye movement

Under normal conditions, the eyes are moved continuously and change direction, about five times per second. The ocular movement has a double purpose: to keep the image of the objects moving on the fovees and to direct the fovea on the various details of the surrounding environment, in order to construct the overall image (Figure 3.2).

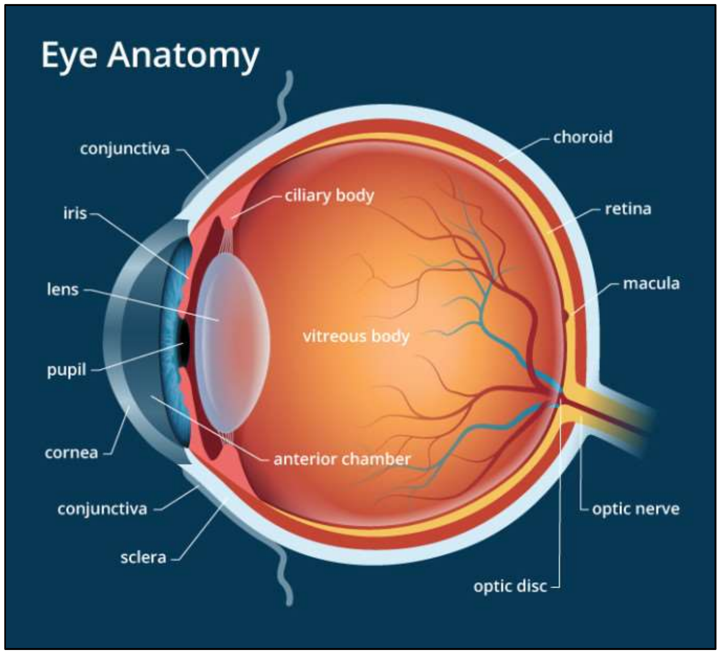


Figure 3.2. Anatomy of the eye

Eye movements can be distinguished in:

- Ductions: monocular movements in all directions;
- Versions: conjugated binocular movements, in which the visual axes maintain their reciprocal position, that is, they move in the same direction;
- Vergences: binocular movements in which eyes move in opposite directions.

In addition, such movements can be distinguished as slow or fast, depending on the speed of movement. The system that regulates such eye movements is a neuroanatomical system, which is very complex and still hypothetical. The main functions of this system can be attributed to six distinct neuronal control systems: physiological nystagmus system, slow motion tracking system (Pursuit), vestibule-ocular reflex system, optocyst movement system, Vergence movement system and ocular saccharide movement system. All these systems exploit, as effectors, the motor neurons of the oculomotor nuclei of the brain stem.

The physiological nystagmus system is a system that affects the involuntary movement of the eyes. It is a slight tremor, due to the movement of some extra-ocular muscles, which involves a continuous change of the image on the retina.

The system of slow tracking movement (smooth Pursuit) keeps the image of the object in the fovee, which moves continuously in the field of gaze. It intervenes mainly when the target moves and the observer remains stationary, so as to keep the image continuously on the fovea. This attitude of the motor system is due to the fact that the nervous system calculates the direction and speed of the movement of the target image on the retina. These operations are controlled by the occipital cortex. The smooth Pursuit system can only operate when the target image is on the retina, so it does not act in the dark, unlike the saccharide system.

The vestibule-ocular reflex system serves to stabilize the eyes when short and sudden changes in the head position occur. This system keeps the gaze in the same direction as before the movement of the head. The signal that gives rise to this reflection depends on the membranous labyrinth of the inner ear. This codifies the movements of the head, in reference to the three axes of the space and this happens thanks to the presence of the three semicircular channels, each of which is placed in direction of one of the three planes of the space. Each semicircular canal contains viscous liquid, called endolymph, which moves inside them, depending on the position assumed by the head (Figure 3.3).

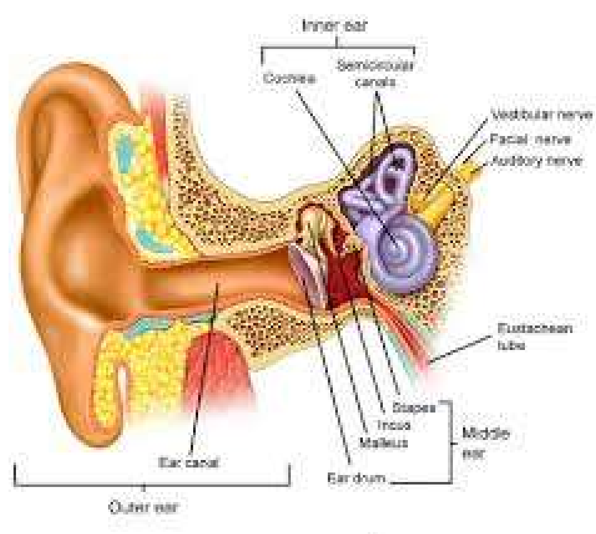


Figure 3.3. Anatomy of the hear.

The end of each semicircular canal has a bulge, inside which there are the receptor organs, which are hair cells able to appreciate the displacements of the endolymph by inertia, when the head is moved laterally, forward or backward, Either up or down. These cells transmit the signals related to the neurons of the vestibular nuclei, which evaluate the variation of the position of the head by integrating the information coming from each channel, then send an appropriate corrective signal to the oculomotor nuclei in order to stabilize the eyes. The movements that derive from this system are present from birth and are also carried out with closed eyes.

The optocytic system is a system that involves the involuntary movement of the eyes, when we make large movements according to the translation speed of the image on the retina. It produces a movement of the eyes in the same direction and with the same speed. The vergence system, on the other hand, is a voluntary movement system, which allows the gaze to converge on the point of fixation.

In eye tracking, the two eye movement systems mainly observed are the saccharide and fixation systems, which will be explained in more detail, since the study of bags and fixations allows to understand the attention and distraction of the driver driving on the various objects around him. The bags and fixings are the two parameters analyzed by eye tracking, in order to obtain information on eye tracking and driver behaviour while driving, to implement road safety (Vetturi, et al., 2019).

3.1.1.3. Saccharide system

The saccharide system presides over the rapid orientation of the fovea towards a target, which is in the visual field and on which the observer's interest is directed; when visual attention is transferred between two fixed areas, with the aim of creating an area of interest in the narrow field of vision (Khan, et al., 2019).

This system generates conjugated eye movements, which are termed saccharide. The saccharides are rapid eye movements from one fixation point to another, which lasts from 30 to 80 ms, in which you do not have a vision. The subject does not perceive visual information along the trajectory of the movement.

According to some medical studies, some cognitive functions are temporarily inactive during the saccharide; the eye does not follow a straight path but may follow different trajectories during this movement (Vitturi, et al., 2019).

The saccharide movement lasts fractions of a second, in particular, it starts 0.2 seconds (latency) after the target detection and is completed in about 0.05 seconds (execution time). They are of a basilistic nature; once the neuronal process, which causes a saccharide movement, is initiated, the control system is unable to generate another, before 0.2 seconds, regardless of the behavior of the target.

To perform a saccharic motion, the system must know the position of the object in space and the position of the eye in the orbit. These parameters are then analyzed by the control system and this provides a certain direction and amplitude.

3.1.1.4. Fixation system

The fixation system keeps images of motionless objects on the fovee. When the eyes and the target are stationary, the fixation can be maintained through a conscious effort, that is, by suppressing the voluntary sacs. During fixation, to avoid the phenomenon of local adaptation (Troxler effect), there are small continuous and unconscious movements of the eyes, of 10-15 minutes of arc width. They consist of: drift, which are slowly drifting movements, which make the fovea move on the image of the fixed object and flick, which are small saccharide movements, which make the fovea return to the target after a drift has removed it too far from it.

A fixation occurs when the eye focuses on a specific area, so the subject perceives only a small part of its visual field. During fixation, there is the cognitive processing of the observed object and the transfer of attention to it. The duration of the single fixation depends on the intensity of the luminance contrast, the complexity of the vision area and the associated cognitive load (Vetturi, et al., 2019). Fixations last from 20 to 60 ms and you have vision (Botero, 2019).

Most fixations are directed at the focus of expansion (the point in space where all the vectors of the optical flux intersect) with the head, which looks upwards (Costa, et al., 2019).

3.1.1.5. Operation of fixation-saccad system

Humans and other foveated animals, such as monkeys and birds of prey, visually scan scenes with a fixed-saccharide-fixed system: periods of stability (fixations) are interspersed with rapid eye shifts (sacs). During fixation, the visual axis (and the high-resolution foveola) is directed toward an object or a place of interest. For humans, the duration of the stability period is of the order of 0.2-0.3 seconds, depending on the complexity of the task and the stimulus. While the bags last between 0.01 and 0.1 seconds, depending on the amplitude of the movement. If the scene contains moving objects, or is the same subject in motion, the stabilization of the gaze on an object requires a tracking fixation or a smooth Pursuit chase. In the latter, the eye rotates to keep the eye fixed on the target.

When the observer's head bounces, due to external disturbances or locomotion, the stabilization of the eye involves compensatory eye movements, vestibulo-ocular and optocystic. These movements cannot be differentiated in terms of oculomotor or neurophysiological properties, therefore they must occur simultaneously (Pekkanen, et al., 2017). We then rotate the head in a comfortable position and then orient our eyes to see something. In this process, the position of the head defines the direction of the gaze on a coarse scale, while the direction of the gaze on the fine scale is determined by the orientation of the eyeball (Khan, et al., 2019).

An important aspect to understand the functioning of fixings and pouches is the modeling of the direction of the gaze, which is based on the visual axis or optical axis. The visual axis, which forms the Visual Axis (Los) and is considered the effective direction of the gaze, is the line that connects the center of the cornea and the fovea. The optical axis, or Optical Axis (log), is the line that passes through the centers of the pupil, cornea and eyeball. The center of the cornea is known as the nodal point (Figure 3.4).

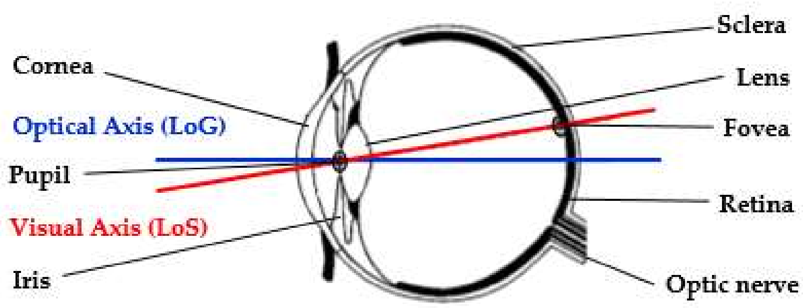


Figure 3.4. Visual and Optical Axis.

Fixations and saccades provide information, which is used for the classification and identification of visual, neurological and sleep conditions.

In the field of medical psychology, fixation data is used to analyze a person's attention and concentration level, while saccharide movements are used in studies of human vision, in drowsiness and vision owl and lizard, because of their similarity to the visual behavior of these animals (Khan, et al., 2019).

In night vision, the lighting values vary from 0.0001 lux, on a night without a moon, to 1 lux, on a night with a full moon; the low night light results in less stimulation of the eyes, which, therefore, tend to adapt. As a result, it is more difficult to assess the data of fixations and pouches, which lead to greater distraction by the driver.

About 95% of retinal photoreceptors are sticks, which are sensitive to light and respond to individual photons. In the periphery of the retina, there is a low spatial acuity, which entails, together with less color vision at night, an adaptation of vision (Gruner, et al., 2017).

3.1.1.6. The psychology of driving

Psychology is the science that studies the psychic, conscious and unconscious, cognitive (perception, attention, memory) and dynamic processes (personality, motivations, emotions). It uses various methods to investigate the personality of individuals, in which, in relation to the study of driver psychology.

Driving behavior is related to emotions, habits and innate or acquired facts. The individual is free to make decisions but is conditioned by social forms, which are positive or negative conditions. Therefore, the assessment of the driver's behaviour at the wheel should not only be theoretical, but also psychological, by asking the subject a series of questions, through interviews or questionnaires.

The driver's performance derives from his personality and this can be detected behaviours, which cause a reduction in the risk to the driver; we analyze, for example, the traffic conditioned by vehicles, therefore we evaluate the different psychologies of drivers, and the attention placed on other drivers.

The first fundamental aspect to investigate about the driver is his perception at the wheel, that is the set of information that the brain receives through the senses, which it then processes, to grasp reality. To perceive space means to recognize the geometric characteristics of an object. Perception is a complex aspect and is linked to optical illusions, which can lead the driver to interpret reality incorrectly and make more mistakes as he loses concentration.

The second fundamental aspect is learning, which is achieved by making experiences, in which the behaviour of the driver adapts to the surrounding environment. Driving, for example, is learned through experience, but not everyone becomes a safe driver; this leads to more accidents and less road safety.

Last fundamental aspect is memory, which refers to a dynamic vision of reality, then to continuous changes. He uses not only perception and coding, but also past experiences (Bucchi, et al.,2012).

Driving is important in the perception of the environment through the senses, ie sight, hearing and smell. In this paper, for the study of eye tracking, of particular interest is the sense of sight. The human eye is a camera, which channels light waves through the opening of the pupils. It is equipped with a natural lens, which focuses the rays of light and transforms them, through the process of adaptation; these rays focus on the retina of the eye. So, when we look at an object, the image will be inverted and two-dimensional on the retina, while the depth and three-dimensionality of the object will be processed by the brain (Bucchi, et al., 2012).

3.1.1.7. Gaze study

The study of gaze is an indirect measure of cognitive processes. The development of eye tracking technology has allowed an accurate assessment of visual behavior, which consists of the behavior of the eye and eye movement.

Through the gaze we can gather information about what other people are observing or we are also able to perceive a multitude of meanings, such as the desire to communicate.

Active detection is a process that allows our senses to be directed toward the environment, to extract relevant information. In fact, the behavior of the gaze can be considered a form of active detection, since we decide where to move the eyes in specific places, in order to sample the useful information of a visual scene. Peripheral vision, however, is not as reliable as central vision, because we can only direct our eyes one place at a time.

In the study of the gaze, two parameters are considered, which are attention and distraction. These are essential for eye tracking, as they lead to a better understanding of the driver's driving behaviour and can be used as a means of reducing road risks. For example, to measure attention and distraction we consider the so-called areas of interest (AOI) related to specific areas of the road pavement (Ghasemi, et al., 2019).

Attention is of fundamental importance for road safety. Drivers must always be aware of the environment around them, going to observe the various elements that make up the visual scene. The attention is opposed to the probability of committing accidents, that is, due in most cases to the development of secondary activities. These are carried out by the driver together with the primary driving activity; the need to perform more than one action, at the same time, leads to the distribution of attention in several spatial positions simultaneously.

Secondary activities induce the driver to a high degree of distraction, leading to a decrease in driving performance and producing a potential increase in road accidents. This can be interpreted as an inability to divide attention between the different tasks performed.

One of the most common secondary activities is the use of the telephone; it is considered one of the main causes of road accidents and one of the main sources of reduced driving performance (Wang, et al., 2017).

Distractions can be visual, manual or cognitive. Input signals (inputs), for example, can be direct, that is, measured directly by the driver, or indirect, that is, measured by the vehicle. The acceleration, steering and braking activities of the vehicle are examples of indirect signals, useful for detecting driver distractions.

There may also be models, which allow drivers to assess distractions, such as mathematical models, rules-based models and models based on machine learning algorithms (Gjoreski, et al., 2020).

3.1.1.8. The techniques used by eye tracking

Eye tracking technology involves the study of eye movement, which can determine what we are thinking, based on where we place our attention.

Eye tracking can be defined as the measurement of movement (activity) of the eyes, while eye tracking is the analysis of data, compared to the visual scene (Chennamma, et al., 2013). The most widely used methods for recording the position and movement of the eyes are: ElettroOculography, Sleral Search Coils, Infrared Ophthalmology and Video-Ophthalmology.

Electro-ophthalmology consists of sensors attached to the skin, around the eyes, in order to measure the electric field, when the eyes rotate. Used for medical purposes, it is easy to use, but it is an invasive method. It is mainly used to detect eye movements during sleep (Figure 3.5).

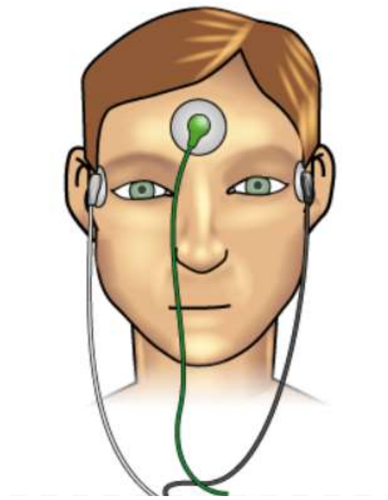


Figure 3.5. The Elecrto - ophthalmology.

Sleral Search Coils consists of small coils, embedded in a contact lens, which allows you to measure reflected light. It has high resolution and precision, but it is an invasive method since it is in contact with the eyes. It is used in medical and psychological research (Figure 3.6).

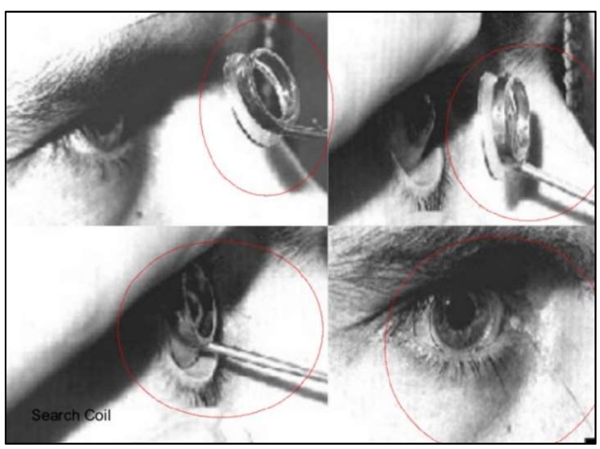


Figure 3.6. The Sleral Search Coils.

Infrared ophthalmology measures the intensity of the reflected infrared light. The light source and sensors can be placed on spherical glasses. Compared to Electro-ophthalmology, it is less noisy but is more sensitive to changes in the external light voltage. It is able to measure eye movement for 35 μs along the horizontal axis and for 20 μs along the vertical axis and is non-invasive (Figure 3.7).

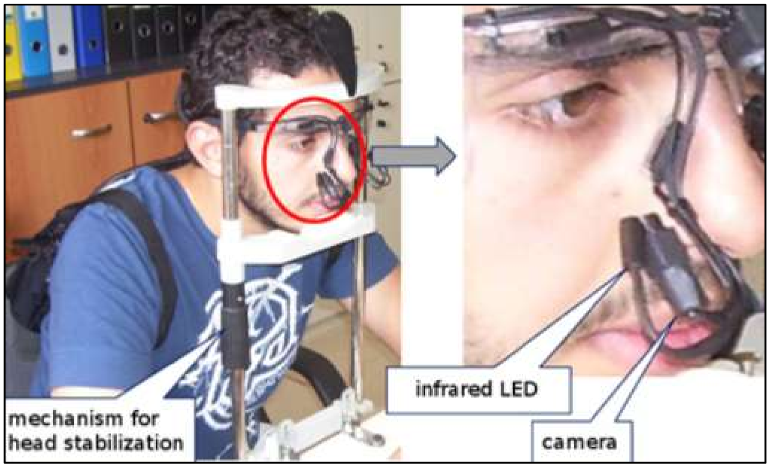


Figure 3.7. Infrared ophthalmology.

Video Ophthalmology is based on the video function, which is the most commercially used. Use single or multiple cameras to determine eye movement using information from recorded images. It can be invasive or non-invasive and visible or infrared light (Chennamma, et al., 2013) (Figure 3.8).

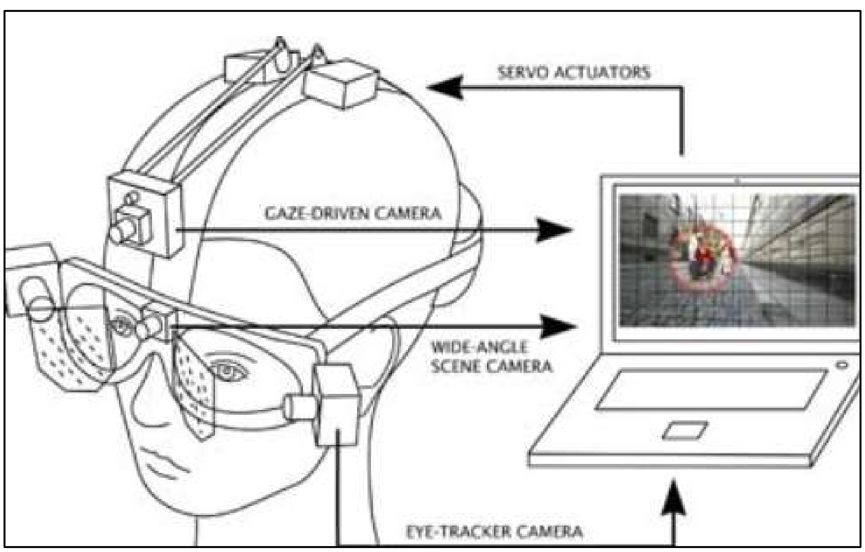


Figure 3.8. Video-ophthamology.

Eye detection methods can be further categorized according to the shape, characteristics and appearance of the eye. Techniques based on the shape of the eye refer to geometric eye patterns, that is, an elliptical or complex eye structure, with the addition of a similarity index.

The elliptical appearance of the eye can serve in daily work. Despite the simple elliptical-shaped models of the eye model features, such as the pupil or the iris, under various viewing angles, these models fail to capture variations and inter-variations of certain eye characteristics.

Instead, the complex models, based on the shape of the eye, are based on the thorough modeling of the shape of the eye. Function-based techniques identify and use a set of unique characteristics of the human eye. These techniques identify the characteristics of the eye and face, which have a reduced sensitivity to changes in viewing angles and lighting.

Techniques based on appearance detect and trace the eyes, using eye photometry, which is characterized by filter response or eye color distribution, relative to the surrounding environment. This technique can be applied both in a spatial domain and transformed, thus reducing the effect of light variations (Khan, et al., 2019).

3.1.1.9. The devices of Eye tracker

Eye tracking technology uses the so-called Mobile Eye tracker as an eye tracking tool. The Mobile Eye tracker is a useful device for measuring the position and movement of the eyes. They are used in research in psychology, psycholinguistics, and marketing, as input devices for human-computer interaction, and in product design. Applications include web usability, advertising, package design and automotive engineering. In general, eye tracking studies, which retain commercial purposes, involve the presentation of a target stimulus to a sample of consumers, while an eye tracker records their eye movements (Figures 3.9, 3.10).

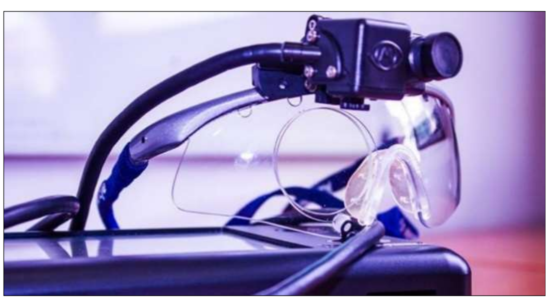


Figure 3.9. Mobile Eye Tracker with lenses.

Figure 3.10. Mobile Eye Tracker without lenses.

Examples of target stimuli may include websites, television programs, magazines, newspapers, and software. The obtained data can be statistically analyzed and graphically reproduced within specific visual models. Fixations, saccharides, pupil dilation, and blink oculars are some of the metrics that are sought, in order to determine the degree of effectiveness of a product.

Eye trackers also provide information on driving behaviour, through monitoring of the user's observation point and through eye movements; this makes it possible to assess the quality of the road safety infrastructure and how the infrastructure influences the behaviour of the various actors in terms of safety performance.

Studies of eye movement date back to the late nineteenth century, but in the eighties a hypothesis was formulated, according to which there is no lag between what is fixed and what is processed; during fixation, the subject elaborates cognitively what observes (Carriers, et al., 2019). In any case, the mechanism involves infrared rays hidden in the monitor so as not to disturb the eye and subsequently recorded by a sensor. Consequently, the analyses that can be carried out are:

- Analysis of fixations on the visual display for some time, in order to search for the overall message of the area of interest;
- Saccades analysis and analysis on visual segments.

The amount of infrared, that is, the illumination received by the eyes, is less than the amount it receives outside on a sunny day and ten to a hundred times less than the amount it receives from the light, to which the eye is exposed for a long time.

Eye trackers can also be remote or portable. The first is fixed to desks to perform tests on the computer screen; they are equipped with a high sampling rate and visual data accuracy and are useful in the data processing.

They are also equipped with a single or multi-camera camera (Figure 3.11).

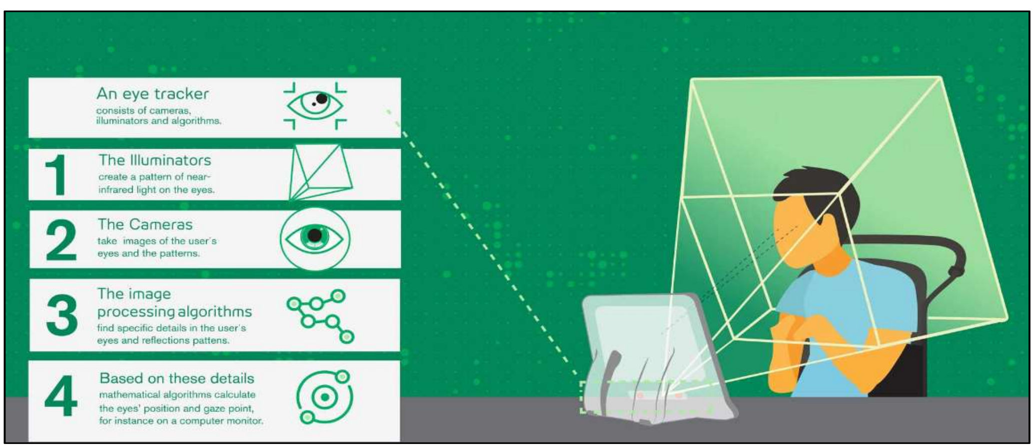


Figure 3.11. Image capture steps via eye tracker.

Portable eye trackers, however, are mounted on the head, using glasses. They are equipped with good mobility for field tests and are excellent in video recording, then used for data processing (Cheng, 2011). Mobile eye trackers are now widely used in eye tracking, as they allow high lightness and mobility. Among the most popular and used are the Mobile Eye XG produced by ASL, Pupil Core and Tobii Pro glasses.

3.1.1.10. Equipment limitations

An essential aspect of eye trackers is the quality of the data, important to verify the validity of the results of the search and the interaction of the gaze. Data quality can be defined as the spatial and temporal deviation between the direction of the actual and measured gaze and the nature of this deviation. The validity of the research results, based on the analysis of eye movement, is clearly dependent on the quality of the eye-tracking data. The same is true for the performance of the look on communication devices. Visual data contains noise and errors, which need to be taken into account.

There are currently no standards or standards for what researchers report on data quality in publications or what manufacturers report on the typical performance of their eye tracker.

Methods exist to deal with low data quality and to maximize the validity of results: correct or abandon data. However, these methods cannot be taken into account without first analyzing the data and identifying noise or errors. Since fixation analysis obscures the quality of the original data, most researchers estimate the quality of their records from various graphs of samples taken.

Researchers wonder if the quality of the eye tracker's data affects the validity of the results and to answer these questions they referred to several effects.

The first effect is the accuracy of the measurements of the residence time. Accuracy (sometimes called offset) is one of the most highlighted aspects of data quality; it refers to the difference between the direction of true and measured gaze. The time of permanence (duration of the look) is the time of observation of an AOI (area of interest), from the entrance to the exit, while the time of total permanence is the sum of all the times of permanence for AOI. Often the noise in the data can be countered by increasing the amount of data, such as with the effect of a low sampling rate on the duration of the tracker fixation (Holmqvist, et al., 2012).

The second effect is precision in the number and duration of fixations. Inaccuracy is not the only problem of data quality that affects the feasibility of research results. Precision refers to the consistency of the calculated points of view when the direction of the gaze is constant. Precision measurements are commonly conducted to locate the eye tracker; this measurement gives an idea of system noise or error.

The third effect is data loss, which refers to samples reported as invalid by the eye tracker. Data losses arise from periods when critical features of the eye image, often the pupil and corneal reflections, cannot be reliably detected and traced. For example, when glasses or contact lenses prevent the camera from capturing a sharp image of the eye tracker (Holmqvist, et al., 2012).

The fourth effect highlighted is the position of the screen on the size of the pupil. Pupil size reacts primarily to changes in lighting but is often used as a measure of mental workload, emotional valence, or as an indication of drug use. A prerequisite for such investigations is that changes in pupil size affect the true change in pupil size and therefore that the eye scanner does not add some systematic error. Factors that affect the quality of the data are the different eye physiology of the participants, the different levels of operator preparation, the recording environment, the camera position and the eye tracker design (Holmqvist, et al., 2012).

The last major limitation of these tools is related to data analysis. In fact, it presupposes a considerable amount of time in relation to frame by frame analysis. In fact, this investigation requires a manual quantification of the frames related to each category of element viewed, without being able to place the least element of output from the program itself.

3.2. Methods

3.2.1. The Mobile Eye Tracker

Applied Science Laboratories, whose acronym is ASL, was one of the first companies to examine eye movements and pupil dynamics. For over thirty years, this company has developed portable eye trackers for eye tracking. These tools are still used in various fields, such as sports, medicine, cars and many others. Among the eye trackers produced by ASL is the Mobile Eye Tracker XG.

The Mobile Eye XG is an eye tracker that allows you to continuously detect the driver's gaze while driving, allowing you to determine, in particular, the point of eye fixation. It is designed for the monitoring and tracking of the human eye's gaze and the main requirements are lightness and mobility, given the absence of cables to external devices (Figure 3.12). In addition, it allows low conditioning of the subject during the test (Mazzotta, et al., 2014).

Figure 3.12. The Mobile Eye Tracker.

The operation of the Mobile Eye XG follows a series of steps, which must be respected, in order to properly adjust the instrument. The Mobile Eye (ME) is an eye tracker designed for eye tracking and tracking applications, suitable for use on drivers. In fact, it is a lightweight instrument that allows good mobility for the user, avoiding the impediment of particular driving maneuvers. This instrument consists of several elements:

1. The Spectacle Mounted Unit (SMU), composed of two cameras: the first focused on the right eye that records all the movements of the papilla, while the second dedicated to the shooting of the external environment. The eye camera, in fact, controls the activity of the eye through a mirror able to reflect the infrared spectrum but not the visible light, so as not to obscure the normal field of view of the subject. The camera scene, on the other hand, is facing forward. Both cameras are mounted on supplied glasses (Figure 3.13).

Figure 3.13. Spectrale Mounted Unit (SMU).

2. Display Transmit Unit (DTU): a small display, with transmission unit (Figure 3.14). This tool is fundamental for two reasons:
   - activate the test recording;
   - monitor, during the analysis, both the external scene and the eye of the study sample.

Figure 3.14. Display Transmit Unit (DTU).

3. a laptop, which is useful during calibration. The software necessary for the subsequent data processing is installed.

Eye camera and scene camera videos can be recorded simultaneously on an SD card memory device, via the DTU, or transmitted directly to the computer via LAN cable or via a wireless connection. The computer, using an application called EyeVision, processes the videos of the eye and the external environment in order to compute the point of the eye's trajectory, on the image of the environmental scene. This can be done in real-time if it is connected to the DTU with LAN cable or with WiFi connection, or it can do the same off-line processing from data recorded on the SD card from the DTU.

In the pc, the point of focus of the look is visualized like a cursor overdubbed to the scene image. It records at a frequency of 30 Hz in a video format "avi" and can also store a digital file containing the recording of the diameter of the pupil and the coordinates of the gaze with reference to the field of view of the camera scene. The software that Eye Vision is able to generate and process are:

- *User file (.evi)*: system and calibration data for each user. These files can be used, with the specific calibration saved, for subsequent uses;
- *Logged data Files (.csv)*: Eye and scene data generated by the track record tool in Eye Vision;
- *Eye and Scene video data (.avm)*: original eye and scene videos, recorded by the DTU on the SD card;
- *Video file (.avi)*: Video and audio recording with viewing point generated by Video Record tool in Eye Vision.

The interface of the software Eye Vision (Figure 3.15) is composed of four main sections:

- the display, where the eye or external scene can be displayed;
- the button panel;
- the side panel;
- the status bar.

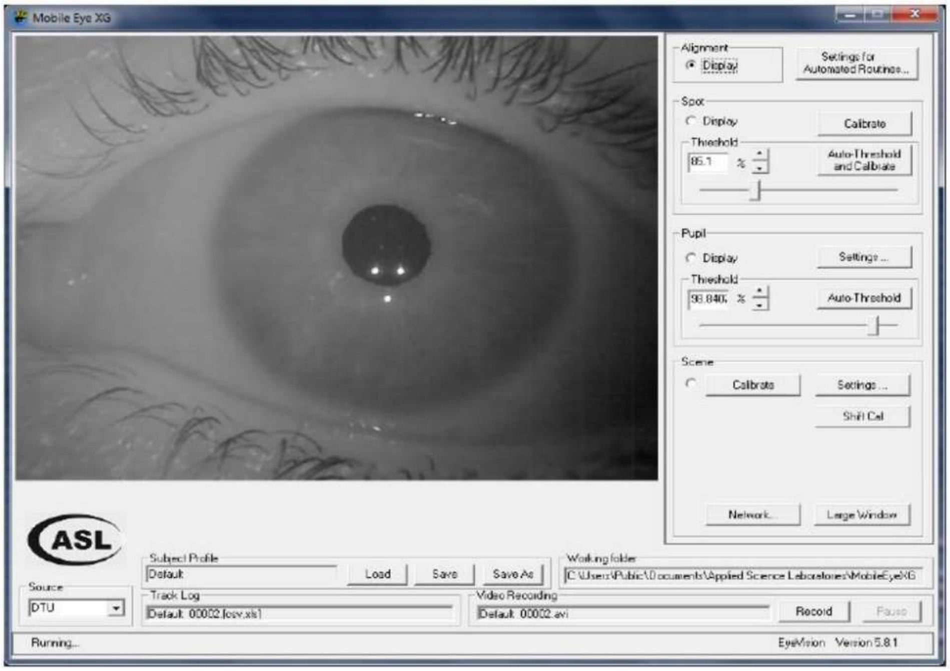


Figure 3.15. Software Eye Vision.

3.2.1.1. Calibration phase

In order to use the Mobile Eye, the corresponding calibration is required. The Mobile Eye uses an eye tracking technique known as "Pupil to CR" tracking. This method uses the relationship between two eye characteristics that are the black of the pupil and the mirror reflections from the frontal surface of the cornea (Corneal Reflections) to compute the gaze within the scene. A set of three harmless infrared (IR) lights is projected onto the eye by a set of LEDs located on the SMU (Figure 3.16). Near-infrared light is visible from the dedicated eye camera.

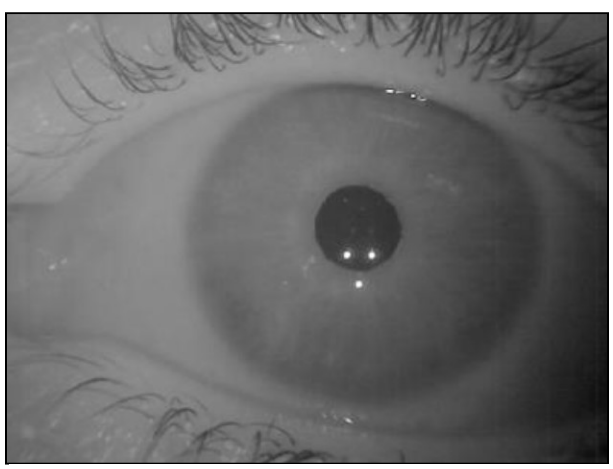


Figure 3.16. Spot cluster.

However, the user is not distracted by it, as he does not perceive it. The mirror reflection of these three lights from the front surface of the cornea appears in the image of the camera as a triangle of three points, placed at a fixed distance between them, called *spot clusters*. When the eye rotates in its orbital cavity, the center of the pupil moves relative to the spot cluster. In it, the eye motion tracking system can calculate the direction of the eye trajectory, evaluating the vector between the pupil and a corneal reflection (CR). The system is then able to relate these angles to the image of the second camera that records the external environment, in order to compute the point of view with respect to the visual field of the latter.

Once this has been evaluated, the glasses have been adjusted. This is done by using the image displayed on the DTU:

1. Use the Eye/Scene display button to display the camera image of the eye and then, with the help of this image, adjust the camera, together with the monocular lens, to obtain a correct image of the eye;
2. Then you adjust the glasses on the user to align the image of the eye on the monitor: you raise the monocular lens, then rotate it until the three points reflected become visible and focused (Figure 3.17);

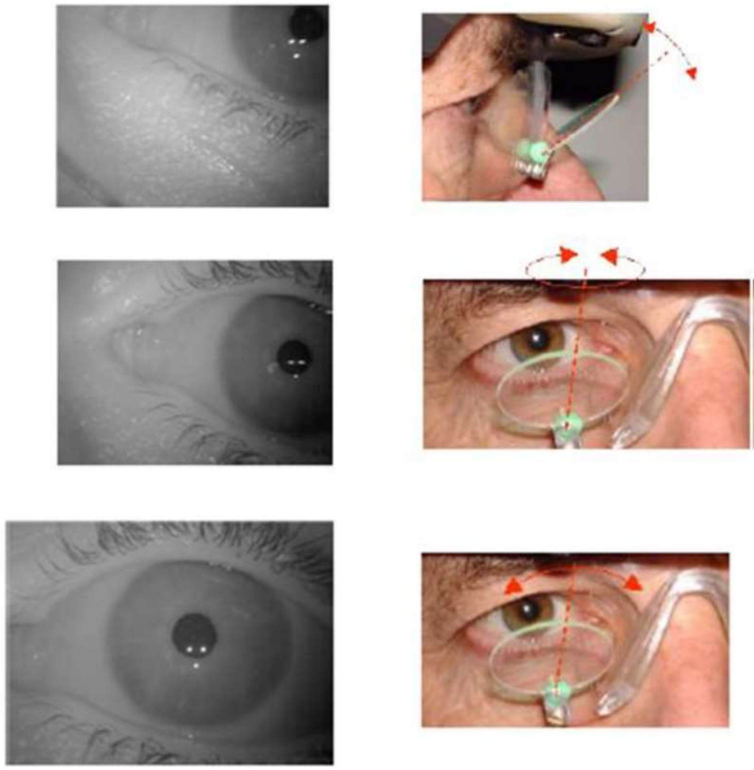


Figure 3.17. Slow rotation performed during calibration.

3. In addition, the camera that competes with the external scene is adjusted by pressing the Eye/Scene display button.

You then open the Eye Vision from the ME PC, choosing to create a new profile for each of the evaluated users. This is done by pressing the "Save as' button (Figure 3.18).

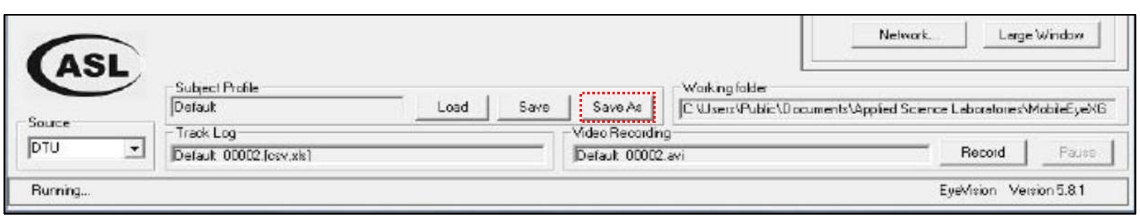


Figure 3.18. Saving Process.

The calibration result can be saved by generating an "evi" file. By selecting "Display" under the heading "Alignment", the procedure of alignment of the image of the eye in the monitor can be followed (Figure 3.19).

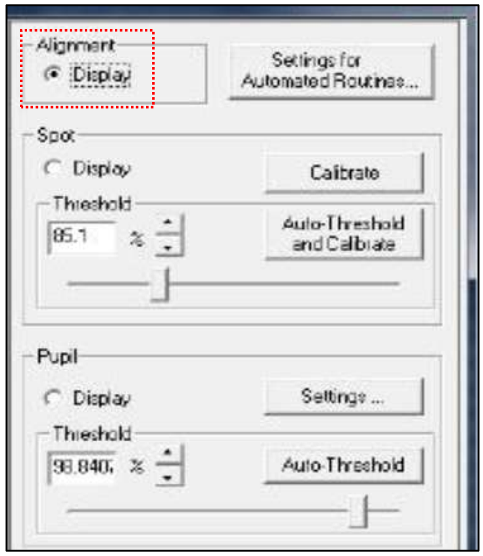


Figure 3.19. Alignment procedure.

For the positioning, the subject must focus his gaze straight ahead. It is important that all three CR points are visible and that they are in or very close to the pupil. It is necessary, at this point, to move to the phase of recognition of two important parameters:

- Corneal reflection (CR): three-point recognition, useful for calibration. Proceed by selecting "Display" under "Spot" in the right panel of the Eye Vision screen. By clicking on "Auto Threshold and Calibrate" the software automatically calibrates the three CR points. They are thus visible on a black background (Figure 3.20).

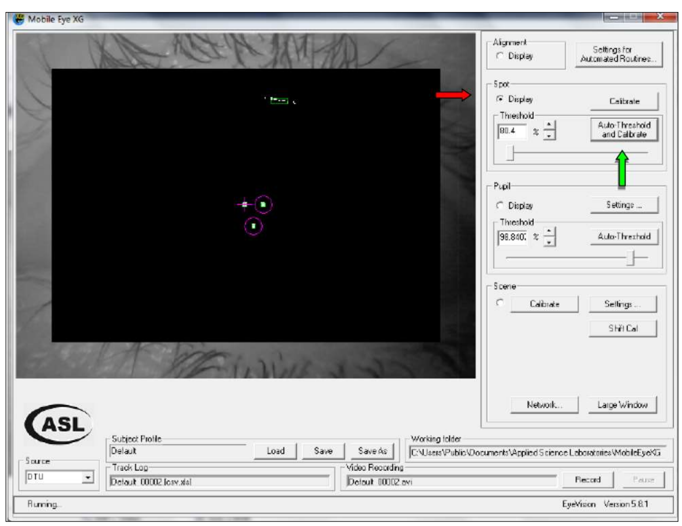


Figure 3.20.The three points of corneal reflection (CR).

- The pupil: is located through a dark square with a circumference inside it. To view it, click on "Display" under "Pupil" in the right panel of the Eye Vision screen (Figure 3.21).

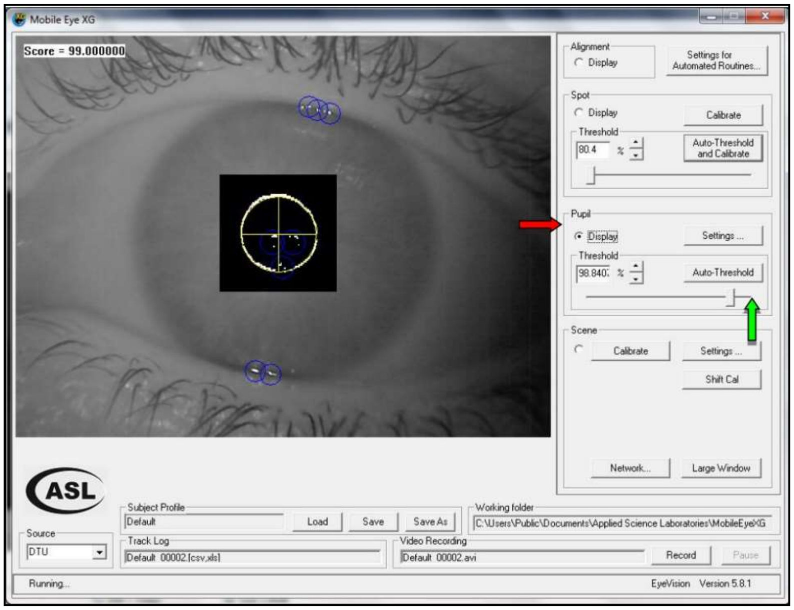


Figure 3.21. Pupil identification.

To perform an automatic recognition click "Auto Threshold" under the heading "Pupil". The edge of the pupil will be indicated by a white line, formed by many points of different thicknesses. When the highlighted object is recognized as the pupil, its perimeter will be drawn through a yellow circle, approximately coinciding with the white outline. It will also be possible to distinguish a cross of the same color, indicating its center. The top left score in the display is a measure of the reliability of the pupil position. It is important to consider that, by falling below a certain limit, the pupil position for that frame is discarded. In fact, when this happens, a certain amount of lost frames are recorded.

The last important phase of the calibration is the mapping of the points fixed on the scene, correlating the positions of the eye characteristics (pupil and CR cluster) to known positions of the external image. Proceed by selecting the "Scenes" section in the right panel of the Eye Vision software. The display will show the image from the camera that takes the scene. The calibration procedure of the eye point is necessary for the system to be able to relate the eye movements with the direction of the eye. The software requires at least three calibrated points (marked with green crosses).

While the user looks at a certain object, the operator makes use of the computer mouse to go and select the corresponding object on the scene image on the monitor. A cursor in the form of '+' will appear in the scene image, as in Figure 3.22. It will turn yellow as data is collected.

Figure 3.22. Points of Calibration.

During this phase, the user must keep his head still and his gaze fixed toward the indicated direction. When the processing is finished, two different points in the monitor can be evaluated:

- the green cursor (positive result);
- the red slider (negative result).

If the processing fails, it means that, probably, one of the characteristics of the eye has not been traced or that the positions of the ocular characteristics were not consistent. If necessary, ask the user to move his head or make the initial steps a new time. Usually, when the eyes are particularly clear and characterized by a lot of liquid, which increases reflections, there are particular problems. You must repeat this process for several calibration points that are distributed in the main nodes of the scene (center-right-left-edges). The minimum number of points is three, but in the various calibrations about seven/eight points have been traced, so as to increase the accuracy of the trajectory displayed. The cursor that led to a positive result remains on the screen until the calibration ends. In this way in the image of the external scene, a marked red cross appears showing the position of the gaze, called the pointer. At this point, the calibration phase can be defined as finished (Figure 3.23).

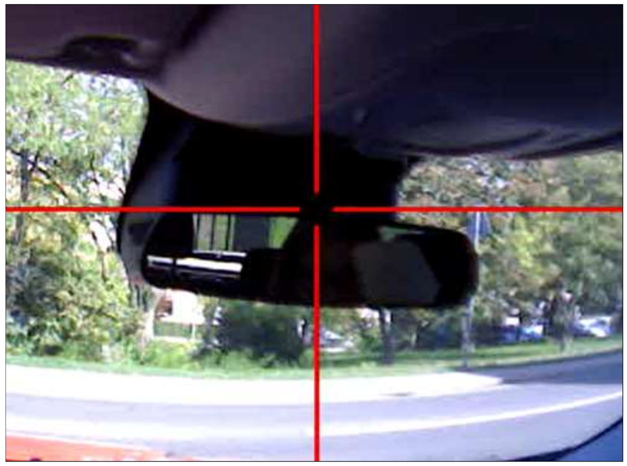


Figure 3.23. Cursor - red cross.

When the system is set and calibrated, Eye Vision can process the image of the eye and calculate the position of the gaze in the corresponding field of the scene. The output of the direction of the gaze consists of a cross superimposed on the video of the scene and a data file in ASCII format (.csv). Once the various instruments have been arranged, the test can begin.

3.2.1.2. Mode Analysis of the Visual Behavior

In the study the second round was analyzed, the actual test. An Excel spreadsheet has been built for each user in which the categories with which the users' points of fixation are cataloged have been inserted. Furthermore, a box was inserted in which the lost frames were inserted (due to intense light or incorrect calibration of the instrument). The identified categories are (Figure 3.24):

- Dashboard: internal part of the vehicle placed in front of the user;
- Prey: vehicle used during the test for the simulated events;
- Signboard: vertical sign;
- Background: all elements outside the driving scene (sky, trees);
- Road: infrastructure (paving, guard-rail);
- Mirror: exterior rear-view mirrors, either left or right;
- Internal Mirror: interior rear-view mirror, to check the situation behind the vehicle (Attention);
- Internal Mirror: internal rear-view mirror, to check the passenger in the back seat while talking (Negligence);
- Car: all the vehicles circulating in the road except the prey vehicle;

- Speaker: operator sitting next to the driver;
- Interior Car: internal part of the vehicle not part of the dashboard.

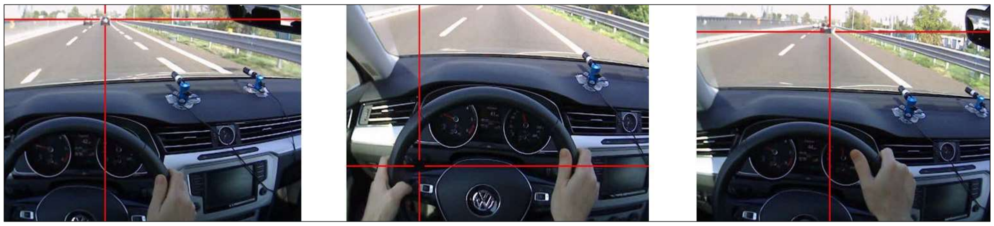


Figure 3.24. Points of view - Car, Dashboard, Street.

During the analysis of the videos, the number of frames relative to the single category was inserted into the file. Table 3.1 shows an example of the file configuration; below each category are inserted consecutive frame values in which the user sets the same category.

The highlighted values refer to a single event, which will be explained in a second sheet in order to analyze the time sequence with which the user sets a specific point.

Tangenziale													
Initial Frame	Dashboard	Prey	Signboard	Background	Road	Mirror	Internal Mirror ATT	Internal Mirror DIS	Car	Speaker	Auto intern	Lost frame	Final frame
57480	7	4517	218	152	1173	107	76	124	524	0	45	604	65026
	1	9	2	3	9	26	25	0	2	0	3	4	
7547	2	47	1	4	2	19	0	26	11	0	1	1	
65026	0	14	7	3	3	0	12	31	11		1	1	
	0	3	9	3	13	17	10	0	14		5	1	
		263	3	3	7	11			13		2	2	
		151	4	2	6	0			10		15	11	
		29	12	2	6				12		2	4	
		10	1	2	3				10		10	4	
		13	8	3	15				1		0	6	
		45		1	2				0			5	
		292		4	2							8	
		74		3	2							28	
		15		1	1							1	
		62		2	4							19	
		14		2	18							3	
		59		0	14							18	
		56			7							2	
		14			1							2	
		61			7							3	
		74			2							4	
		28			8							3	
		62			8							22	
		40			23							1	
		14			17							2	
		62			3							5	
		32			7							1	

Table 3.1. The number of frame.

In the second "events" sheet (Table 3.2) the number of frames in which the user sets a specific category has been entered, within the time interval of the simulated events. Each single frame sequence refers to a single line so that the dynamics of the driver's gaze during the event can be reconstructed. It is also possible to distinguish the moment in which there is the ignition of the stop of the prey vehicle and the moment in which the user brings his gaze to it.

This characterization was useful at a later time in order to assess the perception time of the user with the system switched on or off.

																	On Stop		Instant Perception	
Event	Initial Frame	Dashboard	Prey	Signboard	Background	Road	Mirror	Internal Mirror ATT	Internal Mirror DIS	Car	Speaker	Auto intern	Lost frame	Final frame	Sum Fram	Last frame View	Time	Frame	Time	Frame
	58229	0	292	7	3	2	0	25	0	2	0	1	28	58588	360	58588	32.22.35	58269	32.22.81	58283
			24																	
				7																
			1																	
													8							
													13							
										1										
			218																	
					2															
								12												
1													2							
			21																	
					1															
								13												
													3							
			28																	
						2														
										1										
												1								
													2							

Table 3.2. Number of Frame per Events.

For attention, it has been considered the categories signboard, road, car, prey, mirror, and internal mirror (attention); due to inattention, they were considered dashboard, background, distraction internal mirror, interlocutor and car interior. An exception is represented by the category of external mirrors, which during the events were considered as inattention. In particular, we talk about categories of attention when the elements included allow not to be distracted from the task of driving; by distraction, instead, we mean all the elements that can distract from the primary task.

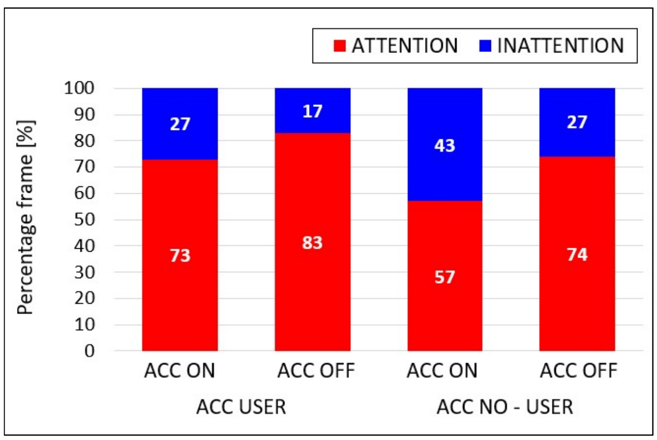
Eliminating the total lost frames, the percentages of attention and inattention on the total frames were calculated.

Once the analysis of the single frames has been completed, we have moved on to the analysis of fixations (table 4.10), where for the latter we mean the fixed gaze at the same point for at least two or more frames. From the literature, in fact, the single frame can be associated with a probable eye movement, called *saccade*. Attention and inattention have also been categorized as fixations. Converting the number of frames in time (multiplying them by 33 ms) the total time expressed in milliseconds was obtained, and the average durations of attention and inattention fixations were calculated. These tables were made for each individual participant in the test and the cases in which the percentages of lost frames did not exceed the 30% threshold were considered valid. User events with percentages of attention / inattention equal to 100% / 0% or 0% / 100%, deemed to be unreliable, were also excluded.

Once the selection of the data useful for the analysis was completed, the driving behavior was compared with the system turned on and off, distinguishing the analysis for single trunks and for events.

3.3. Outcomes

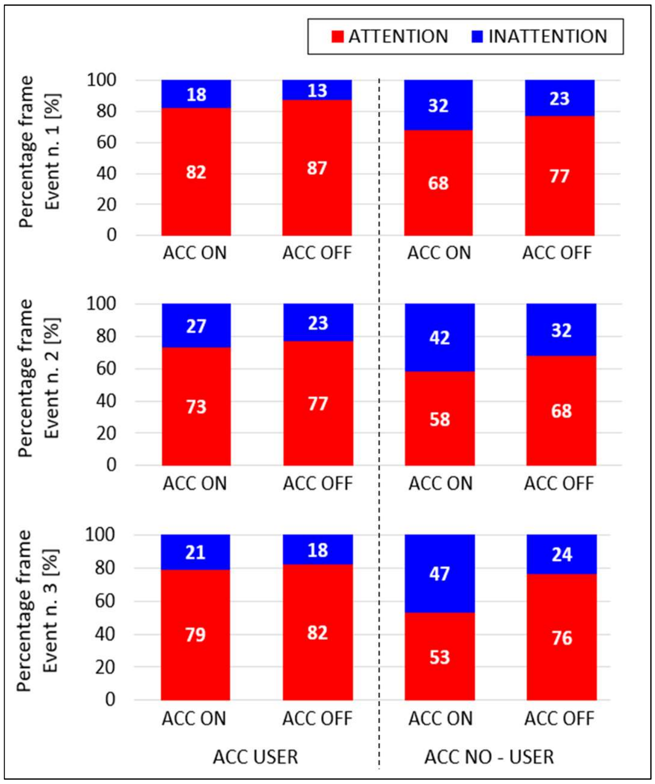
Graph 3.1 shows the influence of ACC on the drivers' visual behaviour. The performed analysis has revealed that the average percentage of the attention frames has decreased using ACC. According to Lin et al. (2008), when ACC controls the vehicle, the drivers feel safer and tend to distract themselves from the driving scene with secondary tasks. Without the system, instead, they more focus on the road ahead. This tendency is independent from the ACC previous knowledge, but it is more evident for ACC no-experienced users (-17%, $\chi 2 = 6.05$, $p = 0.002$) respect the ACC experienced ones (-10%, $\chi 2 = 3.25$, $p = 0.002$).



Graph 3.1. Attention and inattention frames for ACC ON and OFF conditions, between ACC experienced and no-experienced users.

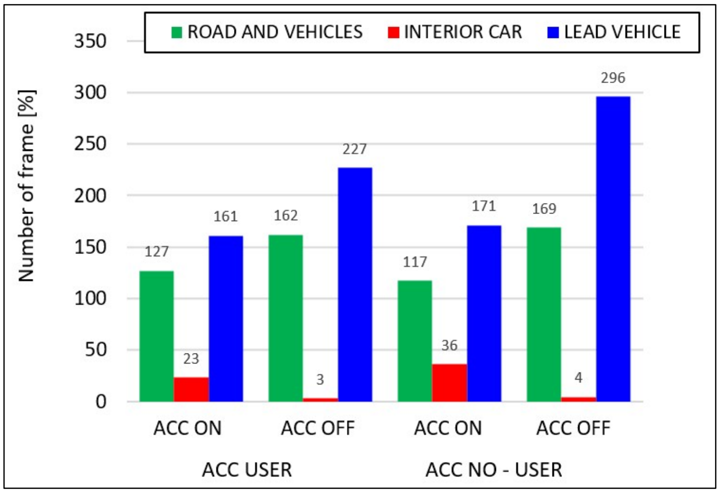
These results have been confirmed during the individual events. The average percentage of attention frames was higher in the ACC OFF condition, even when the driver was engaged in the secondary task (following a braking vehicle and keeping a distance from it to include it within the driver field of view) (288 observations (48 participants - 3 events -2 ACC conditions), $F(1, 288) = 88.59$, $p < 0.001$, $\chi 2 = 0.37$) (Graph 3.2). For the same event, the ACC-experienced users were less distracted from the driving scene respect the ACC no-experienced users.

In the ACC ON condition, the experienced drivers kept almost constant attention during the succession of events. The other ones, instead, showed an attention level that decreased passing from the first to the third event. Although they realized that the vehicle in front of them suddenly brakes, their concentration on the driving scene did not increase. This underlines that users tend to use the Adaptive Cruise Control as a replacement for driving and have a good degree of confidence in the system and its proper functioning.



Graph 3.2. Average percentage of frames during the events, considering ACC state and drivers' ACC experience.

Independently from the previous experience of the system, with ACC the drivers focused more attention on the interior of the vehicle, to monitor whether the system was functioning properly. The average number of frames on the dashboard using ACC (36 for ACC no-users (SD = 12), 23 for ACC users (SD = 17)) was always higher than manually driving (4 for ACC no-users (SD = 8), 3 for expert (SD = 11)) (Graph 3.3). So, they are less focused on the driving scene and vehicles on the road. The average number of frames "road and vehicles" with the ACC on (171 for ACC no-users, 161 for ACC users) was always lower than the ACC off (227 for ACC no-users, 296 for expert) (96 observations (48 participants - 2 ACC conditions), $F(1, 96) = 7.17$, $p < 0.002$, $\chi 2 = 0.12$).



Graph 3.3. Average number of frames on the road and the vehicles, the car dashboard, and the lead vehicle during the events, considering ACC state and drivers' ACC experience.

For both users, this trend was also evident during the events, in which the function of maintaining the correct safety distance was exerted by the ACC. Even in these cases, drivers fixed the dashboard by checking the correct functioning of the system, instead of looking at the vehicle braking. If the ACC was off, they focused attention on the previous vehicle, monitoring its motion and the moment of braking (161 versus 227 frames for ACC user and 171 versus 296 frames for ACC no-user) (288 observations (48 participants - 3 events -2 ACC conditions), $F(1, 288) = 3.91$, $p < 0.002$, $\chi 2 = 0.25$).

3.4. Conclusion

The visual behaviour of users is particularly influenced of the Adaptive Cruise Control. In the study it was possible, in fact, to find how, both for users ACC users and no-user, the percentage of attention is always lower with the system on. This factor is influenced by the user's confidence in the system; however, this situation can turn into a decrease in road safety because, with possible malfunctions of the system itself, the user would be in very dangerous accident situations. This is confirmed by the evaluation of visual behaviour during the events. Even in conditions of imminent danger, in fact, the user does not pay attention to the driving scene, catapulting into a scenario that, in the case of real driving, would lead to a very high probability of collision.

4. THE IMPACT OF ACC ON DRIVING BEHAVIOUR

4.1. Introduction

In paragraph 2 of Art. 2 of the Highway Code are classified roads according to their construction, technical and functional characteristics in the following types:

A- Highway;

B- Main suburban roads;

C- Suburban secondary roads;

D- Urban highways;

E- Urban streets of neighbourhood;

F- Local roads.

In particular, an urban road (D) is defined as a road with independent or separated carriageways, each with at least two lanes, and a possible public transport lane, paved platform on the right and sidewalks, with any intersections at right traffic lights; for the stop there are special areas or side bands outside the roadway, both with concentrated inputs and outputs.

Article 18 of the Code and its art. 28 of its regulations define the bands of respect and the areas of visibility in residential areas. Distances from the road boundary to be respected in residential areas may not be less than:

- 30 m for roads of A type;
- 20 m for roads of D and E type;
- 10 m for roads of F type.

For the construction or reconstruction of boundary walls on either side of the road, the distances from the road boundary shall not be less than 3 m for type A roads; 2 m to the streets of type D.

At clear road intersections, a visibility area identified by a triangle with two sides on the alignments delimiting the buffer strips shall be added to the buffer strips indicated above, whose length measured from the point of intersection of the alignments themselves is equal to twice the distances laid down in the Regulation depending on the type of road concerned, and the third side consisting of the segment joining the extreme points (Figure 4.1).

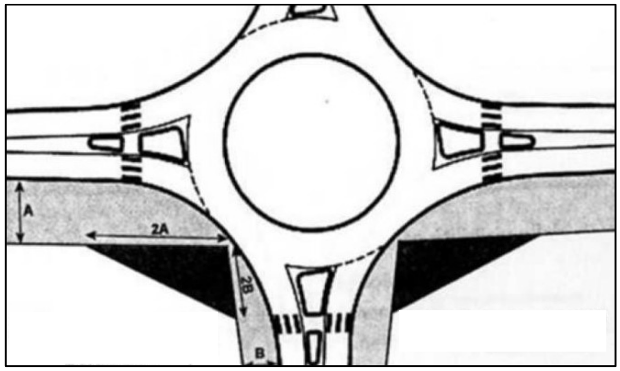


Figure 4.1. Bands of respect and triangles of visibility at the roundabout.

The interventions on existing roads must be carried out by adapting the geometrical characteristics of the roads to D.M. 5 November 2001, as far as possible, in order to better meet the needs of the traffic. The transition between suitable sections and sections where adaptation was deemed not possible should be conveniently resolved to avoid the introduction of additional hazardous situations. In the event that particular local, environmental, landscape, archaeological and economic conditions do not allow full compliance with D.M. 2001, art. 3 of this decree allows different design solutions to be adopted provided that they are supported by specific safety analyses and, as regards urban roads, subject to a favourable opinion of the Board of Governors of Public Works.

4.1.1. The Highway Code

Taking into account art. 3 of the Highway Code some road areas are defined as:

- Pavement: the art of the road, free from any obstruction (vertical signs, margin markers, restraint devices). It is included between the edge of the carriageway and the nearest of the following longitudinal elements: platform, traffic divider, embankment, inner edge of the wedge, and upper edge of the escarpment in the relieved. It is distinguished in "right platform", with the function of the right-sided franc and usually paved, and in "left platform", which is the paved part of the inner margin.
- Roadway: part of the road intended for the movement of vehicles, consisting of one or more lanes, paved and bordered by margin strips.
- Lane: longitudinal part of the road, between road markings, of a width suitable for the transit of a single row of vehicles.

- Safety barrier: a means of preventing vehicles from escaping from the platform. It shall be contained within the divider or outer edge of the platform.
- Band of respect: a strip of land, outside the road border, on which there are constraints on the realization, by the owner of the land, excavations, buildings, fences, plantations, deposits and the like.
- Sidewalk: part of the road, outside the carriageway, raised or otherwise delimited and protected, intended for pedestrians.
- Inner margin: part of the platform which separates the opposite track.
- Lateral margin: part of the platform that separates roadways traveled in the same direction.
- Outer margin: part of the road seat, outside the platform, in which there are eyelashes, bumps, embankments, sidewalks and safety or furniture elements (restraints, railings, supports, etc.).
- Platform: part of the road site comprising one or more coplanar carriageways, the platforms on the right and left, any internal and lateral margins, reserved/specialised lanes and rest areas. It does not include the outer margin.
- Traffic divider: a non-drivable part of the internal or lateral margin, intended for the physical separation of vehicle currents. It also includes the operating space (permanent deformation) of the restraint devices.

4.1.1.1. Geometric and traffic characteristics of sections

The road section project consists of the organisation of the platform and its margins. The number of elements and their size is a function of transport demand and the upper limit of the design speed range respectively. For each type of road, It is possible to have different types of sections, in relation to the territorial scope and the intended user; moreover the dimensions of the road platform must be kept unchanged along the entire route of the road, both natural and artificial as for example in underpass and bridge. The width of the lanes is understood as the distance between the axes of the stripes that delimit them and its dimensions are indicated in special tables in this decree according to the type of road and the territorial scope. In any case, minimum width of 3.50 meters is fixed for heavy goods vehicles. As far as the platform is concerned, its width is to be considered the net of both grassy strips or trees and of restraint devices and cannot be less than 1.50 meters (Figure 4.2).

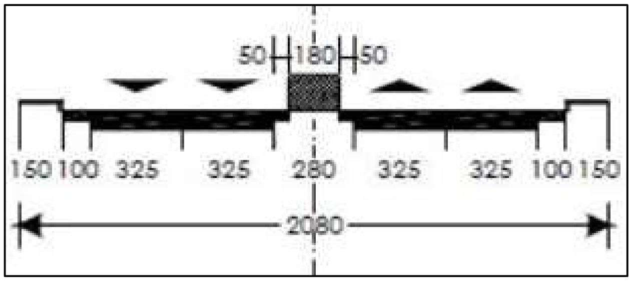


Figure 4.2. Category D - Urban sliding.

4.1.1.2. Marginal and furnishing elements of the road office

- *Internal margin*

The internal margin, as already mentioned, is the part of the platform that separates lanes traveling in the opposite direction. In the case of roads with separate carriageways spaced not more than 12m apart, impassable restraints shall be placed within the margin. The platforms on the left must be paved and have the same slope as the roadway itself. The carriageable section of the inner margin must be interrupted, in principle every two kilometers, by a paved area suitable for the exchange of carriageways (passage) and in correspondence of aforesaid passages must not interrupt the continuity of the devices of restraint, to be realized also of inferior class regarding that current (as will be seen previewed from D.M. n the 223 of the 18/02/1992 and successive integrations and modifications) so they can be easily removed if necessary.

- *Sidewalk*

For roads with an upper design speed limit of more than 70 km/h, the platform shall be protected by restraints. If the intended speed is lower than the above value, the protection may be omitted, but the platform shall be bounded by a contoured edge. The body that owns the road will consider providing the edge of the pavement with suitable protections to protect pedestrians and prevent overtaking of vehicles.

- *Rest areas*

Extra-urban roads B, C and F must be equipped with parking places located outside the platform. These pitches shall have dimensions not less than those indicated in Figure 4.3. They shall be spaced from each other at intervals of about 1,000 m along each of the two directions.

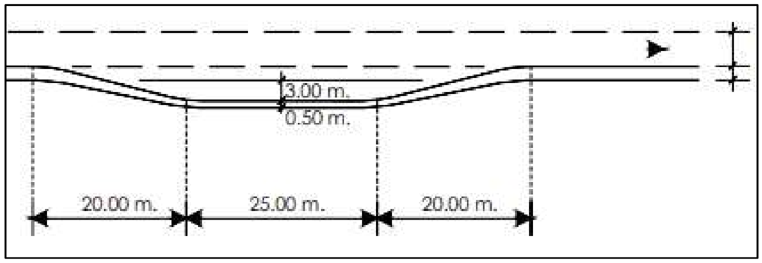


Figure 4.3. Section of the parking pitch.

4.1.1.3. Geometry of the road axis

- *Distance of visibility*

Clear viewing distance means the length of the road that the driver can see in front of him without considering the influence of traffic, weather and road lighting. This distance must be compared with some distances between which the most important is the distance of visibility for the stop, which is equal to the minimum space necessary for a driver to stop the vehicle in a safe condition in front of an unexpected obstacle. It is evaluated by the following expression:

$$D_A = D_1 + D_2 = \frac{V_0}{3,6} \times \tau - \frac{1}{3,6^2} \int_{V_0}^{V_1} \frac{V}{g \times \left[f_l(V) \pm \frac{i}{100} \right] + \frac{Ra(V)}{m} + r_0(V)} dV \qquad [\text{m}]$$

$D1$ = space covered in time t (m)

$D2$ = braking distance (m)

$V0$ = vehicle speed at the start of braking, equal to the design speed (km/h) (km/h)

V1 = Final vehicle speed, where V1=0 in case of a stop (%)

i = longitudinal slope of the track (s) $(m/s2)$ (N)

t = total reaction time g = gravity acceleration (kg)

Ra = aerodynamic resistance m = vehicle mass (-)

f1 = limit quota of the coefficient of adhesion (N/kg)

r0 = unit rolling resistance, negligible

Figure 4.4 shows an abacus to deduce the distance of visibility for stopping as a function of a constant longitudinal slope. In case of the variability of this slope, the average value can be assumed.

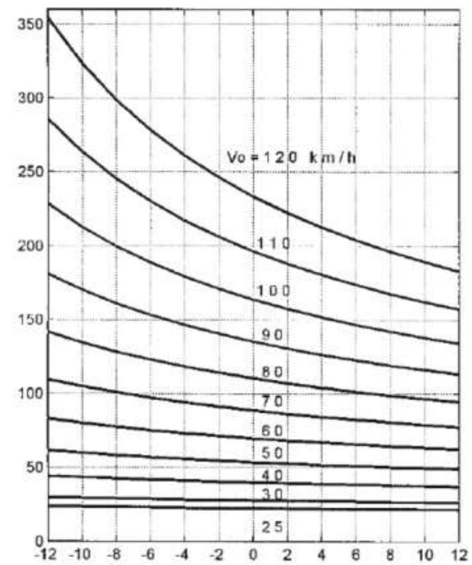


Figure 4.4. Distances of visibility for stopping: vertical axis with visibility distance to stop (m); horizontal axis with longitudinal slope (%).

- *Distance of visibility for overtaking*

In the presence of vehicles moving in the opposite direction, the distance of complete visibility for overtaking shall be assessed with the following expression:

$$Ds = 20 \times v = 5{,}5 \times V \qquad \text{[m]}$$

v (m/s) or V(km/h) = design speed and is attributed equally to both the overtaking vehicle and the vehicle from the opposite direction.

- *Distance of visibility for lane change*

The necessary space for the lane change is evaluated with the following expression; in which the 9.5 seconds include the time needed to perceive and recognize the situation and for the decision and execution of the maneuver of a single lane change (4 seconds).

$$D_c = 9{,}5 \times v = 2{,}6\,V \qquad \text{[m]}$$

v = Vehicle speed in (m/s), or V in (km/h).

4.1.1.4. Decree of the Ministry of Public Works of 19 April 2006

The rules concerning the construction of intersections dictated by the 2006 decree "Functional and Geometric Rules for the Construction of Road Intersections" were also taken into consideration. Of these, diversion or entry maneuvers on the left are not allowed on the main traffic flow of the roads of type A, B and D, while they are allowed on any service roads. As a result of these maneuvers, several characteristic points are created on which the safety conditions of the intersection depend. These points are called "points of conflict" between trajectories and arise from the possible interference of these. They are divided into points of conflict intersection or crossing, diversion and entry.

The most usual intersections are represented by the intersection of two roads (intersections with four arms) or by the grafting of one road on the other (intersections with three arms). Straight intersections, defined by the Highway Code, are distinguished into straight intersections (when intersection maneuvers are allowed) and roundabout intersections (when intersection points are eliminated).

The main components of an intersection are:

- Ramps, connecting branches of an intersection at staggered levels;
- The specialized lanes, intended for right and left turning maneuvers. They can be input, diversion (exit) or accumulation for the left turn.
- The entry lanes consist of the following sections (Figure 4.5):
  - Length acceleration section La,e;
  - Length input section Li,e;
  - Connecting element of length Lv,e.

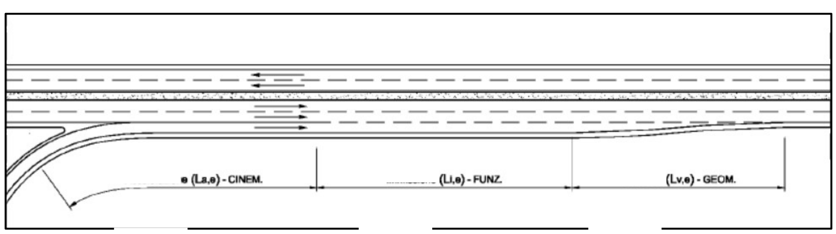


Figure 4.5. Entry lane.

The diversion lanes consist of the following sections (Figure 4.6):

- Stroke of length Lm,u;
- Deceleration section of length $L_{d,u}$ comprising half the length of section $L_{m,u}$.

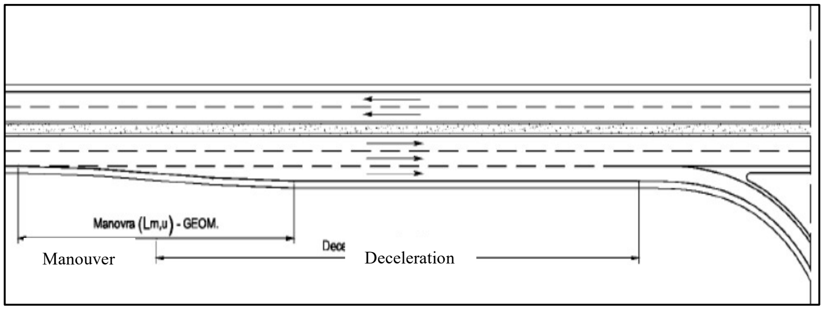


Figure 4.6. Diversion lane of parallel type.

The following expression shall be used to determine the length of the velocity variation sections, both in deceleration and acceleration:

$$L = \frac{v_1^2 - v_2^2}{2a}$$

L = length required for kinematic variation	(m)
v_1 = entry velocity in the deceleration or acceleration section	(m/s)
v_2 = Exit speed of the deceleration or acceleration section	(m/s)
a = acceleration, positive or negative, assumed for the maneuver	(m/s^2)

In the case of deceleration lanes as values of v_1 and v_2, the design speed of the section from which the output vehicles come and the design speed corresponding to the radius of the deviation curve to the other road are taken respectively. The value of a is assumed to be 3 m/s^2 for roads of type A and B, 2 m/s^2 for all other roads. In case of acceleration lanes for v_1, the ramp design speed shall be assumed at the starting point of the acceleration section of the entry lane, whereas for v_2 the value shall be 80% of the design speed of the road on which the lane is entered. a is assumed to be 1 m/s^2.

The length of the Lm,u section for diversion lanes is 30 m in the suburbs and 20 m in the urban areas. The connecting section Lv,e is determined according to the design speed of the road on which the lane is entered (Table 4.1).

Design speed V_p [km/h]	Length of the connecting section Lv,e [m]
$V_p > 80$	75
$V_p \leq 80$	50

Table 4.1. Length of the connecting section.

The section Lm,u in an exit or deceleration lane is determined by the design speed of the section of the road from which the lane branches off (Table 4.2).

Design speed V_p [km/h]	Length of the connecting section Lm,u [m]
40	20
60	40
80	60
100	75
≥ 120	90

Table 4.2. Length of operating section.

4.1.1.5. Roundabouts: types and geometry

The D.M. then distinguishes three types of roundabouts according to the diameter of the outer circumference:

- Conventional roundabouts: with an external diameter between 40 and 50 m;
- Compact roundabouts: with an external diameter between 25 and 40 m;
- Mini roundabouts: with external diameter between 14 and 25 m.

The main characteristic to be evaluated in roundabouts is the deviation of the trajectories that cross it, in fact the central island must divert the vehicles to prevent crossing the roundabout at too high speeds (Figure 4.7).

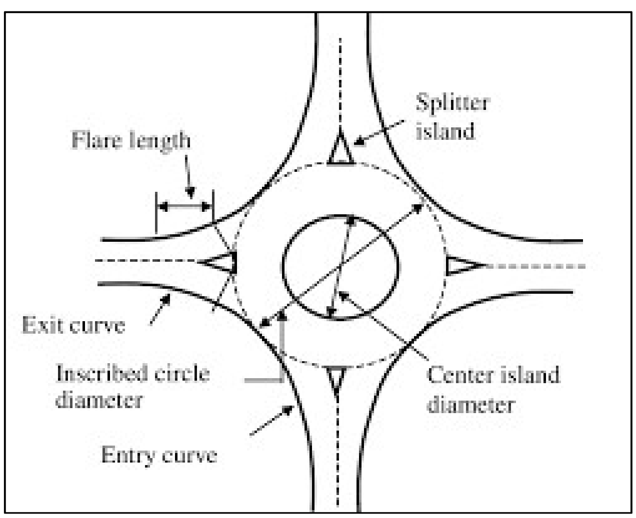


Figure 4.7. Geometry intersection at roundabout.

The main characteristic to evaluate in roundabouts is the deviation of the trajectories that cross it, in fact the central island must divert the vehicles to prevent crossing the roundabout at too high speeds. The value of the deviation is evaluated by means of the angle β, which is determined by the tangent to the edge of the central island after having added to the entry radius $R_{e,2}$ an increment b equal to 3,50 m as can be seen from Figure 4.8. An angle β value of at least 45 β per input arm is recommended.

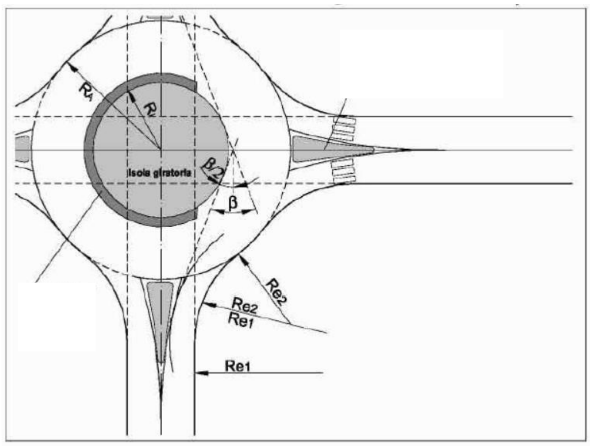


Figure 4.8. Graphic construction for the determination of β.

- *Visibility distances at roundabouts*

In order to ensure the smooth functioning of the intersections, it is necessary to hierarchise the maneuvers in order to distinguish the main vehicular currents from the secondary ones. Therefore, precedence or stop signals are introduced at every point of conflict. For non-priority maneuvers, the checks shall be developed according to the criterion of the triangles of visibility relating to the intersection conflict points generated by the vehicular currents. The visibility triangle shall have the widest side equal to the visibility distance D calculated as follows:

$$D = v \cdot t$$

v = reference speed (m/s), equal to the value of the design speed characteristic of the section in question or, in the presence of speed limits, the value prescribed by the signs.

t = Manoeuvring time equal to 12 s for maneuvers regulated by precedence and 6 s for maneuvers regulated by stop. This value must be increased by one second for each percentage point of the longitudinal slope of the secondary branch above 2%.

The smaller side of the triangle is equal to a distance of 20 m from the side of the main road if the intersection is regulated by precedence, while it is equal to 3 m from the stop line in case of a stop. There shall be no obstacle within the visibility triangle to the continuous and direct mutual vision of the vehicles relevant to the intersection under consideration. Obstacles to visibility are objects with a planimetric size greater than 0,8 m. At roundabouts, drivers approaching them must be able to see the vehicles running along the central ring in order to give way to them. To this end, a completely free view on the left is sufficient for a quarter of the development of the entire ring according to the geometric construction of Figure 4.9, placing the observer at 15 m from the line that delimits the outer edge of the rotating ring.

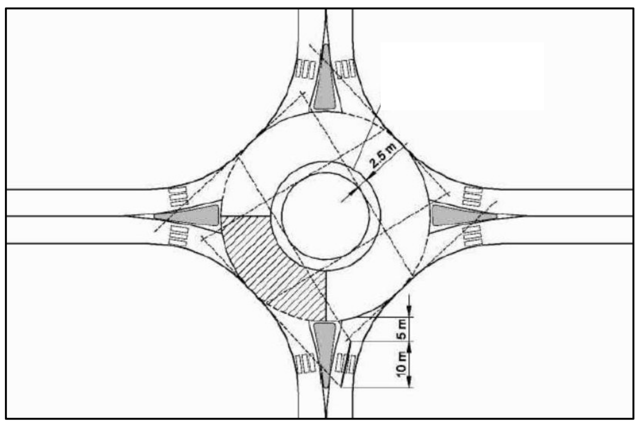


Figure 4.9. Fields of visibility at a roundabout.

4.1.1.6. Guidelines for Road Infrastructure Safety Management

- *Object and purpose*

The guidelines for the management of road infrastructure safety are issued according to art. 8 of Legislative Decree No. 35/2011 for the implementation of Directive 2008/96/EC. They shall establish criteria and arrangements for carrying out road safety checks on projects, safety inspections on existing infrastructure and the implementation of the road safety classification process. In addition, these guidelines aim to guide, coordinate and homogenize the activities of those involved in the safety process, such as local and regional authorities, competent bodies, road owners and managers and road safety experts, This means project controllers and existing road inspectors. In order to harmonise and coordinate actions among themselves, these guidelines aim to provide a tool that identifies the procedural modalities of road safety analysis and activities related to road network classification.

The term "road safety analysis" is taken to mean overall safety checks on projects and inspections on existing infrastructure. This process is preventive, aimed at identifying situations that could potentially cause accidents, the safety check of road projects for new infrastructure or upgrading of existing roads and verification of the characteristics of existing roads in operation. Controls and inspections should not be understood as autonomous steps away from the entire management process but should be part of a cycle of consequential and iterative activities aimed at achieving an improvement in safety through optimized management from the network road. The road infrastructure safety management process shall begin in advance by examining the operation of the road network open to traffic, by analysing the geometrical and functional characteristics of the entire network and subdividing it into homogeneous road sections. This subdivision allows the whole network to be classified in order to identify the inspection program and thus their priority.

The findings of the inspections and the identification of the potential corrective measures lead to a new classification in order to plan the interventions and their priorities for implementation. Some interventions can be implemented as part of ordinary maintenance while others require the activation of the procedures provided for extraordinary maintenance.

- *Road networks*

The scope of D.Lgs. n.35/11 is represented by roads that are part of the TEN (trans-European road network) in the planning, design, and construction or already open to traffic, while for all other roads not belonging to the TEN, the contents of the legislative decree constitute rules of principle until they become binding according to the temporal evolution of the scope.

Directive 2008/96/EC provided for road safety checks to be carried out at the different stages of the project, from the planning stage to the start of the operation of the infrastructure. The Legislative Decree provides that road safety checks are carried out both on projects relating to the construction of new road infrastructure, both on projects which result in a substantial modification of existing road infrastructure with effects on traffic flows, as well as on adaptation projects involving changes to the route. The checks must be carried out for each level of design (preliminary, final and executive) and therefore the Guidelines are organized and structured with specific and distinct contents according to the extraurban and urban environment, the type of road (double or single carriageway), and further subdivided by the three design levels as well as for the construction phases, pre-opening to traffic and for the first year of operation.

Safety inspections on road infrastructure

The inspection program, at full capacity, must necessarily be prepared on the basis of the classification of high accident concentration sections and the security classification of the existing network. Safety inspections consist of "diffuse inspections" on the entire homogeneous road section and "point inspections", or details, located on individual critical or potentially critical sites and on individual points.

The purpose of security inspections shall be to:

- identify critical issues related to incidental events;
- identify potential hazard factors of road infrastructure;
- identify the priority of corrective actions to reduce the number and severity of accidents;
- identify the priority of corrective actions to prevent further incidents;
- keep the safety status of the road network under constant observation.

The preventive analysis of the safety of the roads in operation allows to identify the situations that need interventions that can improve or solve a possible safety problem. The road elements to be inspected are:

- homogeneous road sections, including intersections and all other singular points of the track;
- the individual critical sites, where there has already been a concentration of accidents, and those potentially critical, falling anyway in homogeneous sections and then inspected at the same time;
- the construction sites.

The inspection must be carried out along the road section in both directions of travel with different modes, depending on the type and characteristics of the infrastructure. During the inspections can be performed photographic surveys and video footage, which will be of help during the drafting of the final report.

The diffuse inspection shall be conducted along the road section in a motor vehicle, in both directions. It shall be divided into:

- Preliminary inspection: day and night, to understand general issues.
- General inspection: day and night, to examine more thoroughly the safety problems distributed along the road. The road must be traveled at low speed.

- Detailed, day-to-day and night-to-night spot inspections shall, where appropriate, be associated with diffuse inspections in order to examine security problems located at specific sites.

In the final report of the inspector, are described all the problems, concentrated and widespread, found along the road. In the face of any criticality, the inspector must identify one or more possible solutions, which will then be evaluated and by the managing body in order to identify the most appropriate solution.

4.2. Methods

One of the main purposes of driving behaviour is the implementation of road safety in order to reduce driving accidents due to the loss of respect for the issue of the Highway code. Road safety is one of the most important issues for the Ministry of Infrastructure and Transport. The aim is to increase the ‘road safety’: not a simple set of rules to be imparted, but the result of an ethical maturation, a behavior that puts at the centre the respect for life and for the human person.

The main tools used to achieve this factor are institutional communication campaigns and road education projects. Road safety is often considered to be inversely proportional to the number of accidents, but this definition has limits: accidents are rare events, which depend on chance and systematic factors.

To overcome these limits, the driver and the driving behaviour at an earlier stage are considered, assuming that wrong behaviour is the variable preceding the accidents. To assess the level of safety we rely on surrogate safety indicators, which provide a random basis, to explain complex interactions of time-dependent vehicles. This approach can be represented by means of a safety pyramid, where one goes from undisturbed driving behaviour to accidents. It is a model defined as an "iceberg", since it is as if there was a line between accidents and near accidents, in fact, the latter is ignored (Imprialou, et al., 2017) (Figure 4.10).

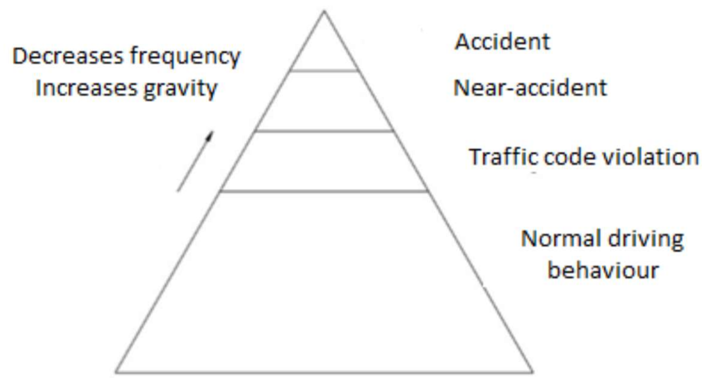


Figure 4.10. Safety pyramid.

The most commonly used indicator for surrogate safety measures is the Time To Collision (TTC). The TTC is the remaining time, before the accident occurs, keeping course and speed. It was found to be an effective parameter for discriminating critical behavior from normal behavior in situations where one vehicle follows another. The main defect of the TTC is the assumption of constant speeds, during the motion of the vehicle, thus neglecting the potentially dangerous situations.

The relationship that expresses the collision time is:

$$\mathrm{TTC(t)} = \frac{\Delta \mathrm{x}}{\Delta \mathrm{v}}$$

Δx = the distance between the vehicle in front and the vehicle in pursuit;

Δv = the speed difference between the two vehicles.

TTC is the main criterion in the study of accidents and especially in situations where one vehicle follows another. It is a fundamental parameter in the implementation of collision prevention systems.

Another way to assess road safety is to use so-called crash databases, which are one of the main resources for the study of safety. The main purpose of these databases is to determine the quality of road safety in order to reduce accidents. Crash data often contains errors due to transcription or incompleteness errors.

Accidents are due to a random chain of events and it is often difficult to understand their origin. To obtain more information, the local authorities provide forms, in paper or electronic form, which must be completed after an accident. The information can be classified according to the five "W":

- “Where?”: crash location;

- "When?": crash time;
- "What?": crash severity;
- "Who?": involved users (and vehicles);
- "Why?": crash contributing factors.

Place and time are the two factors most evaluated in the modules and one must always consider the probability of inaccuracy of the information obtained (Imprialou, et al., 2017).

- *The Video VBox Pro*

To perform the survey and obtain the kinematic and performance data, the test vehicle was equipped with the Video V-Box Pro, which combines a GPS sensor with a pair of high-definition cameras. The recording frequency of the device is 10 Hz, allowing the acquisition of 1 data every 0.1 seconds. The main device (Figure 4.11) is placed inside the vehicle, while the two cameras, given the high speed during the test, were positioned on the dashboard of each car to avoid the risk of loss and/or damage during the circulation (Figure 4.12). The GPS sensor was positioned on the car roof in a central position for greater accuracy of the position (Figure 4.13).

Figure 4.11. V-Box.

Figure 4.12. Posizioning of V-Box cameras.

Figure 4.13. Positioning of GPS antennas.

The specifications relating to the VBox system are listed in Table 4.3.

Speed	Distance
Accuracy 0.2 km/h	Accuracy 0.05 %
Unit of measure km/h or Mph	Unit of measure m or f
Update Rate 10 Hz	Resolution 1 cm
Max Speed 1600 km/h	
Min Speed 0.1 km/h	
Resolution 0.01 km/h	
Ping <160 ms	
Position	Distance
2D Position +5m95% CEP	Accuracy 0.05 %
Height +10m95% CEP	Max 4g
	Resolution 0.01 g
Heading	Lap times
Resolution 0.01	Resolution 0.01s
Accuracy 0.2	Accuracy 0.01s

Table 4.3. V-BOX specifications.

The instrument allows recording on external memory (SD card), on which it creates a video file obtained from the cameras and a ".vbo" file on which all the data collected by the sensors are stored.

The data analysis is performed using special software called "VBOX Tools" (Figure 4.14), which allows the information gathered to be processed by examining the parameters of interest and simultaneously monitoring the video recorded during the test. The program interface gives back, in addition to the video recorded during the test, also a graph that represents the kinematic features, the map of the route and the selection of the available parameters. The data can then be exported in Excel format for analysis.

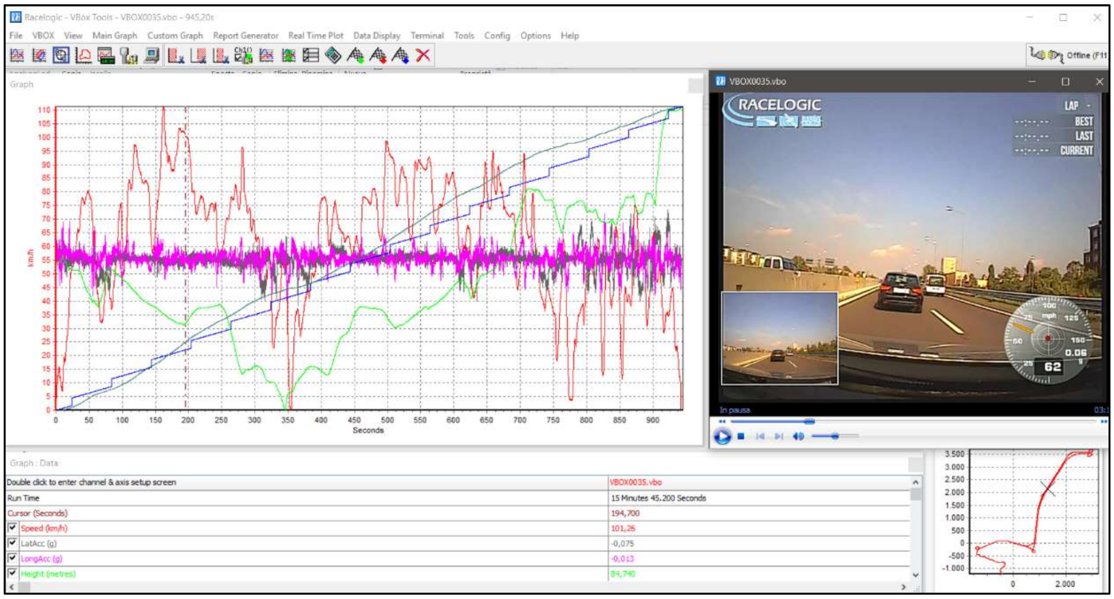


Figure 4.14. V-Box Tool.

The software can display in a diagram the trend of a series of variables that we choose from a list of possibilities, depending on the time or distance traveled. The data we can extract are (Figure 4.15, 4.16):

- Vehicle speed (km/h);
- Lateral and longitudinal acceleration (g);
- Vehicle direction (°);
- Altitude (m), Latitude (MinutesN) e Longitude (MinutesW);
- Absolute Time UTC Time;
- Distance traveled (m) e Time traveled (s);
- Turning radius (m) and deviation from the central line;
- Combo G (ratio between transversal and longitudinal acceleration).

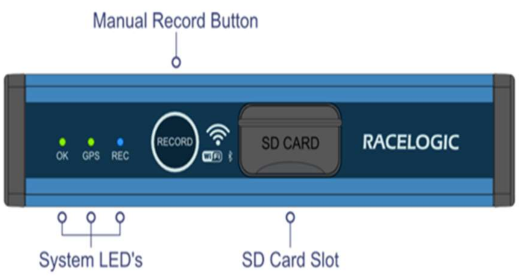


Figure 4.15. Features of Video VBox.

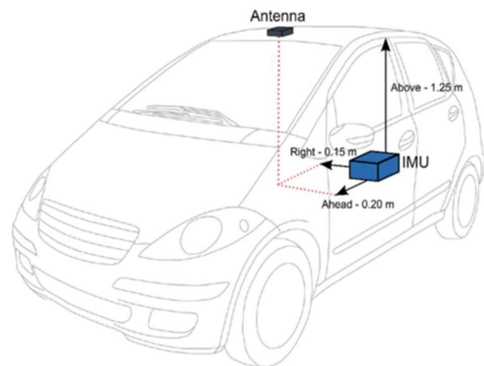


Figure 4.16. The position of the Vbox.

The GPS instrumentation was inserted inside the test vehicle, with the two cameras, while the antenna is positioned outside the vehicle. The different parameters supplied in output from the GPS and emitted with a frequency of 10 Hz are the position along the circuit; the lap times; the speed (accuracy of ± 0.1 km/h); the acceleration (1% accuracy), and distance with a 20 Hz sample rate.

4.2.1. The response time of ACC (VRT)

For each critical event performed during the test lap (the 2nd one), for both ACC on and off conditions, the response time of ACC (VRT) has been calculated. The average value for each condition (ACC on and ACC off) was taken into consideration.

The response time of ACC, thanks to the synchronization of the speed data and the eye-tracking data obtained by the methodology used by Costa (2018), has been evaluated as the difference between two different times:

- the frame in which the prey vehicle braked, its led stop become red and the driver saw the stop, evaluated thanks to the Mobile Eye;
- the time in which the driver braked, after having looked at the led stop of the prey vehicle. This time has been evaluated from the Video Vbox-Pro output video (Figure 4.17).

Figure 4.17. Time of breaking.

4.2.2. The Perception-Reaction Time (PRT)

For the evaluation of the Reaction-Perception time of the driver, a new indicator is introduced. This represents the time of the first-fixation of the red led stop belonging to the prey vehicle (Figure 4.18).

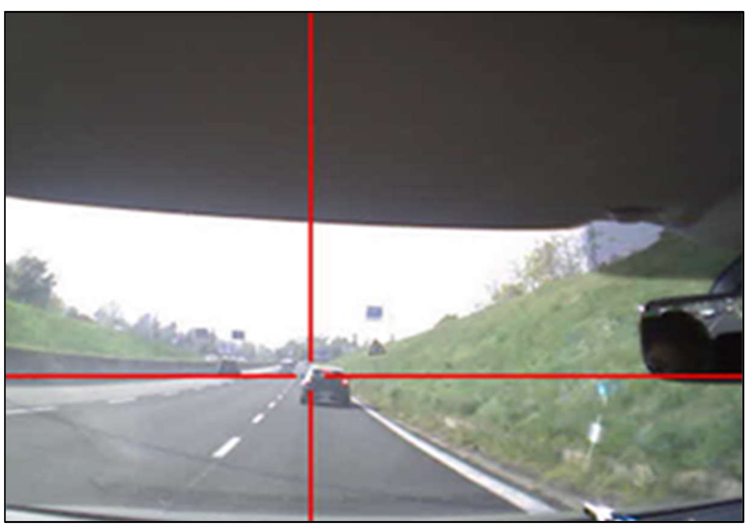


Figure 4.18. The red led stop of the prey vehicle.

In figure 4.19 it was possible to highlight the range, corresponding to the Perception-Reaction Time.

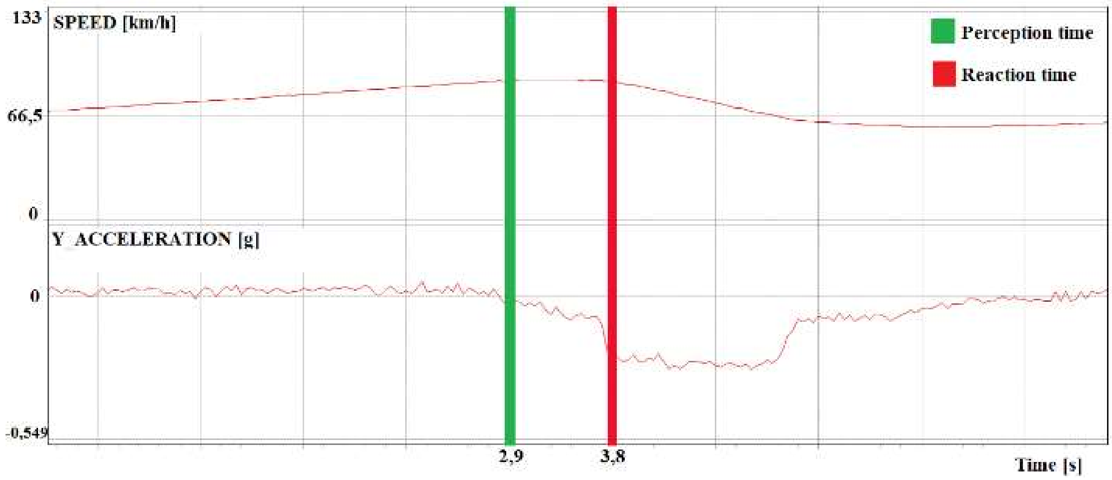


Figure 4.19. Evaluation of the response time of ACC.

In fact, it is included between the green line indicating the led stop time, in which the prey vehicle starts to brake and the user views it and the red one, which is breaking time, in which the test vehicle brakes in turn.

4.2.3. Assessment of the influence of circulating traffic

The traffic count consisted in how many vehicles stood in front of the vehicle during the test. Distinctions have been made for:

- Light vehicles (mass in running order less than 35 quintals);
- Heavy vehicles (mass in running order greater than 35 quintals);
- Motorcycles (two-wheeled vehicles of a cylinder capacity exceeding 50cc);

The service level (LOS) of the road was analysed using the Highway Capacity Manual (HCM).

The LOS is a qualitative measure that describes the operating conditions of the flow on a trunk road as the flow varies. In reference to the a definite limit speed of the road, there is a free flow speed (SBB), which affects the definition of LOS. The HCM manual provides the relationship between SBB, expressed in km/h, and LOS. Each service level corresponds to a maximum density, understood as vehicles per kilometre per lane. In table 4.4, there is 5 levels of service from LOS A to LOS E in which we have an increase in density and consequently a worsening of driving conditions.

EXHIBIT 21-2. LOS CRITERIA FOR MULTILANE HIGHWAYS

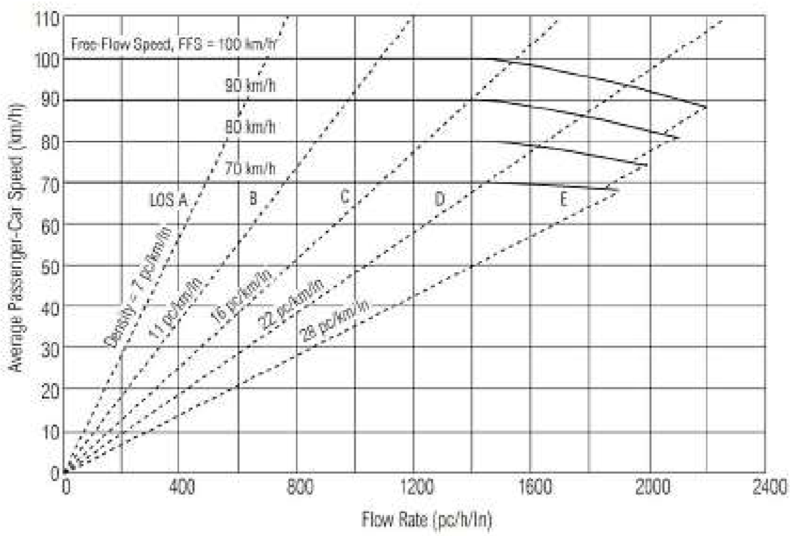
Free-Flow Speed	Criteria	LOS A	LOS B	LOS C	LOS D	LOS E
100 km/h	Maximum density (pc/km/ln)	7	11	16	22	25
	Average speed (km/h)	100.0	100.0	98.4	91.5	88.0
	Maximum volume to capacity ratio (v/c)	0.32	0.50	0.72	0.92	1.00
	Maximum service flow rate (pc/h/ln)	700	1100	1575	2015	2200
90 km/h	Maximum density (pc/km/ln)	7	11	16	22	26
	Average speed (km/h)	90.0	90.0	89.8	84.7	80.8
	Maximum v/c	0.30	0.47	0.68	0.89	1.00
	Maximum service flow rate (pc/h/ln)	630	990	1435	1860	2100
80 km/h	Maximum density (pc/km/ln)	7	11	16	22	27
	Average speed (km/h)	80.0	80.0	80.0	77.6	74.1
	Maximum v/c	0.28	0.44	0.64	0.85	1.00
	Maximum service flow rate (pc/h/ln)	560	880	1280	1705	2000
70 km/h	Maximum density (pc/km/ln)	7	11	16	22	28
	Average speed (km/h)	70.0	70.0	70.0	69.6	67.9
	Maximum v/c	0.26	0.41	0.59	0.81	1.00
	Maximum service flow rate (pc/h/ln)	490	770	1120	1530	1900

Table 4.4. LOS

To obtain the LOS of the road the number of cars counted in the single trunk, divided on the length of the trunk and on the two lanes of the road were considered.

These assessments were necessary in order to assess the reference service level (LOS) for each road section; LOS is in fact a measure describing the quality of traffic conditions on a road section. The HCM (Higway Capacital Manual) provides the table (Graph 4.1) that allows to evaluate it according to the following main indicators:

- the mean or free-flow velocity, which in this study was assumed to be 90 km/h, or the limit imposed by the highway code for that stretch of road, is shown on the ordinate axis;
- line lines delimit vehicle density per km per lane;
- flow rate is indicated on the axis of the x-axes.



Graph 4.1. LOS (HCM).

The table in the HCM manual divides the level of a general road section into different service segments.

- A: Flow conditions are free, with no air conditioning between vehicles.
- B: Runoff conditions are characterized by certain restrictions on freedom of movement, while the conditions of physical and psychological comfort are still high.
- C: Multiple lane changes and frequent overtaking to maintain the desired speed.
- D: The flow is still stable but the freedom of manoeuvre is greatly reduced; this leads to a reduction in the physical and psychological comfort of the drivers.
- E: The conditioning is almost complete and the comfort level is poor; this level represents the flow conditions marked by frequent and sudden power stops, ie with 'stop and go' gear.

In order to differentiate the level of service in Table 4.5, different colourations have been assigned in preparation for the verification of the road trunks under study.

A	B	C	D	E
Veic/km=<7	7<Veic/km=<11	11<Veic/km=<16	16<Veic/km=<22	22<Veic/km<25

Table 4.5. Table for the LOS.

4.3. Outcomes

Thanks to the VIDEO V-BOX PRO, it has been possible to evaluate the driving behavior in terms of average speed during the test and minimum average distance from the lead vehicle during the events. The video analysis started by synchronizing the eye-tracking videos from the ASL mobile eye tracker with the VBOX videos, which allows for associating the drivers' visual gaze behavior with the driver's speed. Considering the LOS A recorded, the ACC didn't influence the vehicle speed during the test. The average lap speed was 67 km/h (SD = 12.2) and 70 km/h (SD=11,4) for ACC users and 61 km/h (SD=10.8) and 62 km/h (SD= 9.7) for no-users, respectively for ACC ON and OFF conditions. The minimum average distance from the lead vehicle, instead, increased with ACC (18.93 m and 28.3 m for ACC users, and 16.4 m and 21.7 m for no-users, respectively for ACC OFF and ON conditions), confirming the active safety role of the system (288 observations - 48 participants - 3 events - 2 ACC conditions), $F(1, 288) = 2.21$, $p = 0.02$, $\chi 2 = 0.041$). The LOS calculated was A.

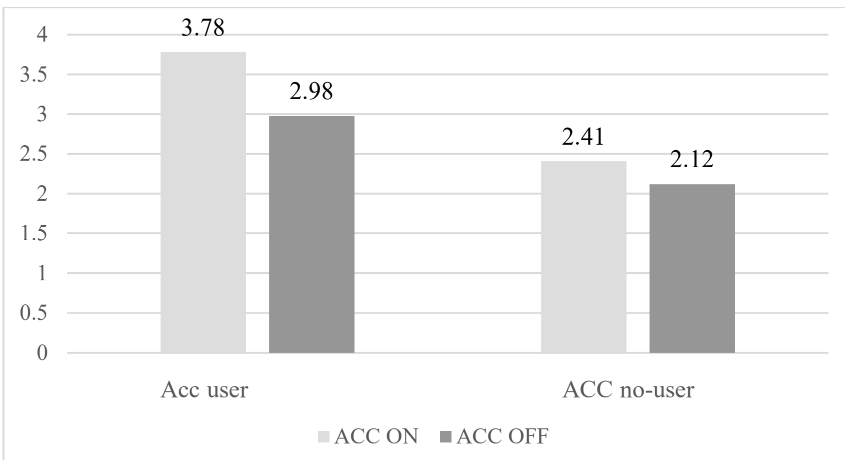
The table 4.6 shows the data regarding the reaction time of all the participants in the experiments. From the calculation of the average, it can be seen that the drivers with no experience of the system react faster in both test situations. The most important data, certainly, concerns the reaction of the drivers when the system is active; the data leads to the assumption that the inexperienced user tends not to trust the use of Adaptive Cruise Control, confirming what has already emerged in the previous analyzes.

	ACC no-user		ACC user	
User	ACC ON	ACC OFF	ACC ON	ACC OFF
1	5,200	2,600	2,950	1,840
2	3,025	1,767	5,140	3,967
3	2,975	2,375	4,000	3,600
4	4,000	1,675	3,450	3,000
5	1,733	2,480	3,640	2,525
6	1,550	3,075	3,950	2,400
7	3,300	3,200	4,340	2,600
8	2,275	2,167	3,250	2,700
9	1,640	2,600	2,900	2,733
10	1,667	1,583	2,667	2,467
11	2,200	1,625	4,300	3,000
12	2,050	1,850	4,520	3,800
13	2,575	2,100	7,433	4,375
14	2,767	3,060	3,333	2,567
15	2,267	2,550	3,025	3,200
16	2,333	2,750	4,000	2,433

17	1,750	0,980	4,150	2,400
18	2,325	1,400	3,775	3,075
19	1,500	2,733	2,800	2,600
20	2,825	2,733		
21	2,243	1,600		
22	2,075	1,740		
23	2,000	1,380		
24	1,867	1,533		
25	2,350	1,700		
26	2,400	1,867		
Average	2,419	2,120	3,875	2,910

Table 4.6. Time of reaction.

Calculating the average of reaction times for experienced and inexperienced users, the trend is confirmed according to which the times in the various events are greater when the system is switched on (Graph 4.3).



Graph 4.2. Average reaction time.

The results of the analysis, both for experienced and inexperienced users, related to the averages of speed, minimum distance and time headway, illustrates similarities in driving behavior in system situations ON and OFF for both categories of drivers (Table 4.7). It is possible to see the tendency of all the users to maintain a higher speed when the system is turned OFF, this highlight a greater confidence in their own capabilities rather than in those recognized to the system. Furthermore, with regard to distances, both spatial and temporal, the inexperienced user tends to maintain a lower distance than the prey vehicle unlike the expert user who maintains a more appropriate distance.

	ACC no-user		ACC user	
Event	ACC ON	ACC OFF	ACC ON	ACC OFF
Average velocity [km/h]	60,21	62,59	67,31	69,40
Minimum distance [m]	21,71	16,35	28,34	18,86
Average TH [s]	1,30	0,94	1,82	1,16
Average TTC [s]	6	6	9	7

Table 4.7. Comparison of Velocities, distances, TH and TTC of the two type of drivers.

Finally, regarding inexperienced users the data indicate, like the results of the self-report, a considerable expectation in the functioning of the system, meanwhile the experience and the knowledge of the system will lead on keeping greater distances and consequently to a greater road safety.

4.4. Conclusion

From the driving behavior analysis, it was possible to observe the average speeds maintained during the test were lower than the speed limit, although it is necessary to remember how they were instrumented and controlled by operators on board. It was also shown that the user in the case of system OFF tend to be closer to the prey vehicle; these results mean that the Adaptive Cruise Control system can be considered an effective driving aid to maintain the right distance between vehicles, especially in high-speed roads, such as the Tangenziale of Bologna.

The comparison between the two type of user highlights that inexpert driver tends to be much closer to the previous vehicle compared to the experienced drivers.

Moreover, the perception / reaction time of the users was evaluated, for both situation: ACC ON and ACC OFF. The data obtained on this time confirm what emerged from the driving distraction assessments, regarding driving with an active adaptive speed control system. In fact, it turned out that the generic user tends to respond more slowly when the system is in operation, than when the guide is autonomous. In conclusion, it can be stated that, according to the data obtained, the Adaptive Cruise Control appears as an effective aid considering the to maintaining safety distances, both in terms of length and in terms of time. On the other hand, driving with this active system determines longer response times, induces distractions, and increase stress which should be avoided in order to increase a safe in driving. To prevent distraction and accelerate response times, which are essential for greater driving safety, one think could be the introduction of tools that recall driver attention when the ACC detects a decrease in the safety. Equipping, for example, the ACC system with an acoustic signal or a vibration of the steering wheel, or other warning systems, the performance of ACC users could be more efficient and, consequently, improve safety.

5. THE IMPACT OF ACC ON DRIVERS' WORKLOAD

5.1. Introduction

The term Workload refers to the mental load that an individual is subjected to while performing an action. It is a fundamental parameter in the field of road safety since it allows us to estimate how the infrastructure engages the human mind. Therefore, depending on the cognitive load, it is possible to estimate the level of performance of drivers.

5.1.1. The role of workload

Low workload levels correspond to low performance levels, where inattention prevails. The level of performance increases with the growth of the mental load required, until a maximum peak level is reached, then decreases drastically. The probability of error increases as the level of performance exhibited decreases. It is necessary, therefore, that the mental load is neither too high, not to exceed the reaction-decision ability of the driver, nor too low, not to cause inattention in the same. For these reasons, the risk of road accidents is greater in geometric elements or specific tasks to which workloads compete or very low or very high (Kantowitz et al., 2000; Cuenen et al., 2015; Lyu et al., 2017).

The term generally indicates the mental workload to which an individual is subjected during an action. The determination of its level has been analyzed by scholars of different disciplines as it is possible to talk about different types of workloads (physical-motor, communicative, etc.). The relationship that links the mental workload and the level of performance is represented by the Yerkes-Dodson law, which relates stimulus and performance (Figure 5.1). In this way, it is possible to underline how the performance increases with increasing mental or psychological stimulation, to the point where the workload becomes too high and causes a decrease in performance (Kantowitz et al., 2000).

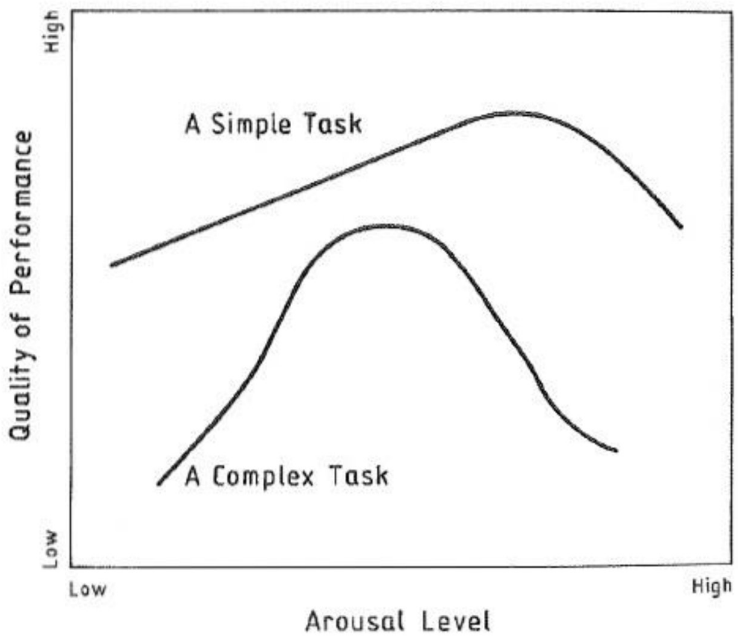


Figure 5.1. Yerkes-Dodson Law.

Generally, the greater the commitment to the task to be performed, the more work users must do to complete it. Increasing the mental workload increases the delay with which users manage to process information since the amount of information exceeds their processing capacity. On the other hand, when the workload is too small, users become less concentrated and tend to make mistakes.

5.1.1.1. Definitions and theories related to workload

A simple workload definition is that it is a request to a subject. However, this definition only attributes the workload to an external condition. Actually, the workload is better defined if it refer to experience. The workload is not only related to a specific task but also relates to the specific person performing that task (Rouse et al., 1993). A definition was proposed by Verwey (1999), who states that "the mental workload is related to the amount of attention required for making decisions". Young & Stanton (2001) propose the following definition of mental workload (MWL): "The mental workload of a task represents the level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support, and past experience", and "represents the level of attention resources required to understand both objective and subjective performance criteria, which is mediated by tasks, external support and past experience."

Other more articulated definitions of the concept are, for example, that of Wickens (1984): "it is possible to define mental workload as a multidimensional construct that reflects the individual level of attentional involvement and mental effort". Hart and Staveland (1988) describe workload as "the perceived relationship between the amount of mental processing capability or resources and the amount required by the task" that is "the perceived relationship between the number of resources (or capacity) of a mental process and the amount required by the tasks to be performed". It is from this last definition that one of the most known theories on the subject is well understood: the multiple resource theory (MRT) of Wickens in 1984 (Figure 5.2).

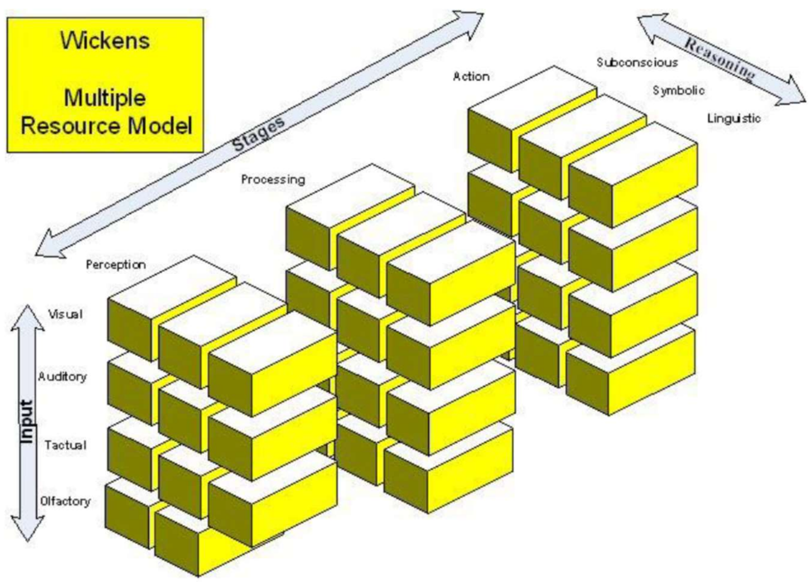


Figure 5.2. Wickens MRT theory.

From this theory, it can be inferred that the human operator does not have a single piece of information to control, but several wells of resources from which to draw so that the tasks to be performed may or may not be controlled simultaneously. Each box in the figure represents a cognitive resource. Depending on the nature of the task, these resources may have a sequential information process, if the different tasks require the same resource well, or can be performed in parallel if they require different resources. Wickens' theory shows the decrease in performance as a lack of these different resources because the individual has a limited ability to develop information. Citing Dadashi (2013) "the increased demand for resources from which to draw can cause an overload of work in the user". In fact, an excess workload is caused by a task that requires you to use the same well of resources and this causes problems, resulting in poor or slow performance. Wickens' theory follows organized systems to predict when tasks can be performed simultaneously, when they interfere with each other, and when the increase in the difficulty of a task results in a loss in the performance of another task. McCracken and Aldrich (1984), like Wickens, describe a process that does not have a central resource, but more resources: visual, cognitive, auditory, and physico-motor (VCAP). Each task can be broken down into these components: the visual and auditory components that are expected external stimuli, the cognitive component that describes the level of information required, and the physico-motor that describes the physical activity that is required to perform this task. McCracken and Aldrich have developed a rating scale for each VCAP component that corresponds to the rating of the degree to which each resource is used. The workload has also been defined by Senders as a measure of the effort an operator is subjected to while performing a task, regardless of the performance of the task itself. Venturino (1990) defines mental workload as an expenditure of the mental capacity necessary to perform a task or a combination of activities. Another definition of workload was given by Knowles (1963) and consists in the answer to two questions: how much attention is needed? How well can the operator perform additional tasks?

5.1.1.2. The workload in the road field

The World Health Organization (WHO) indicates that road accidents are the ninth cause of death among young people aged 18 to 29. Often one of the main causes is the onset of mental fatigue or drowsiness (Maglione et al., 2014). Driving a vehicle in the 21st century is, increasingly, a complex task involving extreme swings in mental workload (Baldwin & Coyne, 2003). Considering the increasing difficulty of driving tasks and the multitude of information that drivers have to process and manage inside and outside the vehicle, there are multiple factors potentially triggering the driver’s mental workload. Increased traffic intensity and the introduction of new information technologies within the vehicle create increased levels of complexity in the driving task (Engström et al, 2005; Jahn et al, 2005; & Makishita Matsunaga, 2008; Pauzié & Manzano, 2007; Piechulla et al., 2003). The increase in information technology in the road sector (RTI: Road Transport Informatics) and in the various systems for driving aids (IVIS - in-vehicle information systems) means that the evaluation of workload research techniques is of great importance in the road sector. For this reason, Michon (1971, 1985) and

Janssen (1979) tried to propose a model of the guiding task according to which the latter is described as a complex task with processes comprising three hierarchical levels.

At the upper level, the strategic level, strategic decisions are made, such as the choice of means of transport, the setting of a route to follow and the choices related to the route while driving.

At the intermediate level, the maneuvering level, reactions to instantaneous situations occur, including reactions to the behavior of other road users.

At the lowest level, the control level, the basic control processes of the vehicle take place, such as lateral position control. At this level processes are automatic, while at a higher level process control is required. The problem can therefore arise that driving aids such as collision avoidance, traffic information or navigation systems can individually help motorists, But their combined use may cause an overload of their information processing system (Verwey, 1990). Under certain circumstances it is possible that a new driver aid technology may have the opposite effect of "overload" the driver, that is, it may bring monotony into the task. This could happen, as Kantowitz (2000) pointed out if the new devices fully control the vehicle. Currently, driver deactivation situations are mainly confined to driving on the highway. The number of these low stimulus conditions, in which the driver can "deactivate", can increase if more functions are taken over by the technology. A list of factors affecting the driver's workload can be summarised (Table 5.1).

Driver *State* Affecting Factors
monotony
fatigue
sedative drugs
alcohol
Driver *Trait* Factors
experience
age
strategy
Environmental Factors
road environment demands
traffic demands
vehicle ergonomics (RTI)
automation
feedback

Table 5.1. Factors involved with the Workload.

Messer (1980) was one of the first to define *workload* in relation to the road environment: "the workload is the time interval in which drivers must perform a certain amount of driving activity". In particular, it specifies that the workload is mental (e.g. information processing) rather than physical, and increases with increasing geometric complexity. With reference to Yerkes-Dodson report (1908) and since, generally, with the decrease in performance the probability of error increases, the link with the level of road accidents is immediate (Figure 5.3). It can be observed that the accident rate is higher for both very high workloads and extremely low workloads. It is therefore evident that a workload too low involves less safe driving, due to the low concentration and easy distraction, but also an excessive workload decreases performance equally.

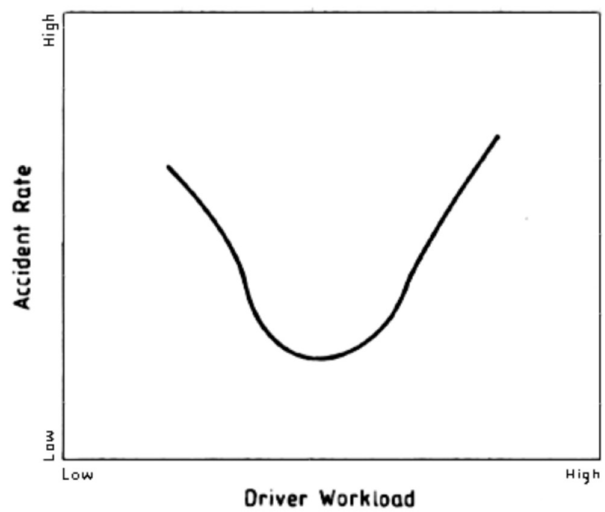


Figure 5.3. Relationship between workload and accident rate.

There is therefore an optimal level of workload for which the performances are maximized, and consequently the accident rate decreases. For the research of this optimal level, Meister proposed in 1976 a model of evaluation that predicts the existence of three regions: region A, region B and region C (Figure 5.4). In Region A there is a weak demand for tasks, a low workload and a high level of performance. If demand increases in this region, performance efficiency is not compromised. In Region B the operator’s performance level decreases due to increased task demand, resulting in an increased workload. In Region C, there is a drastic decrease in performance due to increased task demand levels and high workload levels.

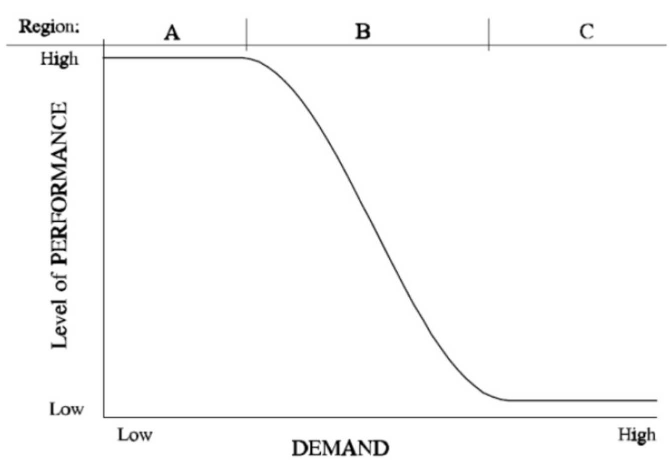


Figure 5.4.Workload regions according to Meister (1979).

De Waard (1996) sought to complement the Meister model by proposing the introduction of an additional region D (disengagement), located before region A and reflecting the effects and implications on the performance of monotonous tasks. The latter can increase the difficulty of running the same, as you are in a state of boredom that requires more capacity to perform the same task, resulting in increased workload and reduced performance capacity. In support of this region D inserted by Da Waard there are many recent studies that evaluate workload levels in drowsy conditions. For example, in 2014 Maglione showed that sleep deprivation adversely affects driving performance, reducing the driver’s ability to react effectively in hazardous situations.

Although the described model can help to understand the process extremes, there is no clear specification of where the boundary lies between a high, moderate or low workload, and what is the optimal workload level (critical time) defined by De Waard and Kantowitz (2000) as a red line. The notion of the red line is associated with the limits of the available resources by the operator and reflects the moment when performance is drastically reduced. Given that, in recent years, the answer to the question "(...) when the workload is too much?" has received particular attention in the context of road research, the concept of a red line for mental workload has been suggested by many authors. For example, Reid & Colle (1988) report that the zone par excellence where performance decreases (i.e., the positioning of the red line) is in the transition from region A to region B. De Waard, By discriminating the exact moment at which performance reduction occurs, it proposes a partition of region A into several sub-regions (Figure 5.5). Thus, in the central part of region A (called A2), the operator can still easily handle a request for tasks to be performed and the performance remains at a stable level even with an increase in tasks (that is, there is no increase in mental effort); in sub-region A3, the operator fails to maintain the level of performance without increasing the effort, but the evaluation measures do not show a drop in performance. In this sub-region performance remains high but with increased mental effort; however if peaks of work begin to happen too often or if the effort lasts too long to ensure performance, stress states emerge, disability and at this point, a critical moment may arise, when the operator may lose control of the situation.

Considering the critical line depending on the relationship between demand and performance, it seems plausible to assume that the critical moment of mental workload is placed in the transition from sub-region A2 to A3. In turn, the transition from region D to region A1 is associated with monotony suffered by the operator when he undertakes a great effort not to decrease the level of performance. In summary, we can classify several regions as follows (Figure 5.5):

- region D, the operator's status is affected by a high workload and low performance;
- region A2, the performance level is considered optimal, and the operator can easily handle the task demands;
- regions A1 and A3, performance does not change, but the operator must use mental effort to maintain such performance;
- in region B, there is a drop in performance, with a start of the increase in workload;
- in Region C, performance remains at a minimum level and the operator is overworked.

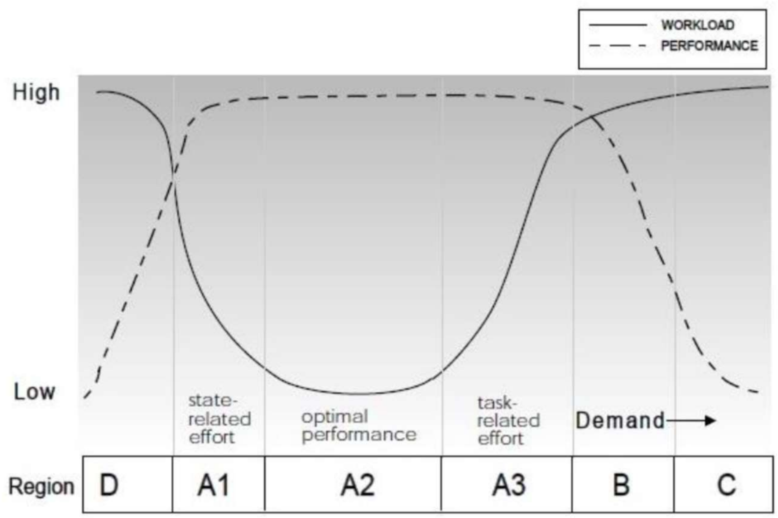


Figure 5.5. Change in workload and performance across regions.

Numerous studies also show that different factors influence the total amount of workload, among which road geometry undoubtedly plays a key role (Pecchini et al., 2017). The workload to which the driver is subjected varies considerably depending on the complexity of the route and the frequency with which the user is subjected to the driving activity. It has been discovered, in fact, that complex road paths require more attention from the driver than straight paths, and these difficulties can be aggravated if you drive a heavy vehicle. Tight radius curves associated with sudden gradient changes, as well as compound curves, have been identified as a threat to truck and car control, contributing to serious accidents (Sweatman, et al., 1990).

It follows that the influence of road geometry on drivers' workload is of primary importance in terms of road safety. Properly designed roads and intersections allow drivers to identify easy and correct trajectories. Moreover, the such workload is strongly influenced also by the abilities of the guide of the pilot and from the expectations that the last one has regarding the road that is about to cover. The presence of inconsistent elements along the track therefore inevitably leads to an increase in the workload on the driver. A more recent study (Lamm et al., 1999), finally, states that the driver's workload also increases in relation to the time available to process a certain amount of information that decreases, for example, due to increased speed and/or reduced visibility distance.

5.1.1.3. Methods of measuring the workload

In literature, the criteria for measuring the workload are divided into three main categories (Brookhuis, 1993; Wierwille & Eggemeier, 1993; Hancock et.al, 2001):

- performance assessment, where the driver's ability to drive can be monitored in terms of lateral and longitudinal control of the vehicle. Generally, this methodology is examined by driving simulator tests (Wickens, 1984; Cantina et al., 2009; Veltman et al., 1996);
- subjective assessment carried out by examining driving performance on the basis of reports by observers and self-reports by drivers. Known examples are the NASA - Task-Load Index (NASA-TLX) and the Rating Scale Mental Effort (RMSE) (Ikuma et al., 2014; Harbluk, 2007);
- the evaluation of the physiological parameters, considering a workload of "natural" type, based on an evident physical response due to the increase of a mental effort. Mental workload has an impact on changing cardiac, cerebral, respiratory and visual activity. The problem with physiological responses is that they are not affected by a single event while driving, but also depend on the subjective experience of the driver.

According to this consideration, it is necessary to evaluate the elements of the road environment that are most fixed by users, in order to increase road safety (Mulder, 1980; Mulder, 1986; Mulder, 1988; Jessurun, 1997, Borghini et al., 2014).

- *Physiological measures*

Physiological measurements are based on the idea that the body responds with a physical reaction to the amount of a mental workload. It would seem that these methods derive the most accurate measurements since they are objective and scientific measurements. However, this is not always true, because the human body responds according to the experience of the individual and therefore the resulting results may be distorted. For example, a person who is anxious or insecure about other non-driving-related problems may have rapid heartbeats. This is why every physiological measure should be related to the context of the individual and his physical and mental activity.

Most research in this area considers five physiological areas: heart activity, respiratory activity, visual activity, speech measurement, and brain activity. Heart activity is the most widely used because it is easy to evaluate and is a clear workload indicator. This type of measure is easily applicable to real situations as it is not an invasive examination. The evaluation of cardiac activity takes place through the electrocardiogram (ECG), that is, the graphic reproduction of the electrical activity of the heart: the onset of impulses in the myocardium leads to the generation of potential differences. They vary in space and time and can be recorded via electrodes. The characteristic pattern of a healthy person is characterized by traits called waves, which are repeated at each cardiac cycle, indicated in figure 5.6.

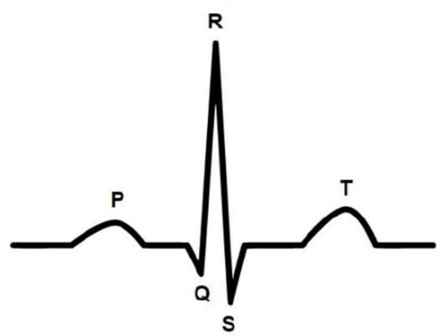


Figure 5.6. Normal ECG path.

The peak of each cycle is called the R wave, the distance on the x-axis between two successive R waves is the time interval between two beats (IBI). The main measures that can be obtained from the ECG for the analysis of the workload are therefore the IBI and the HR (heart rate) that is the heart rate or the average number of beats per minute. Generally, for an increase in workload the HR increases and therefore the IBI decreases. It’s important to remember that heart activity varies from person to person, so when using ECG as a workload measure you need to find a basic heart rate measure to compare it to changes due to new events and tasks.

Another cardiac measure is HRV, or heart rate variability, which takes into account the fact that the time that passes between one beat and the other is not constant. Each of them presents a natural variability of heart rate in response to factors such as the rhythm of breath, and emotional states. In a healthy individual, the heart rate responds quickly to all these factors, changing rapidly depending on the case. A good degree of heart rate variability results in a good degree of psychophysical adaptability to the different situations that may arise.

There is no single method of measuring HRV; the convention is to calculate the IBI standard deviation over a given time or a given number of beats.

An index for HRV can be obtained by spectral analysis. The frequency of the spectrum can be divided into 3 parts: the lowest band is that associated with the regulation of body temperature (0.02 Hz to 0.06 Hz), the average band is that associated with the regulation of blood pressure (0.07 Hz to 0.14 Hz) and the highest band is associated with breathing (0.15 Hz to 50 Hz).

The high-band relationship between breathing and heart rate lies in the fact that during breathing in the inspiration phase HR increases, and in the exhalation phase HR decreases.

The second band is associated with the change in blood pressure (BP) that presents fluctuations, that is, peaks and depressions, and to these, the heart responds by varying the heart rate; nn fact, if the blood pressure is too high, the heart will regulate the pressure itself by decreasing the HR (by pumping less). The frequency related to blood pressure fluctuations is 0.10 Hz.

The middle band is one of our greatest interests as it is strongly linked to mental effort. An excess of workload, in fact, reduces the sensitivity of the HR-BP adjustment and this reduction of adjustment leads to a lower HRV value.

Some research has found that an increase in workload leads to a decrease in HRV; others have found that HRV is not affected by workload. An explanation for this discrepancy could be a respiratory activity which, if too excessive, does not allow estimating HRV (Brookings, 1996).

IBI (or heart rate) is generally sensitive to both the driver’s attention level and computational effort, while the 0.1 Hz component of HRV is not sensitive to compensatory effort but solely to the computational effort.

De Waard, Van der Hulst & Brookhuis (1996) clarified the change in HR during the completion of an action (Figure 5.7).

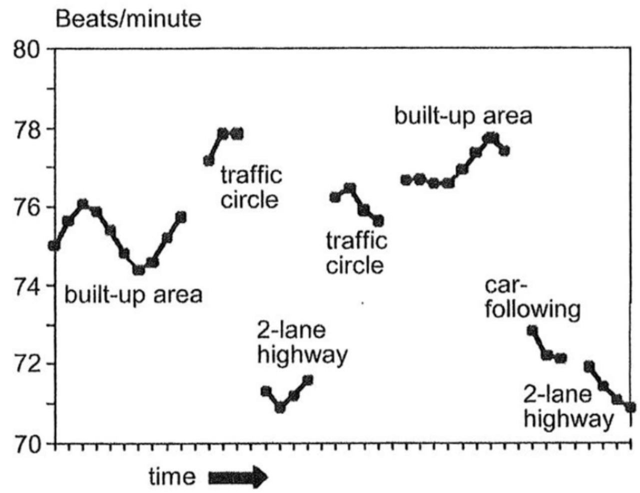


Figure 5.7. Heart rate change in the road environment.

An average HR of 22 subjects was reported in this figure. The data was taken from a simulator study, in which subjects drove in different road and environmental conditions. The change in HR is evident: driving on a roundabout (traffic circle) coincides with an increase in heart rate, while on a two-lane highway (2-lane highway) the heart rate is slower.

Figure 5.8 shows the 0.1 Hz component of the HRV, compared with the rest of the measurements when the driver is stationary in the car. Component 0.1 Hz is suppressed when the driver is employed in a computational mental effort, you can always notice it by comparing the two-lane main road with the roundabout. Standing still at the red light increases HRV, in fact, you have minimal mental effort.

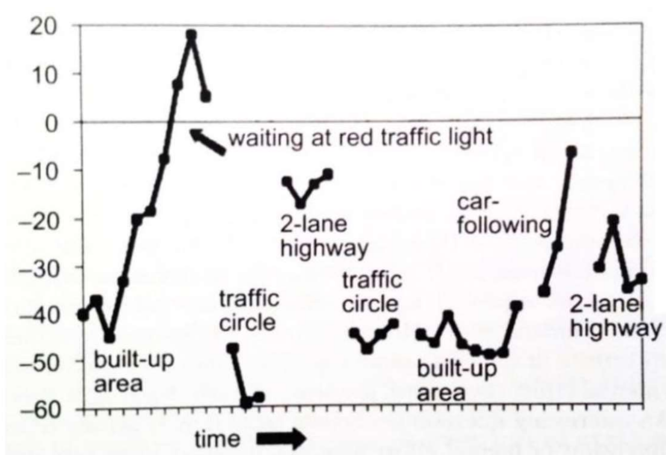


Figure 5.8. Variation of HRV in the road environment.

The study carried out by Bor-Shong Liu and Yung-Hui Lee analyzed the workload of drivers, who proposed a secondary task such as the telephone conversation at the wheel. The driving situation also included an urban road and a motorway. The type of physiological measurement used was the ECG for heart rate measurement. The results of the study show that the use of the mobile phone increases the reduction of safety distance compared to the vehicles in front, thus confirming that the use of mobile phones while driving decreases safety and increases distraction, with increased heart rate resulting in increased workload.

The second physiological area is the one related to respiratory activity, for which the respiratory rate or the number of breaths in a given time is calculated. The number of breaths can be used as an index of emotional stress and is related to the variability of heart rate. The most important problem is taking data when breathing is interrupted by speech. The third physiological area is a visual activity. Although the gaze is primarily associated with the visual workload, it has been shown that it can also predict a mental workload. The measurement is associated with the calculation of several factors related to the eye: the horizontal movement of the eye (HEM), the blinking (speed and frequency), the closing interval, the fixation of the eye and the dilation of the pupil. Blinking generally decreases as the workload increases. Workload sensitivity to blinking was studied under three components: the frequency of heartbeat, the duration of the heartbeat and the latency of the eye beat. Kramer states that, as latency increases, the closure duration decreases with increased task demands. Stern et al. (1994) conclude that increased heart rate is a significant indicator of fatigue.

Pulse rate was analysed in a series of driver workload studies with mixed results. Heger et al. and Recarte et al. analyzed the rate of eye beat in a single and a double task (cognitive task plus visual research) and found that the rate of pulse increases for all cognitive tasks (listening, speaking, and calculating) in comparison to the control condition. They also found a decrease in blink frequency for more demanding visual tasks than less demanding visual tasks. They concluded, therefore, that "according to the blink of the eye, the visual and mental workload produce opposite effects: the inhibition of the beat for a higher visual demand and the increase in the frequency of the beat for a greater mental workload".

Also, the frequency of the beat was investigated in the function of highly automated driving, with systems of lateral control of the vehicle and control of the longitudinal direction. Systems like these are typically designed to reduce a driver’s mental workload. However, several studies have found an increase in heart rate during highly automated driving compared to the normal driving situation (Cha et al., 2003, Merat et al., 2012). It has been shown that the duration of the heartbeat decreases with the increasing mental workload. The authors examined the effects of information systems in the vehicle (IVIS) on the blinking of the eye while performing a task such as a lane change (LCT) while driving. The results showed a blink duration inhibition for the dual-task (LCT and IVIS task) compared to the single operation condition (LCT). According to the authors, this inhibition can occur to prevent the loss of visual information.

Fixation time is a widely used measure and typically increases with increasing demands of the mental task. O'Donnell & Eggemeier (1986) report that an increase in workload is accompanied by an increase in fixation time. Backs & Walrath (1992) also determined that the fixation time ('dwell time') differs according to the characteristics of the tasks to be performed and that it increases by monochrome stimuli rather than by coloured stimuli. May et al. (1990) report a significant decrease in the saccharide range (that is, small rapid and involuntary movements of the eye) to the increase in a mental workload.

The fixation of the eyes can be measured by recording the electrooculogram (EOG) or by using a video camera that records the corneal reflex, superimposed on a video showing the image of the visual field. The equipment that allows the execution of the latter mode is the Mobile Eye-Tracker. Both techniques have the disadvantage of requiring intense work, especially in terms of time, both for calibration and data analysis. Measuring eye movement in subjects with glasses is very difficult.

Interesting is the evaluation of the number and duration of the eye fixation on the instruments inside the car in particular in the mirror, while driving, which provide a good indication of the user's driving strategy. Parkes (1991) refers to the measurement of eye fixation as "eye allocation", that is, it summarises parts of the visual field in which the observation point is placed according to the boundary situation. Three categories were analysed:

- Relevant traffic fixations: the driver looks straight forward, into traffic, into a blind spot;
- irrelevant fixing of traffic: the gaze is turned into the other carriageway (which is irrelevant for driving on the highway), or on the road, in the air;
- mirrors and dashboard ('other focus points').

If the workload decreases, the opportunity to look at irrelevant stimuli increases. A more challenging environmental circumstance requires an increase in the time spent looking at the road, that is to say, more time spent looking at objects, such as other traffic-sharing cars, road signs, and road layout, including mirrors.

If it is not the external environment that requires extra attention but a device inside the car, we may have the opposite effect: less time will be spent looking at relevant objects in traffic.

Pupillometry, the pupil diameter evaluation, can also be used as a workload indicator. Recarte and Nunes (2000 and 2003) show a significant increase in pupil diameter during secondary verbal tasks. Palinko (2010) and Kahneman (1973) concluded that the increased need for processing activities was reflected in the increase in pupil diameter.

Table 2.2 summarizes some ocular parameters useful for the evaluation of the workload and its influence on it. It is noted that an increase in workload corresponds to an increase in the heartbeat of the eye, an increase in the percentage of closure of the eyelid (PERCLOS), an increase in the fixation time, an increase in the diameter of the pupil, a decrease in the duration of the heartbeat and the variability of the gaze.

Di Stasi et al. (2013 and 2015), for example, conducted a study involving 44 users who interacted with a PC responding to different tasks within a simulation of a forest fire, with the aim of extinguishing the fire as soon as possible. Each user wore a Mobile Eye Tracker. The results obtained confirmed the use of gaze-related measures as indices of mental workload in complex tasks. In particular, they showed an increase in the fixing time as the workload increased and a decrease in the diameter of the pupil at each change of environment at the boundary.

Saeed et al. (2015), on the other hand, have subjected 46 users to a simulator trial within a highway and moderate traffic scenario. Using the Mobile Eye Detector have shown that the most reliable tool to evaluate mental workload is the change in pupil diameter.

A very important study using eye movement for workload evaluation is that carried out by Strayer et al. in 2013. In this study, driver distraction was analysed due to the secondary activities available on board the vehicles. Three experiments designed to systematically measure cognitive distraction are described. In the first, participants performed eight different tasks without the parallel operation of a motor vehicle. In the second experiment, participants equally performed eight tasks while driving a simulator. In the third experiment, participants performed the same eight tasks while driving an instrumented vehicle in a residential area of a city. In each experiment, the tasks involved are a basic condition of single-task (i.e., without concomitant secondary task), simultaneous listening to the car radio, simultaneous listening to a book on tape, conversation with a passenger sitting next to the participant, the conversation on a handheld mobile phone, the simultaneous conversation on a mobile phone via Bluetooth, sending an email and replying to an email via voice.

Examination of eye movements was used to evaluate the workload. This measure is important because it has direct implications for driver safety. Unlike other measures, look coding can be obtained in a fairly non-intrusive way and is sensitive to changes in cognitive demand. It has been seen that in general when drivers engage in a cognitive task of secondary distraction, they tend to look away from the front road less often. Left and right look up as the workload increases. In addition, there is a systematic decrease in scanning for hazards to increase workload.

The fourth physiological area concerns the measurements of speech which, however, are rarely used for the impossibility of grasping the different aspects of language. In general, there are three measures of the workload: intonation, rhythm and volume, which increase with increasing difficulty of the tasks to be performed. Cardiac, respiratory, visual, and speech activities are all actually affected by the signals that the brain sends when faced with a workload. This is why we prefer to calculate the workload by directly measuring brain activity. The biggest problem in this measure is the equipment needed to perform the measurement, which is cumbersome and inexpensive, plus it turns out to be an invasive examination for field tests. The measurement is carried out by studying the electroencephalogram (EEG). As with the ECG, bands can be detected by spectral analysis. For the EEG there are four bands: Delta waves (above 4 Hz), Theta waves (4 to 8 Hz), Alpha waves (8 to 13 Hz) and Beta waves (over 13 Hz), since 2000 a new band has been introduced, Ultra Beta waves (31 to 42 Hz). The increase in mental workload predicts the prevalence of some waves over others. The breakdown into frequency bands serves as an indication of the driver's status with respect to alertness and alertness in different driving conditions. In particular, delta waves are present during deep sleep, while beta waves are present when the subject is alert. Alpha waves and Theta waves in general are associated with alert moments. In various workload studies using EEG frequency analysis, a higher sensitivity of alpha and theta waves is generally reported. (Kramer, 1991) and Sirevaag et al. (1988) reported a decrease in Alpha activity and an increase in Theta performance during multiple tasks compared to individual tasks. The use of EEG frequency analysis is widely used in the assessment of operator status, for example, to assess excitation levels during supervisory situations (Wilson & Eggemeier, 1991).

There are also many other physiological parameters related to workload, such as electrothermal activity measurement (EDA), which measures electrical changes on the skin. An increase in EDA corresponds to an increase in mental effort, as in the study of Michaels (1962) or Zeier (1979).

- *Subjective measures*

Subjective methods are individual assessments of driving performance. These assessments can be provided either directly by the sample performing the experiment (self-report methods) or by external, typically competent personnel. Unlike physiological measurements that are more precise, these methods are more practical, as the easiest way to understand if a subject is subjected to an excessive workload is to ask directly to the person concerned. Moreover, they are definitely the least invasive, the most flexible, the cheapest and require the least execution and processing time.

Unlike physiological tests, these can only be performed before or after the experiment, so they do not guarantee a continuum measurement. In addition, a 15-minute delay in carrying out this test could lead to a different score, due to the fact that the workload amount is forgotten by people over time. De Waard indicates a maximum delay of 30 minutes beyond which the tests are no longer reliable.

Another problem with subjective measurements is the scale of assessment, as the context strongly influences the results. In fact, subjective methods can be divided into two categories: one-dimensional and multidimensional. One-dimensional assessments have only one dimension and are easier to use. An example is the Modified Cooper-Harper Scale (MCH), the Overall Workload scale (OW) or the RSME developed by Zijlstra. In the RSME stress assessments at once are indicated by a cross on a continuous line. The line goes from 0 to 150 mm and is marked every 10 mm. Along the line, at several points, statements relating to the effort invested are indicated, for example: 'Almost no effort' or 'extreme effort' (Figure 5.9). On the RSME should be indicated the amount of effort invested in the task, and not the more abstract aspects of mental workload (for example, mental demand, as in TLX).

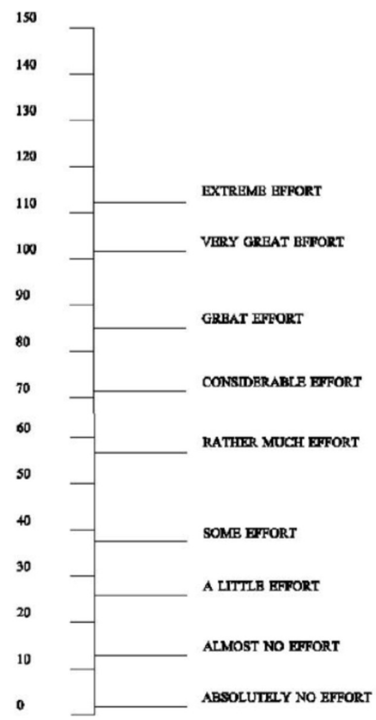
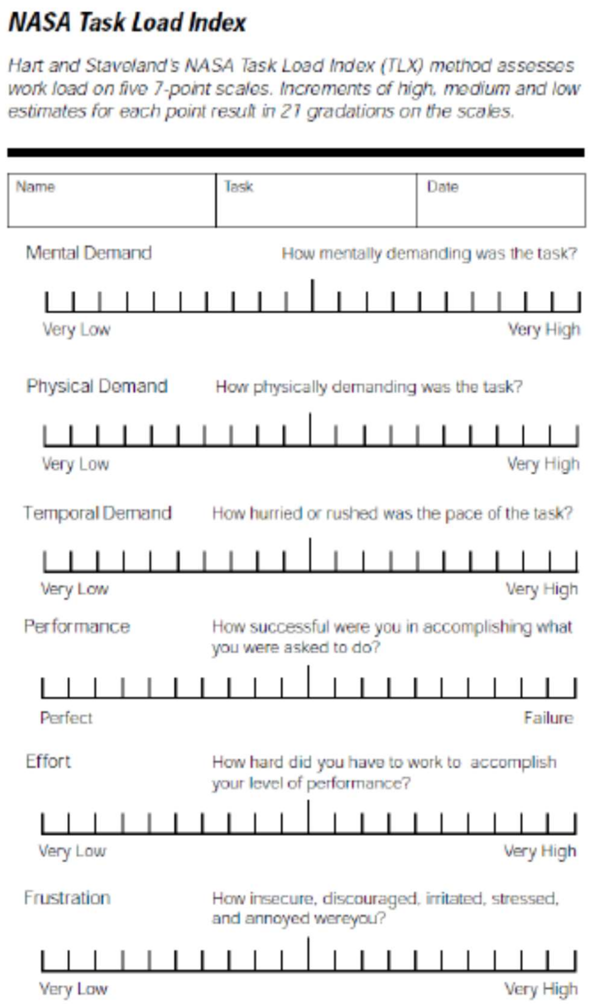


Figure 5.9. RSME scale.

Zijlstra, Van Doorn and Meijman (1989) used the RSME one-dimensional scale in their research. The focus of the study was on the assessment of the effects of traffic on the mental workload of users, especially when entering and leaving the motorway. The testing mode consists in dividing the possible scenario into three traffic conditions: the presence of light vehicles, the presence of a mix (light and heavy vehicles), and the stacking of heavy vehicles, and in two weather conditions (and visibility) clear skies and fog, which have little influence on the results except with the adaptation of user speeds. The results of the RSME have shown that of the three traffic conditions, what makes the task of entering and exiting traffic more challenging mentally is certainly condition 3, or the queuing of heavy vehicles. Another one-dimensional assessment is the Activation Scale. The aspect of this scale is comparable to the RSME; the activation scale also consists of a single axis with reference points.

Multidimensional evaluations, on the other hand, are more complex and require a longer evaluation time, because they can reach up to six dimensions. As the workload's evaluation complexity increases, the size increases. There are two most widely used multidimensional scales that use the self-report methodology: SWAT (Subjective Workload Assessment Technique) and NASA Task Load Index (NASA-TLX). SWAT uses three levels, low, medium and high, for three dimensions: time load, mental load and physiological stress load. There are three steps to analyzing the workload: the first step is to find all possible combinations of three dimensions in 27 cards. The individual arranges the cards in an order that reflects their own perceptions of the workload. This order is then used to develop a scale with interval properties. The second step is to evaluate the workload. The third step is to convert the score into a scale from 0 to 100, using the scale developed in the first step.

NASA-TLX uses six dimensions for workload evaluation: MD mental request, PD physical request, TD temporal request, OP performance, EF effort and FR frustration. The score you get for each scale goes from 0 to 20. The operator is required to choose in which dimension he claims to have had an excessive workload, in order to attribute a weight to each dimension. The final result, ranging from 0 to 100, is obtained for each task by considering the weight attributed to each for each scale, summing the scales, and dividing by the total weights (Figure 5.10).



NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Physical Demand — How physically demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

Figure 5.10. NASA Tlx.

Referring to the road field, the six dimensions were studied in the case of low traffic conditions (LTD) and high traffic conditions (HTD), and it was seen that in LTD due to a good OP, MD is low. While in HTD, MD and FR increase resulting in increased mental workload. Recently from this scale has been developed an equivalent, the NASA Raw Task Load Index (NASA-RTLX), obtained by the sum of the TLX and dividing by six. In a driving assignment, Park & Cha (1998) noted that the latter is more sensitive to mental demand than the former.

Between SWAT and NASA-TLX, the latter is generally preferred, as the number of evaluation factors is higher in NASA, the data is easier to interpret and the procedure is lighter in comparison to SWAT.

Almost all road context studies investigating workload variations on users report the use of subjective questionnaires, especially NASA's TLX or RTLX.

Fairclough et al. (1991), for example, used NASA-RTLX in a study that aimed to analyze changes in the workload in performing a dual task (leading and entertaining a conversation). They found an increase in the overall workload in the dual-task condition compared to the single task, which was guidance only.

RTLX was used in the study by Vaughan et al. (1994). The experiment, in this case, consisted in subjecting users to messages in three forms: auditory message, auditory message and continuously visible on a display, auditory message and temporarily (15s) visible on a display. The end result of the RTLX showed that a lower mental workload is developed for the second condition, namely the auditory signal and continuously reported on a display. Another study, more recent, that exploits the subjective measures, was carried out in a simulator (Teh, et al., 2013). The purpose of the experiment was to analyze the effects on the driver workload as a function of changing two factors: traffic flow and lane change. In this case, several subjective measurements were used simultaneously to confirm the validity of each of them: the NASA RTLX, the RSME and later also another minor scale called Continous Subjective Rating (CSR), which consists in subjective evaluation of the workload also within the experiment itself.

As shown in previous studies, also in this case the results of the questionnaires demonstrate an increase in workload with the increase in traffic flow. Participants assessed a larger effort when they are "boxed" by the presence of other vehicles, especially heavy vehicles. As regards the lane change factor, drivers reported an increase in workload when changing lanes in their front field of view, especially if in the immediate vicinity, which was defined as an area "margin of safety": in this area the presence of other vehicles triggers an emergency reaction in the driver. Literature also makes available many studies that also use other subjective measures (Janssen et al., 1994; Baldauf et al., 2009), a few years later, in their studies found that the sum of the SWAT scale feedback was just as sensitive to increases in workload as the RSME scale.

- *Performance based methods*

The level of performance of the primary task makes it possible to understand whether the driver is driving correctly, in accordance, in practical terms, with all the prescriptions indicated in the theory, although a range of deviations from the theoretical requirement is allowed, which still allows you to remain safe. The problem lies in identifying the deviation beyond which you are no longer safe.

The principle on which this method is based is the subdivision of the actions in primary or secondary tasks, and the decrement of the performance in one or the other tasks is calculated. This subdivision reflects MRT theory, as primary tasks require a certain amount of resources, and the remaining resources are employed in secondary tasks.

Performance in primary tasks is a direct, non-invasive measure. The primary task must be identified and specified for each type of situation. Parkes (1991) defined the primary task of the driver as maintaining safe control of the vehicle. The tasks that allow "vehicle control" in the road field are mostly:

- the measurement of steering movement of the steering wheel, which does not require sophisticated equipment and in particular the reversal of steering is more sensitive to changes in workload;
- the lane-keeping, that is the deviation from the central or lateral line of the lane, for carrying out this measure is necessary, however, a more specialized equipment;
- speed control, the speed is in fact more moderate for excessive workloads;
- time to line crossing (TLC) means the time it takes for a vehicle to reach either the center or the lane boundary, without any further steering correction. Typically if the workload increases, TLC increases, (Godthelp et al., 1984 - 1988).

The performance of secondary tasks is additional to the previous tasks and is measured as the difference between the mental capacity engaged in the main tasks and the total available capacity. The advantage of calculating secondary performance over primaries is that they are able to determine any mental reserve capacity. Some examples of secondary tasks are: following a car, checking the mirror. As for the performance measurements of primary tasks, the lane-keeping task is typically used via the Vehicle Lateral Position Standard Deviation Parameter (SDLP). The SDLP increases if the concentration of the pilot is not optimal, which may also be due to the intake of substances that alter the concentration such as drugs, sedatives or alcohol. The secondary tasks, that often come side by side, are additional tasks, such as a phone call, this is reflected in the primary task with an increase in the SDLP. In addition, the SLDP is often belittled by the driver as the primary task compared to the performance of a secondary task like the phone call, the opposite of what you would expect.

One of the first studies that use the standard deviation as a measure of performance is the one developed by Green et al. (1993), which found an increase in the SDLP when the user travels wider lanes. The SDLP is often accompanied by the study of steering movements, as in the research of Macdonald & Hoffmann, (1980) and Godthelp et al., (1984). The measurements related to steering can be simple, that is, the degrees of rotation of the steering (McLean & Hoffmann, 1975), or they can be more complex measures, that involves the analysis of the frequency of the reversals of steering direction: "Steering wheel Reversal Rate" (SRR) (McLean & Hoffmann, 1971). Both the SDLP and the movements of the steering wheel are the most used measures on straight road, as they are the simplest ones. According to Miller (2001), however, steering movement is generally preferred to the SDLP to investigate workload levels for three reasons: first of all because the vehicle angle is approximately the integral of the steering position over time, and the lane position is about the integral of the steering angle over time, if you consider a straight track. Secondly, the task of lane-keeping in experienced drivers is significantly influenced by the so-called 'control level' process", a kind of automatism that requires almost no resource from the user. A more recent study that reports as performance measures the movement of the steering wheel is that carried out by Pecchini et al. (2014), carried out in Fiorenzuola d'Arda in Emilia Romagna, whose purpose was to investigate workload levels in the presence of roundabouts. In this study the presence of GPS devices allowed to obtain the real trajectories, the speed and the movements of the vehicle; moreover a camera, placed over the driver's seat, allowed to record the steering angles and the actions of the driver. The "Steering wheel Reversal Rate" (SRR) has been calculated, the frequency of times the steering wheel direction was reversed and the results of that study show that there is a high level of difficulty for roundabout manoeuvres. Considering, moreover, that in the carried out study the traffic was absent, the workload of the driver, in real conditions, would have reached peaks still taller.

An additional measure of the performance of the primary task, often used in the literature, is TCL (time-to-line crossing) which represents the time required by the vehicle to reach the centre line or the edge of the lane, if no further corrective movements of the steering wheel are made. This parameter is often used to analyze the effects of sedative drugs as in the Riedel study (1991). Sometimes speed measurements are also used in performance evaluation. Both Jordan & Johnson (1993) and Fairclough et al. (1991) found that user speeds decreased when they were given a secondary task, such as setting up a stereo or having a conversation, than normal driving conditions along the same route.

Brown et al. (1969) found an increase in the time needed (and thus a reduction in speed) to finish the circuit as a result of using a phone while driving, while Van Winsum et al. (1989)

They found the same effect when users were guided in the path by a navigator (map and voice indicator).

As for the use of secondary tasks in literature, those most commonly used are conversation, both telephone and non-telephone, and the pursuit of a vehicle, as in the studies done by Brookhuise et al. (1994). According to Janssen, (1979) Michon (1985) lane parameters (SDLP, SRR - primary tasks), reflect control performance, while secondary parameters such as car-following reflect manoeuvre level performance. The main parameter of performance on the car-following is the delay of the response to changes in speed of the leading vehicle. In addition to delay, "consistency" or the accuracy of the chase is also calculated, and "the module" is the amount of reaction to speed up the changes by the car tracker (Porges et al., 1980). There are other secondary tasks, whose performance is often used to evaluate the driver's workload.

PDT is the acronym of Peripheral Detection Task and consists in subjecting the user to tasks that fit into his side field of view; Most often the task is to turn off a flashing light located on the periphery of the user's field of view and calculate the reaction time of this task.

Two secondary tasks are frequently used in the Baldauf study (2009): the auditory rhythm test (PASAT) and the peripheral detection task (PDT). During driving, short visual stimuli were repetitively presented in the periphery of the subject's visual field (between 11 and 23 degrees of view) for 1s. If the driver detected the stimulus, he had to respond with a push of a button. Typically the increased demands of the workload force the driver to concentrate their visual attention in a narrower field and respond more slowly to lateral stimuli. Martens and van Winsum (2000) using this technique in a simulator, and Olsson and Burns (2000) in a road study, also confirmed that the PDT reflects changes in workload demands when the driver encounters obstacles. Patten's study (2006) which always uses PDT showed that drivers with less driving experience have a longer reaction time than those with more experience. In general, the PDT is useful for assessing driver distraction, (Tijerina, 2000). This secondary task, however, has some disadvantages: Jahn et al. (2005) stressed that performance from PDT is often influenced by movements of the head and eyes (Jahn et al., 2005; Tornros and Bolling, 2006; Zhang et al., 2015; Martens et al.,2016)

Finally, other secondary tasks include, for example, checking the mirror: "mirror checking". The results of this parameter are mixed, so it is the least used. In Van Winsum's study et al (1989) the frequency of looking inside the machine was traced back to a high workload condition. Instead, Brookhuis et al. found fewer looks in the rearview mirror when there is a high mental workload, for example, when driving on busy streets or when handling a headset.

Another approach to the study of the driver's workload through secondary activities, this time related to the geometric characteristics of the road, is that of Kantowitz (1995). He used a driving simulator to study three levels of road curvature: narrow curves (radius of curvature from 150-550 meters), easy curves (radius of 600-1000 meters) and straights, in relation to four secondary activities including reaction time (RT) for reading an odometer and the RT for a single letter indicating the geographical direction. The results showed that the odometer reading task is a sensitive index of the workload imposed by the geometry of the road. The task of perceiving a figure presented orally is an appreciable indicator of the workload imposed by traffic density.

5.2. Methods

5.2.1. Measurement of the driver's workload: the electrode brain helmet (EEG)

To assess the "physiological" workload of drivers in the experimental test, an electrode brain helmet (EEG) was used. The brain electrode helmet (EEG) allows continuous monitoring of the driver's brain activity. More precisely, the helmet or cuff is made of elastic textile material of a specific size to be chosen from time to time depending on the size of the head of the experimental subject, acts as a support to keep the measurement electrodes in specific positions, according to a standard defined with the name Sistema Internazionale 10-20 (Figure 5.11).

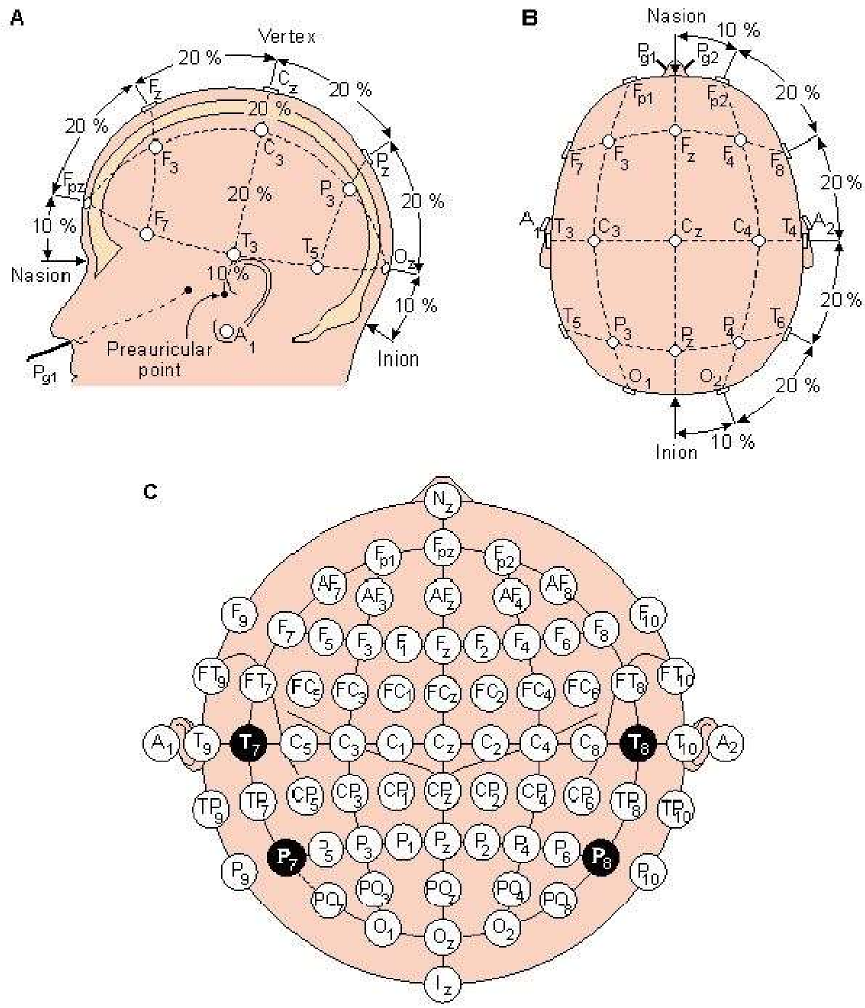


Figure 5.11. International System 10-20.

Brain activity is measured by electroencephalography (EEG), which is the recording of the electrical activity of the brain. The technique was invented in 1929 by Hans Berger, who discovered that there was a difference in electrical potential between needles driven into the scalp, or between two small metal disks when they were placed in contact with the clean skin of the leather hair.

The electrodes consist of a metallic conductor (gold or silver) in contact with theskin through a thin layer of gel. The use of a conductive gel promotes contact between the electrode and skin, minimizing the movements of the electrode itself. Moreover, the gel allows a reduction in the impedance of the biological surface, improving the measure of biopotential.

The basic parameters of the EEG are the frequency (measured in Hz) and the amplitude (measured in μV) of potential oscillations, or EEG rhythms. According to these parameters, waves with different frequencies and amplitudes are distinguished: alpha, beta, gamma, delta and theta. The variation of these waves is specifically related to physiological events (activity, concentration, sleep, sensory stimulation, etc.) and pathological events (tumors, hematomas, epilepsy, etc.).

The interpretation of an EEG trace is based on the study of the mentioned parameters. Five main EEG rhythms can be determined (Figure 5.12):

Alpha rhythms (α) or of Berger: the basic rhythm or frequency present in an EEG is the alpha rhythm. This differs in slow alpha (8-9 Hz), intermediate alpha (9-11 Hz) and fast alpha (11.5-13 Hz), with an average amplitude of 30 μV.

This frequency is recorded in a person awake with closed eyes; when the subject opens his eyes, the alpha activity disappears and is replaced by a low voltage one, called the beta type. The waves or alpha rhythm are characteristics of waking conditions, so they are not present in sleep or in a state of mental rest. When a subject is instead subjected to slightly greater brain activity, the presence of a beta rhythm begins to be recorded.

Beta rhythms (β): the beta rhythm is divided into slow beta (13.5-18 Hz) and rapid beta (18.5-30 Hz) and has an average electrical voltage of 19 μV. These also indicate a highly activated cortex and are mostly concentrated in the frontal and central parietal areas. Beta waves are dominant in a subject with open eyes and engaged in any brain activity.

Theta rhythms (ϑ): the rhythm of theta waves is dominant in the newborn, present in many adult brain diseases, in states of emotional tension and hypnosis. It is distinguished in slow theta (4-6 Hz) and rapid theta (6-7.5 Hz), with an average voltage of 75 μV. In normal conditions, the theta phase occurs in the first minutes of falling asleep when one is still in a state of drowsiness.

Delta rhythms (δ): at about 20 minutes hypothetical from the beginning of rest, one should enter a deeper sleep, also called slow waves, but which is not REM sleep yet and which is called N-REM sleep. Here delta waves appear, characterized by a frequency between 0.5 and 4 Hz and an average electrical voltage of 150 μV, which are not present in physiological conditions in the waking state of adulthood.

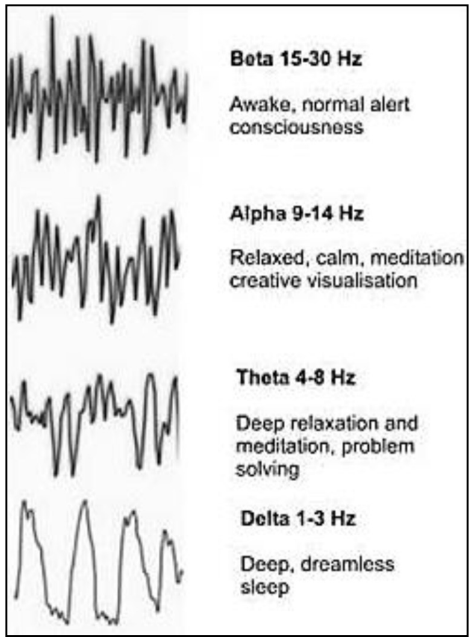


Figure 5.12. Main EEG rhythms.

Initially, this technology was not commonly used for testing and experimentation, due to the requirement of the bulk. Recently, there are many smaller, non-invasive items available on the market that allow these tools to be used in a wide variety of research fields, even in real and non-simulated conditions.

In this experiment, the Be Microsystem of the EB Neuro Spa (Florence, Italy) was used. The advantage of the system lies in the compactness of the amplifier, which allows both the recording and the real-time display of the EEG activity on the PC, and, as in our case, the recording in holter mode (Figures 5.13 and 5.14), the data are temporarily saved on the internal memory so that they can be downloaded later on the PC, so as to minimize the invasiveness and the overall dimensions of the system during the experiment.

Figure 5.13. Holter.

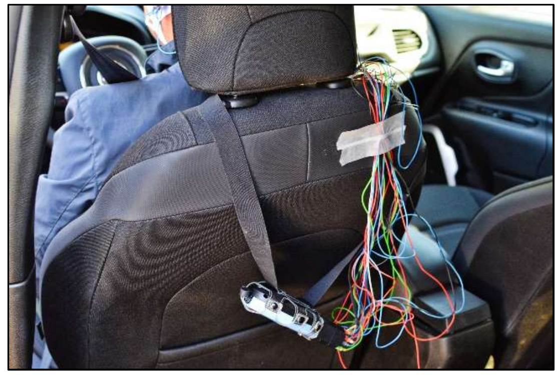


Figure 5.14. Holter positioning while driving.

EEG data were acquired from 12 electrodes (FPz, AF3, AF4, F3, Fz, F4, P3, P7, Pz, P4, and P8), so as to include the Frontal and Parietal cortical areas, these being the areas directly involved in the workload (Figure 5.15). All the electrodes were acquired with a sampling frequency of 256 Hz, referred to the average potential recorded in the lobes of both ears, and using the Cz electrode as a ground electrode (ground). The EEG signals of each subject were processed in order to obtain a workload index.

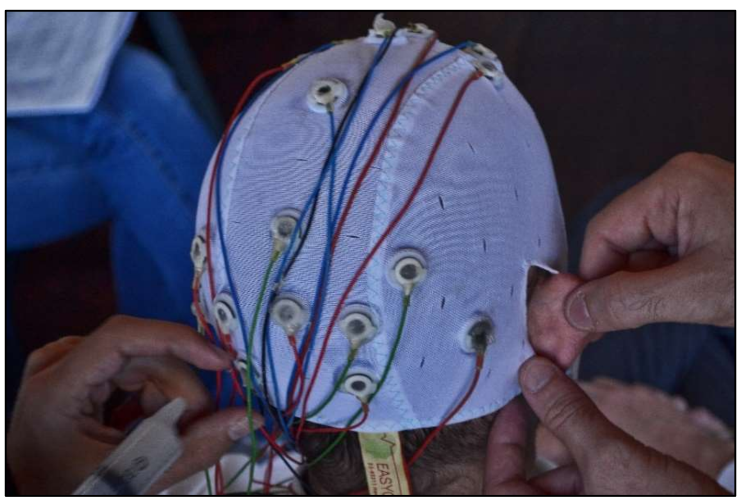


Figure 5.15. EEG headset positioning.

5.2.1.1. The computation of Workload

During the experiments the EEG data have been recorded without any signal conditioning, the whole processing chain has been applied offline. In particular, EEG signal has been firstly band-pass filtered with a fourth-order Butterworth filter (high-pass filter cut-off frequency: 1 Hz, low-pass filter cut-off frequency: 30 Hz). The Fpz channel has been used to remove eyes-blink contributions from each channel of the EEG signal by using the REBLINCA algorithm. This step is necessary because the eyes-blink contribution could affect the frequency bands correlated to the mental workload, in particular the theta EEG band. This method allows to correct EEG signal without losing data. For other sources of artifacts (i.e., environmental noise, drivers' movements, etc.), specific procedures of the EEGLAB toolbox have been employed. Firstly, the EEG signal is segmented into epochs of 2 s (Epoch length), through moving windows shifted of 0.125 s (Shift), thus with an overlap of 0.875 s between two contiguous epochs. This windowing has been chosen with the compromise to have both a high number of observations, in comparison with the number of variables, and to respect the condition of stationarity of the EEG signal. In fact, this is a necessary assumption in order to proceed with the spectral analysis of the signal. The EEG epochs with the signal amplitude exceeding ±100 μV (Threshold criterion) are marked as "artifact." Then, each EEG epoch has been interpolated in order to check the slope of the trend within the considered epoch (Trend estimation). If such a slope is higher than 10 μV/s, the considered epoch is marked as "artifact." Finally, the signal sample-to-sample difference (Sample-to-sample criterion) has been analyzed: if such a difference, in terms of absolute amplitude, is higher than 25 μV, i.e., an abrupt variation (no-physiological) happened, the EEG epoch is marked as "artifact." At the end, the EEG epochs marked as "artifact" have been removed from the EEG dataset with the aim to have a clean EEG signal to perform the analyses. From the clean EEG dataset, the Power Spectral Density (PSD) has been calculated for each EEG channel for each epoch using a Hanning window of the same length of the considered epoch (2 s length, that means 0.5 Hz of frequency resolution). Then, the EEG frequency bands of interest has been defined for each subject by the estimation of the Individual Alpha Frequency (IAF) value. In order to have a precise estimation of the alpha peak and, hence of the IAF, the subjects were been asked to keep the eyes closed for a minute before starting the experimental tasks. Finally, a spectral features matrix (EEG channels × Frequency bins) has been obtained in the frequency bands directly correlated to the mental workload. In particular, only the theta band [IAF – 6 ÷ IAF – 2], over the EEG frontal channels, and the alpha band [IAF – 2 ÷ IAF + 2], over the EEG parietal channels, were considered as variables for the mental workload evaluation. At this point the automatic-stop-StepWise Linear Discriminant Analysis (asSWLDA), a specific Machine-Learning algorithm (basically an upgrade version of the well-known StepWise Linear Discriminant Analysis) previously developed, patented and applied in different applications by the authors has been employed. On the basis of the calibration dataset, the asSWLDA is able to find the most relevant spectral features to discriminate the Mental Workload of the subjects during the different experimental conditions (i.e., EASY = 0 and HARD = 1). Once identified such spectral features, the asSWLDA assigns to each feature specific weights (wi train), plus a bias (btrain), such that an eventual discriminant function computed on the training dataset [ytrain(t)] would take the value 1 in the hardest condition and 0 in the easiest one. This step represents the calibration, or “Training phase” of the classifier. Later on, the weights and the bias determined during the training phase are used to calculate the Linear Discriminant function [ytest(t)] over the testing dataset (Testing phase), that should be comprised between 0 (if the condition is Easy) and 1 (if the condition is Hard). Finally, a moving average of 8 s (8MA) is applied to the ytest(t) function in order to smooth it out by reducing the variance of the measure: its output is defined as the EEG-based Workload index (WLSCORE). For the present work, the training data consisted in the Easy segment of the 2nd lap during the Normal condition and the Hard segment of the 2nd lap during the Rush condition (they have been hypothesized the two conditions characterized by respectively the lowest and highest mental workload demand), while the testing data consisted of the data of the 3rd lap of both the conditions. Here below the training asSWLDA discriminant function (Equation 1, where fi train(t) represents the PSD matrix of the training dataset for the data window of the time sample t, and of the i th feature), the testing one (Equation 2, where fi test(t) is as fi train(t) but related to the testing dataset) and the equation of the EEG-based workload index computed with a time-resolution of 8 s (WLSCORE, Equation 3), are reported.

$$y_{train}(t) = \Sigma_i \, w_i \, train \cdot f_{i\,train}(t) + b_{train} \quad (1)$$

$$y_{test}(t) = \Sigma_i \, w_{i\,train} \cdot f_{i\,test}(t) + b_{train} \quad (2)$$

$$WL_{SCORE} = 8MA(y_{test}(t)) \quad (3)$$

5.2.2. Self-evaluated workload using NASA_TLX questionnaire

At the end of the test, drivers were asked to complete two NASA-TLX questionnaires relating to one off and one on the system.

The NASA-TLX test consists of 6 questions that allow the driver to calculate the mental load index self-assessed. The questions that can be answered with a score on a scale from 0 to 100, are:

- Mental Demand: how do you evaluate mental commitment with the system turned on (off)?
- Physical Demand: how do you evaluate the physical commitment with the system turned on (off)?
- Temporal Demand: how do you evaluate the time commitment and the required rhythms with the system on (off)?
- Performance: how do you rate your performance during the test with system turned on (off)?
- Effort: How do you rate, the overall effort you had to make to complete the test with the system turned on (off)?
- Frustration: Did you felt insecure, discouraged, irritated, stressed during the test with system turned on (off)?

A second questionnaire, called *DS*, drawn up in collaboration with experts from the Department of Psychology of the University of Bologna; it was given to the participants in order to find other information (general information/attitudes). It was composed of two parts: the first, prepared ad hoc for the test, aimed at identifying the subject and the driver's self-assessment of his style and driving habits; the second one, destined for the evaluation of the subject towards the ACC system. In addition, a driving style self-assessment questionnaire was also given to drivers to assess their driving perception (Figure 5.16, 5.17).

QUESTIONARIO
Autovalutazione dello stile di guida

Nominativo (indicare le prime tre lettere del nome unite alle prime tre lettere del cognome, esempio: MARIO ROSSI: MARROS): ____

Data del test: ____________________________

Età: _________

Sesso: M F

Livello di istruzione:
a) diploma di scuola superiore
b) laurea triennale
c) laurea magistrale
d) master
e) dottorato di ricerca
f) titolo professionale
g) nessuna delle precedenti

Tipologia di patente: ___________________

Esperienza di guida (quantificata in anni): ________________

Che auto utilizza attualmente? ________________

In quale contesto stradale guida abitualmente?
a) ambito urbano
b) autostrada
c) ambito extraurbano

Quanto frequentemente utilizza l'automobile?
a) ogni giorno
b) ogni settimana
c) ogni mese
d) mai

Durante l'ultimo anno, ha subito o provocato incidenti? SÌ NO
Se sì, quanti? ________

Ha una conoscenza pregressa del percorso? SI NO

Come giudica il suo stato di allerta, vigilanza, durante la guida in questo studio?

Molto scarso	Scarso	Intermedio	Buono	Ottimo

Come giudica la difficoltà di guida del percorso effettuato nello studio?

Molto bassa	Bassa	Intermedia	Alta	Molto alta

Figure 5.16. Questionnaire of driving style (1).

Riporti la frequenza delle seguenti situazioni relativamente al tuo stile abituale di guida su una scala da 1 a 6 come specificato qui sotto:

Mai	Quasi mai	Occasionalmente	Abbastanza spesso	Spesso	Quasi sempre
1	2	3	4	5	6

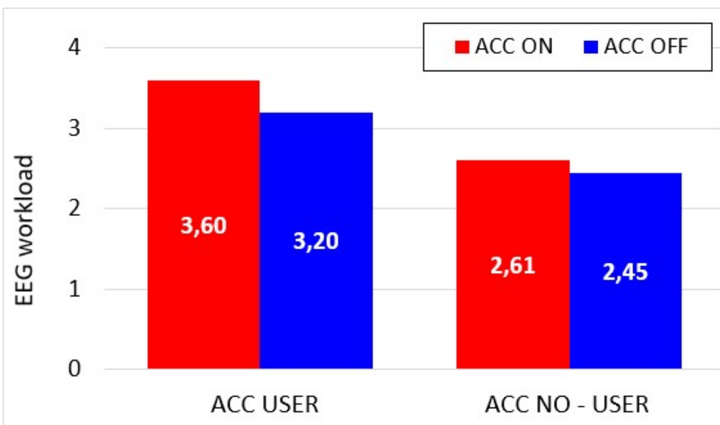
SCENARIO	FREQUENZA
1. Tamponare qualcosa che non si era visto mentre si fa inversione	
2. Dovendo andare nella destinazione A, rendersi conto improvvisamente di essere sulla strada per una destinazione B	
3. Guidare parlando o messaggiando al cellulare	
4. Imboccare la corsia sbagliata approcciando una rotatoria o un'intersezione	
5. In coda per girare a destra su una strada principale, l'attenzione è tutta concentrata sulla strada principale che quasi si tampona la vettura che precede	
6. Non notare dei pedoni che attraversano, mentre si svolta su una strada laterale da una strada principale	
7. Suonare il clacson per mostrare il proprio disappunto ad un altro automobilista	
8. Non guardare lo specchietto retrovisore mentre si svolta o si cambia corsia	
9. Frenare troppo bruscamente in una strada scivolosa o sterzare nella direzione sbagliata mentre l'autovettura sbanda	
10. Andare talmente avanti in un'intersezione mentre si dà la precedenza, che l'autovettura con diritto di precedenza è obbligata a fermarsi	
11. Non rispettare il limite di velocità	
12. Attivare qualcosa, ad esempio le luci, mentre in realtà si voleva attivare qualcos'altro, ad esempio, i tergicristalli	
13. Accorgersi di stare per investire un ciclista che sta procedendo sulla fiancata interna mentre si svolta a destra	
14. Non rispettare il "Dare la precedenza" e trovarsi in pericolo di collisione con i veicoli che hanno la precedenza	
15. Partire in terza dopo un semaforo per scattare più velocemente	
16. Tentare di sorpassare un'autovettura che aveva segnalato con la freccia la svolta a sinistra	
17. Arrabbiarsi per il comportamento di un altro automobilista e inseguirlo per rimproverarlo	
18. Rimanere fino all'ultimo in una corsia che si sa essere interrotta più avanti e passare all'ultimo momento nella corsia disponibile	
19. Dimenticare dove si è parcheggiata la macchina	
20. Sorpassare a sinistra un veicolo molto lento	
21. Scattare velocemente quando arriva il verde al semaforo in modo da battere in velocità l'automobilista a fianco	
22. Non interpretare bene le indicazioni e sbagliare l'uscita in una rotatoria	
23. Guidare molto vicino al veicolo che precede senza rispettare una adeguata distanza di sicurezza	
24. Passare il semaforo con il rosso	
25. Arrabbiarsi per certe condotte di guida e manifestare la propria rabbia con ogni mezzo possibile	
26. Rendersi conto di non avere un ricordo chiaro di una strada appena percorsa	
27. Sottostimare la velocità di un veicolo proveniente dal lato opposto mentre si sorpassa	

Figure 5.17. Questionnaire of driving style (2).

5.3. Outcomes

To characterize the mental behaviour, the workload has been evaluated both objectively and subjectively. In the first case, the EEG-based neurometric of workload computed from the driver's brain activity was used; in the second case, the subjective workload has been evaluated through the NASA-TLX questionnaire.

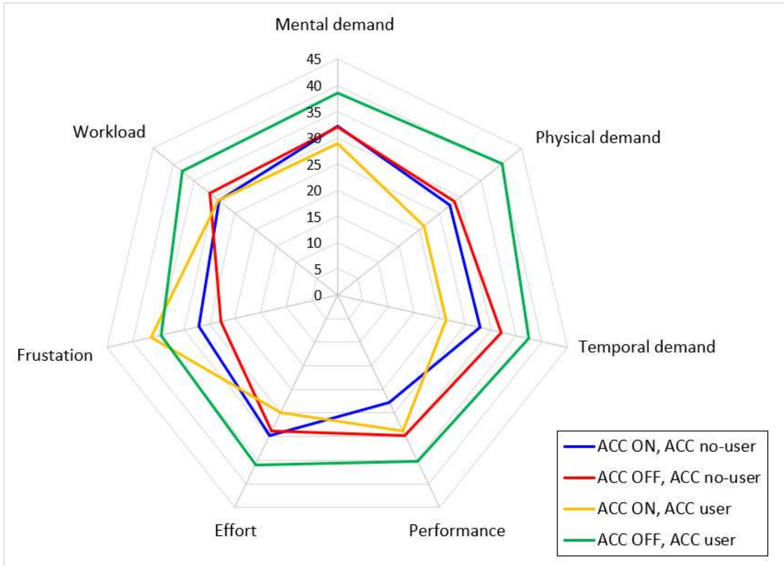
Independently from the previous experience of the system, in the ACC ON condition the EEG drive workload was higher (96 observations (48 participants - 2 ACC conditions), $F(1, 96) = 3.29$, $p < 0.02$, $\chi 2 = 0.04$) (Graph 5.1). If considering the Eye Tracker analysis outcomes, the driver seemed more involved in monitoring the interior car in continuous search of the certainty of the correct functioning of the system when the ACC was enabled. In this way, the overall mental demand increased, resulting in a more difficult driving task compared to the manually condition In this way, monitoring the ACC system actually acted as a sort of secondary task, increasing the overall mental workload, but likely decreasing the attentional resources allocated on the primary task, i.e. driving the car.



Graph 5.1. EEG workload considering ACC state and drivers' ACC experience.

The analysis of the NASA TLX results showed that for all drivers the experienced workload was quite low. The driving task was not particularly difficult, hard and tiring. Regardless of the experience of the system, the workload with the ACC off was higher than with ACC on, because the use of the system made easier the driving activity (Graph 5.2).

The expert users felt a greater difference between using or not the system. This result is probably related to a habit factor, which affects them when they drive without the system that they normally use.



Graph 5.2. Results from the NASA-TLX questionnaire (score from 1 to 100).

These results have been confirmed from the DS and Q-ACC answers (Table 5.2). The driving test wasn't difficult and demanding. Independently form the ACC previous experience, all the drivers did not realize the inattention connected with the use of the system. They thought they have maintained a high level of attention during the test and they have been able to deal promptly with sudden and dangerous situations. They were favorable and inclined to the use of the Adaptive Cruise Control and they appreciated its utility in terms of traffic safety. The non-users appreciated the ACC less than the users because they needed more time to be aware of the new system.

Questionnaire	Question	ACC NO-USER		ACC USER	
		Mean	SD	Mean	SD
DS (rating scale 0-5)	Exceed the speed limits	2,8	1,4	3,5	1,3
	Danger driving behavior	1,7	0,4	1,8	0,5
Q-ACC (rating scale 0-6)	Level of attention	4,6	1,3	4,7	0,9
	Test complexity	3,1	0,9	3,4	0,8
	ACC evaluation	3,4	0,6	4,1	0,5
	Utility of ACC	4,0	1,5	4,8	1,8

Table 5.2. Results of the DS and Q-ACC questionnaires.

5.4. Conclusion

The results obtained demonstrated the reliability and effectiveness of the proposed methodology based on human EEG signals, to objectively measure driver's mental workload, considering also the influence of the Adaptive Cruise Control.

The proposed approach should allow investigating the relationship between human mental behavior, performance and road safety. Results from this study demonstrate that ACC system induced behavioral adaptation in drivers, in terms of changes in workload and hazard detection. NASA-TLX questionnaire, however, showed there was higher subjective workload in the manual condition compared to the ACC condition. These data are even more significant considering that subjects wore eye tracking glasses and EEG cap, drove an unfamiliar car and knew that their driving behavior was being studied. One may assume that their driving style was more careful than under real-life conditions. From a larger point of view, the present study also demonstrated how such a multimodal evaluation, integrating traditional measures (e.g. car parameters) with innovative methodologies (i.e. neurophysiological measures such as EEG and ET), could provide new and more objective insights. Actually, contrarily to the self-perception, to drive with ACC ON produced higher workload, probably because the drivers were distracted other actions within the car. Therefore, the higher workload could be considered as an indirect effect of ADAS systems, since actually the mere action of driving is perceived as easier by the drivers. This preliminary study paves the way to the application of these methodologies to evaluate in real conditions human behavior related to road safety, also considering the recent technological advancements that are making this instrumentation less invasive and easier to use.

6. THE EXPERIMENTAL COMPARISON BETWEEN VISUAL DATA ANALYSIS USING THE NEURAL NETWORKS TECHNIQUES

6.1. Introduction

The birth of Artificial Intelligence (AI) occurred in 1950. John McCarthy, considered one of the founding fathers of the subject, in 1955, established the following definition (McCarthy et al., 2007): "Artificial intelligence indicates the science and engineering needed to make intelligent machines. The term intelligence identifies the computational part of the ability to achieve goals in the world".

In computer science, one of the main themes of AI is the study of "intelligent agents": any device perceives the surrounding environment and takes actions whose purpose is to have the greatest possible chance of achieving a set goal. In other words, when we talk about AI we mean a machine that emulates the cognitive functions that humans associate with other human minds. The fields in which this technology is most used are reasoning, knowledge, planning, learning, natural language processing (communication), perception and the ability to move and manipulate objects (Figure 6.1).

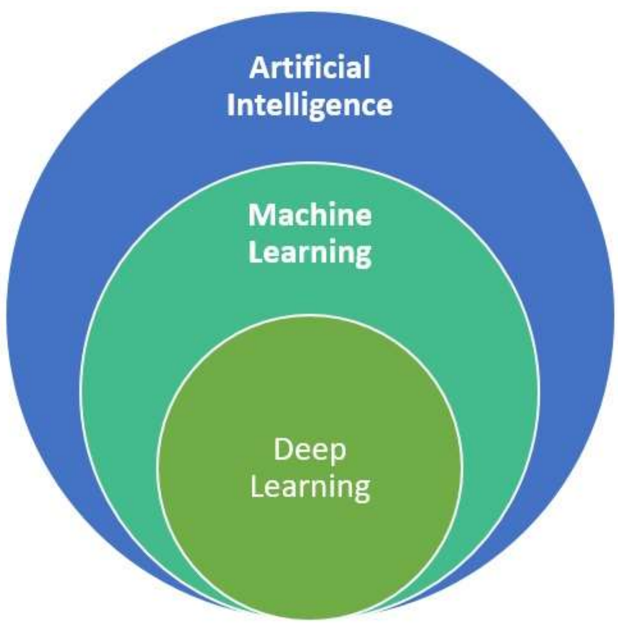


Figure 6.1. AI, Machine Learning e Deep Learning.

Machine learning (ML) is a subfield of artificial intelligence and represents only a part of what is needed for a system to become an AI, as it only provides the learning part; deep learning (DL)Instead, it is a particular type of machine learning that uses artificial neural networks (ANN) as computational models.

6.2. Artificial neural networks

Artificial neural networks are information processing systems that simulate within a computer system the functioning of human biological structure in relation to the nervous field, consisting of nerve cells (neurons) interconnected in a complex network.

A definition of artificial neural network (ANN) in the literature is provided by the inventor of one of the first neurocomputers, Dr. Robert Hecht-Nielsen. He defines it as: "A computational model consisting of a series of simple and highly interconnected processing elements, which process information by their dynamic state response to external inputs."

In the human nervous system there are about 86 billion neurons connected by more than 1014 synapses. In the biological network (Figure 6.2), the dendrites carry the signal to the cells of the body where they are added and, if the result is higher than a threshold, the neuron is activated (shoot), that is, sends an electric impulse (spike) through the axon.

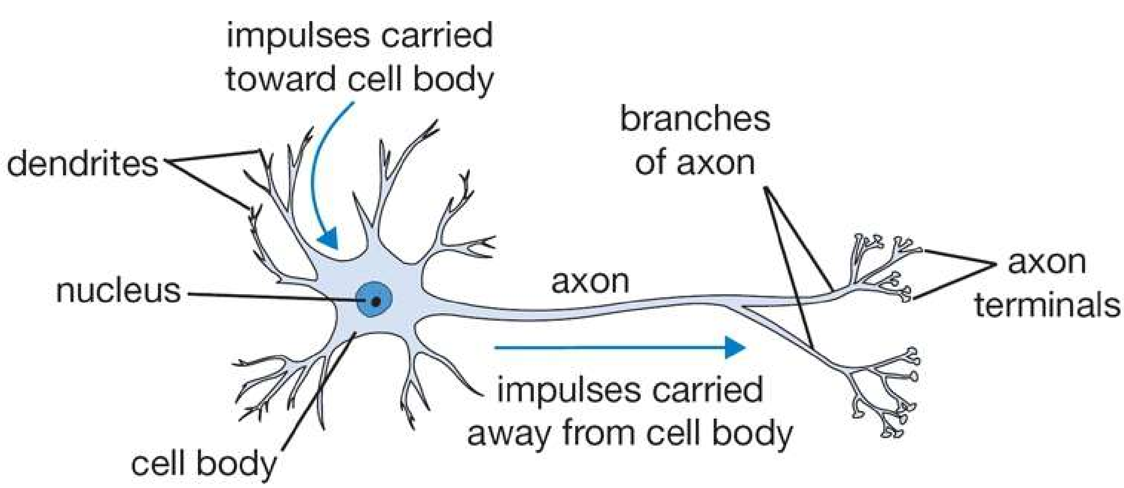


Figure 6.2. Biological Neuron.

Artificial neural networks are also formed by interconnected neurons (called nodes or units), of which they are the fundamental element. The neuron receives input signals through connections with other units (or external sources) and produces an output. Specifically, it is necessary to enter the values of the inputs (xi), their weights (wi) and biases (b), to establish the activation threshold of the same neuron (Mueller, et al, 2019) (Figure 6.3).

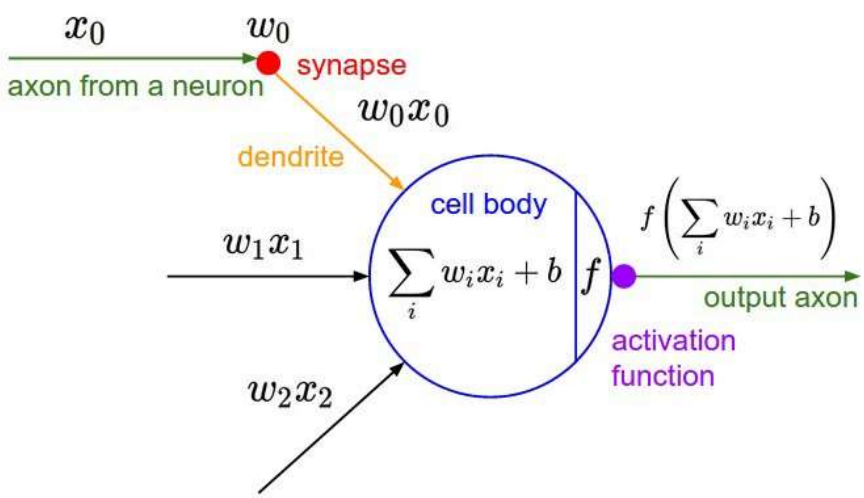


Figure 6.3. Artificial Neuron.

The objective is to understand the effects of synaptic forces (w weights), to control their influence and direction, which can be excitatory (positive weight) or inhibitory (negative weight) of one neuron on another.

In artificial neural networks, only the frequency of activation provides information. This frequency is therefore modeled with an activation function (e.g. sigmoid or Softmax), which represents the frequency of the electric impulses along the axon. The neural network system is capable of processing large amounts of input data and producing a response output (Fumo, 2017).

6.2.1. <u>Architecture of a neural network</u>

The architecture of a neural network is defined by the number of nodes forming a layer, the number of hidden (or intermediate) levels, and the connections between nodes (Figure 6.4), in particular:

- Input nodes (Input level): they constitute the data source and provide the information to the next level (often hidden type). These nodes do not compute because they do not process data.
- Hidden nodes (hidden layer): are the nodes where the process (or computation) takes place, in these units (Hidden nodes) act the activation functions that process information and transfer signals from the input level to the next, This can be another hidden layer or the output layer. These levels are not always present in networks.
- Output nodes (output level): Within these nodes the activation function is used to get the output signals.
- Connections and weights: it indicates a network resulting from a multitude of neurons connected by connections, in which the output of the predecessor neuron (i) becomes the input of the successor neuron (j). Each connection is assigned a weight (Wij).
- Trigger function: defines the output of the given node as a series of inputs. The nonlinear activation feature allows networks to calculate nontrivial problems using only a small number of nodes. In artificial neural networks this function is also called transfer function.
- Learning rule: a rule (or algorithm) that modifies the parameters of the neural network based on data inputs to produce better output. This learning process often involves changing weights and thresholds.

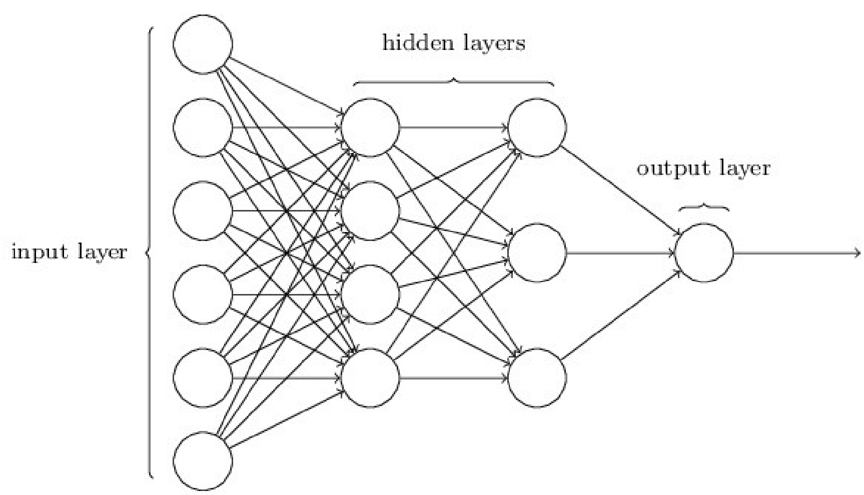


Figure 6.4. Architecture of an artificial neaural network.

To increase the computing capacity, nodes are merged into layers that can be of different types (layers):

- Fully Connected layers: in which a neuron, with its relative weight, is connected to all neurons of the previous level. It is a type of model that does not require particular assumptions but which, however, involves a considerable cost in terms of memory because of the numerous connections.
- Convolutional layers: In this type of level, each neuron is connected to a limited number of adjacent neurons belonging to the lower level. This configuration is often used for image analysis, where features are local. The small number of connections makes convolutional levels particularly economical, both in terms of performance and memory. The operation is based on the sliding of filters on the input image: in fact, a filter (kernel) of various sizes is applied to the input data that produces an output with a certain step (Figure 6.5).

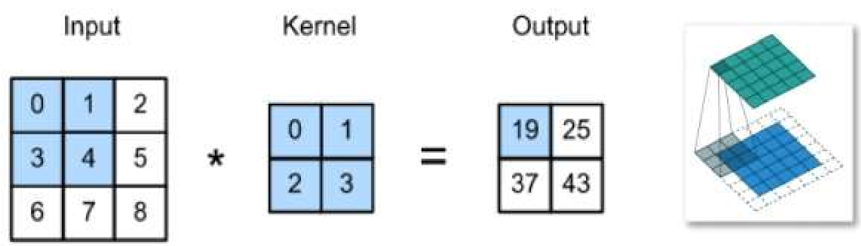


Figure 6.5. Example of application of the kernel.

If the kernel is smaller than the input size, the output is smaller than the input. To avoid this situation, producing images of the same size, we apply padding with as many zeros as are necessary to enlarge the mask to the edges of the input (Scala, 2018).

- Pooling layers: Often used levels together with convolutional ones in order to change the spatial dimensions (height and width). This choice brings performance benefits from a computational point of view and makes training easier. One of the most commonly used pooling levels is max-pooling, which performs a grouping: a window slides over the input image and outputs a value equal to the greater of the window. It is important to note that the parameters to be established are the layer on which to apply the convolution, the step by which to apply the filter and the size of the same (Figure 6.6).

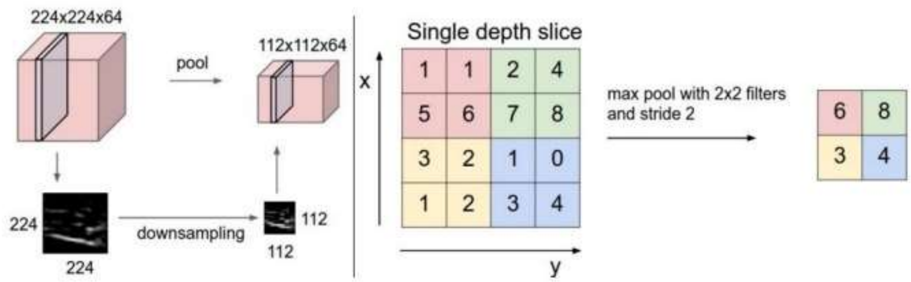


Figure 6.6. Max-pooling.

- Dense layers: They are particular levels fully connected and are the most used in artificial neural networks (Figure 6.7).

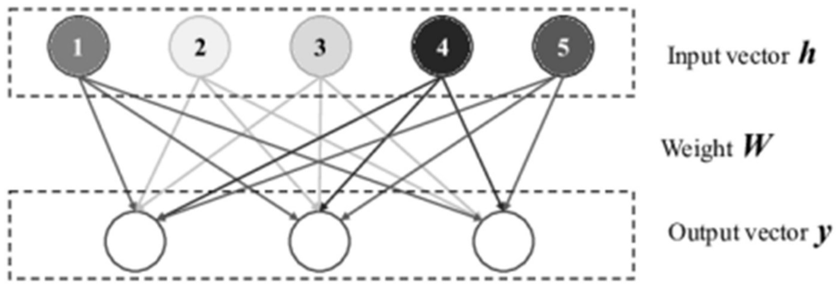


Figure 6.7. Dense layer.

Within these levels you can apply several activation functions, including the Relu. It consists in the application of the function f(x)=max(0,x) to each element of a tensor without changing its spatial and depth characteristics. Also, consider all output values as follows:

- if positive, does not change;
- if the value is negative, it turns it into 0.

6.2.2. Types of Neural Network

In the vast field of artificial intelligence, it is possible to evaluate different types of neural networks, including:

- Feedforward Neural Network: Connections between nodes do not form a loop or loop. The information then moves in only one direction (forward) from the input neurons, through those hidden (if any), to the output neurons. However, it is possible to differentiate this type of network into:

- Single-layer Perceptron: consists of a single layer of output nodes and is free of hidden layers. The term "Single" derives from the fact that the level count does not include the input, as it does not perform any calculation.
- Multi-layer perceptron (MLP): consists of several levels of computational units interconnected in a feed-forward way that is where each neuron has direct connections to the neurons of the next layer (Figure 6.8). In many applications the nodes of these networks use a sigmoid function as an activation function. MLP networks are widely used because they are able to learn nonlinear representations (in most cases the data presented are not linearly separable).

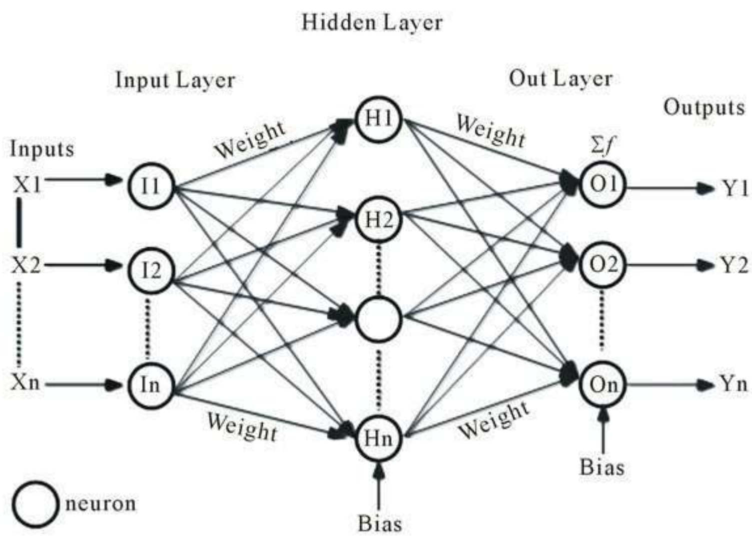


Figure 6.8. Multi-Layer Perceptron.

- Convolutional neural networks (CNN): they are inspired by the organization of the visual cortex as units respond to stimuli in a restricted region of space known as the receptive field. These overlap partially, covering the entire field of view. The response of the unit can be mathematically approximated by a convolution operation. Their application ranges from image and video recognition to natural language processing systems. CNN requires large data to train on.
- Recurrent neural networks (RNN): they have connections between units that can form a direct loop, propagating data both forward and backward. This allows dynamic time

behavior. Unlike feedforward neural networks, rnns can use their internal memory to process arbitrary input sequences. They are applicable to activities such as handwriting or voice recognition.

Neural networks are usually used in contexts where data can be partially wrong or where there are no analytical models that can address the problem. Typical use is in OCR software, facial recognition systems and more generally in systems that deal with data subject to errors or noise. Neural networks are also used as a predictive means of financial, meteorological or bioinformatics analysis.

6.2.3. Machine Learning

Machine learning allows you to evolve and refine the behavior of a system through learning information obtained from data. The creation of an artificial neural network can be summarized in three phases: Collection, Learning and Validation. The first includes the collection and selection of data necessary for the implementation of the network; it is the step that takes the most time because often the quantity and quality of data must be high and consistent with the goal. In the learning phase (or training set), the aim is to make the neural network learn, based on the data collected in the previous phase, the relationships between the input data obtained and the output data. Finally, in the validation phase, we evaluate which input data are influencing the output result, so as to eliminate the remaining part.

6.2.3.1. Collection phase

The heart of machine learning is the algorithm, a procedure designed to solve a specific problem. The most used algorithm is backpropagation, which can modify the weights associated with network connections according to the propagation of the error. Basically, you compare the output value obtained with the real result and you get an error; then you proceed in the opposite direction going to distribute the error among all the elements of the network. This type of algorithm is used in the field of supervised learning, where the real value is available.

In the realization of the algorithm, the first step is to insert an input vector into the network; this is propagated forward (feed-forward), it crosses all the layers of the network reaching the output one. Following the propagation of the input in the network, the difference between the network output and the expected output is defined as an error (or loss) function (Scala, 2018). On the form of the error function two hypotheses are made:

1. Definition as an average:

$$E = \frac{1}{n}\sum_{i} E_i$$

n = the sum of the last individual trainings

E_i = error functions for individual training.

This is necessary to generalize the gradient of the error function, also calculated for a single training case.

2. Definition as a function of the outputs of the network under consideration (Nielsen, 2005).

The objective is to minimize the error function so that the expected result is as close as possible to the real one: to do so, the algorithm calculates the errors of the neurons belonging to the output layer and, later, propagated in the network in the opposite direction (back, note), to the point where each neuron is associated with an error value weighed according to its contribution to the final output. At this point, the algorithm proceeds with the calculation of the gradient of the loss function, which is used during optimization to update the weights and thus reduce errors.

To get the combination of weights that minimizes the error, the backpropagation uses the gradient descent, with which you want to calculate the steepest descent direction (Figure 6.9).

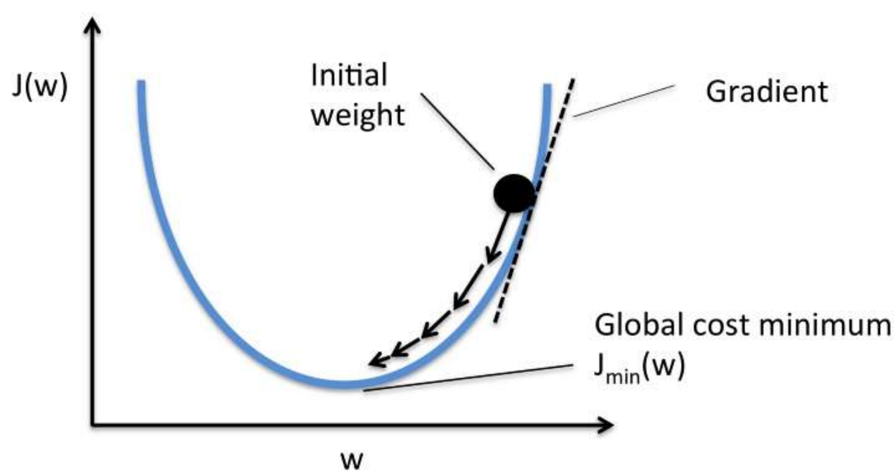


Figure 6.9. Stochastic descendent of the gradient.

The risk, however, is that for deep neural networks (with a large number of hidden levels) the gradient decreases until it disappears during propagation in the farthest layers. In order to optimize the gradient descent method, you can use variants based on the amount of data collected to evaluate the gradient. Among them is the stochastic descent of the gradient (SGD), in which the update of the parameters is performed one instance at a time, evaluating their variation at each observation. This method, however, takes longer to arrive at convergence and can lead to high values of variance in the error rate. A second method is ADAM: this evaluates adaptable learning rates for each parameter. This method takes into account the weighted average of the gradients obtained at the previous steps:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

This method is also able to consider the weighted average of the previous square gradients:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

m_t = is the estimate of the first moment (and mean of the gradients);

v_t = represents the second moment (or non centered gradient variance).

6.2.3.2. Learning phase

The learning phase consists therefore of the definition of the optimal synaptic weights and can be of two modalities:

- Unsupervised learning: The values of the model of the artificial neural net are modified only in function of the data of input, therefore we do not have notions a priori on the obtained values in the output. In this method, the algorithm modifies the data, for example by determining classes or recombining the data into completely different new values, in order to be more useful for the following analyses. The behavior of these algorithms is similar to that of human beings when they try to understand if certain objects or events belong to the same class, using as an association criterion the degree of similarity between two objects (Mueller, et al., 2019).
- Supervised learning: represents an algorithm capable of acquiring notions from a set of input data of which the correct output values are also known. The fields of application range from regression (numerical) problems to classification problems in which, for example, objects must be distinguished into classes. It's the most common type of learning. Since you know both the input data and the actual output values, the weights are modified

according to the difference obtained between the corrected values and the values obtained from the output network. One of the most used supervised methods to train the network is the one that involves the use of the backpropagation algorithm: at first, the network produces output data without varying weights and biases, Then the error between the real data and the product of the network is evaluated, through an update process that changes weights and biases up to the input level. One of the most delicate aspects of supervised learning is to determine which and how many examples to use during training: considering an excessively large or small sample could generate overfitting. This is a phenomenon in which the model fully adapts to the sample to which it has been subjected, losing its effectiveness on external data.

- Reinforcement Learning: Here too, the algorithm is provided with data without a solution (as in the unsupervised case). The algorithm is able to find a solution to which it is possible to give a positive or negative assessment. Reinforcement learning is used in situations where the system has to make decisions with consequences (therefore the result is prescriptive, indicating what should be done, and not just descriptive, as happens in unsupervised learning) (Mueller, et al., 2019).

6.2.3.3. Validation phase

The validation phase aims to evaluate and validate the entire system on a set of data (validation set), these must be different from those used in the learning phase. This last step is also called *generalisation set*. If the system response does not match the desired results, a cause search process is initiated and the network undergoes a new learning cycle. When the third phase is completed, the product and related hardware and software are developed.

6.3. Deep Learning

Technological innovation and advancement in neural networks have led to the development of deep learning. The ANN began to use CPUs and GPUs, making network training accessible to those who do not have a super computer. As described above, neural networks learn from a dataset and, by increasing the amount and variance, can improve its performance. In some cases, however, large networks are needed, with multiple layers and neurons and therefore with an increasing degree of complexity. These multilevel networks are the backbone of the concept of Deep Learning (Goodfellow, et al).

The DL can be defined as a set of machine learning algorithms that aim to learn on several levels; on each level information is processed and sent to the next layer, which calculates the values based on the data provided to it by the previous level. The goal of the DL is to have a structure that can modify the output gradually taking into account the assessments made by previous levels of the network and converging toward the solution. The term "deep" refers to the multilevel structure of this category of networks. The idea behind deep learning is the assumption that data is generated by a composition of factors, divided into a structure at many hierarchical levels.

6.3.1. Deep learning applied to image classification field

Discovered in the eighties, convolutional neural networks are able to offer performing results due to the classification of images. In convolutional networks, filters are applied to the image matrix that, depending on the type, modifies, highlights or deletes some parts. Convolutional filters can be applied to edges or to specific shapes and allow to extrapolate from the image details useful for classification.

Compared to the human case, the individual is able to recognize a car because it has a certain shape and certain characteristics, not because they know all kinds of cars. A standard neural network is linked to the inputs that are given to it and, if these are represented by a pixel matrix, the network recognizes shapes and peculiarities based on their position in the matrix. Convolutional neural networks, on the other hand, are more suitable for image processing because they specialize, through filters, certain neurons to identify specific shapes. In addition, such networks group parts of an image on a single value (pooling), not creating a direct relationship between the identified forms and their location. In this way the network is able to distinguish the shape in any rotation or distortion, ensuring a high generalization capacity.

Among the latest regularization techniques is the 'dropout', very common among deep convolutional networks. This approach temporarily and randomly ignores some connections between units in the network calculation process (Figure 6.10). This prevents the network from being dependent on certain learning links. The dropout allows the network to rely on the notions present in many neurons. This information is less subject to dropout because it is part of a significant number of connections.

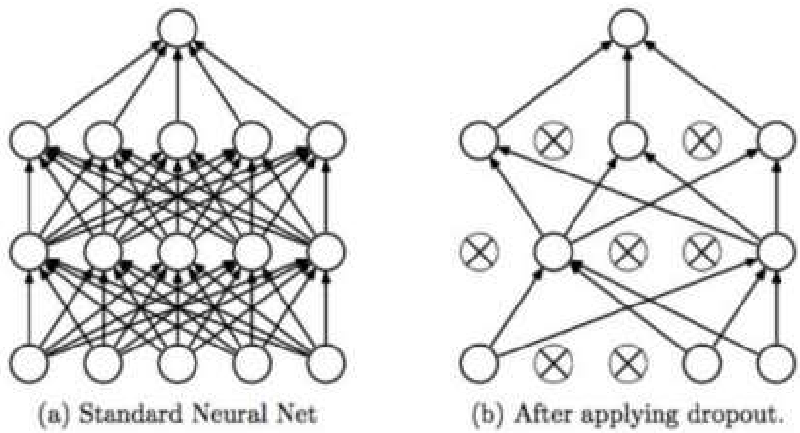


Figure 6.10. Dropout Technic.

6.4. Methods

6.4.1. Step 1: Code to implement the Network

The main objective of the study is the classification of images belonging to video recorded by the Mobile Eye Tracker tool (See section 3.2.1), considering the same conditions found in the experiment illustrated in Chapter 3. To facilitate the task of classification of images, a convolutional artificial neural network has been created capable of handling the individual frames of the videos recorded during the test and divide them into classes. The code to implement the aforementioned network has been written in Python language and is composed of two models: one takes into account the viewfinder in the image, the other instead analyzes the frame without considering the pointer. In particular:

- The model with a viewfinder is made with Keras. Two inputs were defined (input-A and input-B), each of which was able to add the different layers related to the image analysis: Conv2D, MaxPooling2D, Dropout, Flatten for input-A, Dense for input-B (Figure 6.11).

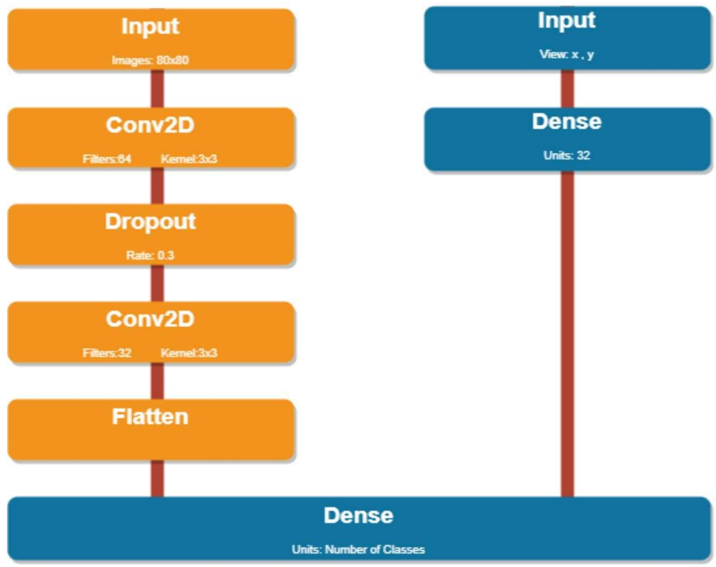


Figure 6.11. Model.

Creating the z variable, ie classes, applies a fully connected layer and the softmax activation function. The model will then have as input the variables x and y obtained as combinations of more layers and, in output, the variable z (Figure 6.12). The model without the viewfinder, on the other hand, is cascaded: the layers necessary for the classification of the image are added, similar to the previous model (Figure 6.13).

```
#modello con mirino
# define two sets of inputs
        inputA = keras.Input(shape=(self.reshape_height, self.reshape_width, self.channels))
        inputB = keras.Input(shape=(2,))

        # the first branch operates on the first input
        x = keras.layers.Conv2D(64, kernel_size=3, padding = 'same', activation='relu', data_format='channels_last')(inputA)
        x = keras.layers.MaxPooling2D(pool_size=(2, 2),data_format='channels_last')(x)
        x = keras.layers.Dropout(0.3)(x)
        x = keras.layers.Conv2D(32, kernel_size=3, padding = 'same', activation='relu',data_format='channels_last')(x)
        x = keras.layers.Flatten()(x)
        x = keras.models.Model(inputs=inputA, outputs=x)

        # the second branch opreates on the second input
        y = keras.layers.Dense(32, activation="relu")(inputB)
        y = keras.models.Model(inputs=inputB, outputs=y)

        # combine the output of the two branches
        combined = keras.layers.concatenate([x.output, y.output])

        # apply a FC layer and then a regression prediction on the
        # combined outputs
        z = keras.layers.Dense(Model.CLASS_LEN, activation='softmax')(combined)

        # our model will accept the inputs of the two branches and
        # then output a single value
        model = keras.models.Model(inputs=[x.input, y.input], outputs=z)
```

Figure 6.12. Viewfinder.

```
#modello senza mirino
 model = keras.Sequential([
             keras.Input(shape=(self.reshape_height, self.reshape_width,self.channels)),
             keras.layers.Conv2D(64, kernel_size=3, padding = 'same', activation='relu', data_format='channels_last'),
             keras.layers.MaxPooling2D(pool_size=(2, 2),data_format='channels_last'),
             keras.layers.Dropout(0.3),
             keras.layers.Conv2D(32, kernel_size=3, padding = 'same', activation='relu',data_format='channels_last'),
             keras.layers.Flatten(),
             keras.layers.Dense(Model.CLASS_LEN, activation='softmax')
```

Figure 6.13. Model without viewfinder.

Once the models are defined, the activation functions are evaluated:

1. ReLu: a neuron with Relu activation function accepts all real values as input, but is activated only when this input is positive, otherwise it returns null values.
2. Softmax: in the case of multiclass problems, it allows to calculate for each element of the probability of belonging to a specific class. In this function, the probability that a given z sample belongs to the i-th class takes into account a normalization term to the denominator, given by the sum of all linear functions M, as given in the following formula.

$$P\left(y=i\mid z\right)=\phi_{softmax}\left(z\right)=\frac{e_i^z}{\sum_{m=1}^{M}e_m^z}$$

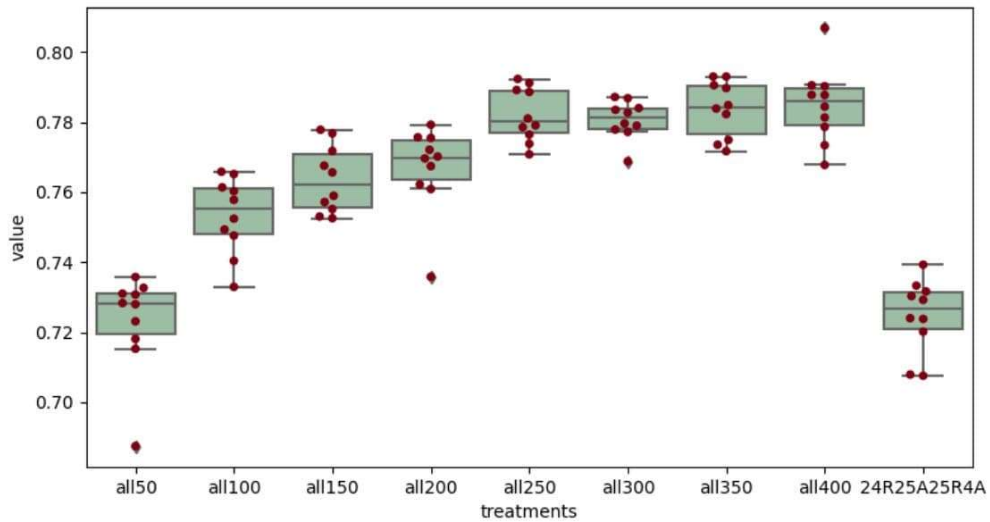
The goal is to realize a model that can generalize without incurring overfitting.

6.4.2. Step 2: Training

Once you have chosen the model, you proceed with the training of the network, the second step of the process of realization of an ANN. It is necessary to divide the sample of available videos into two types: those to be used during the training phase and those to be assigned to the actual test (validation). 300 frames from each of the six classes were examined:

1. Interior car;
2. Car, meaning all vehicles on the road;
3. Background: vegetation and sky;
4. Interior mirror (rear view mirror);
5. Side mirrors;
6. Road i.e. pavement, and safety barriers.

The value 300 was established after several tests as shown in Graph 6.1. It shows the ANOVA test, which certifies this value as the compromise between variability and accuracy. Note that for values between 250 and 400 the network reaches a plateau in terms of accuracy.



Graph 6.1. ANOVA Test.

In the graph, moreover, on the horizontal axis are represented models that vary the number of frames for each class, while on the vertical axis the accuracy is expressed, that is the precision, defined like the relationship between correctly classified frames from the net and total frames.

At this point, it is necessary to assign specific weights for each class: through the dict function, you create a dictionary (data) in which are collected the classes (keys) mapped in their corresponding values, as you can see in the following script.

```
#pesi delle classi
        class_weights = dict()
        num = 0
        for key in datas:
            try:
                class_weights[num]= (1/datas[key])*(total/len(self.CLASS_NAMES))
            except:
                class_weights[num]= 1
            num = num +1
```

The relative weight of a class is inversely proportional to the number of frames present in the same class; for example, in this case, the class 'Machine' has a lower weight than the class 'Mirrors' as it includes a greater number of images.

The training at this point focuses on the use of the model.fit function, imposing the number of epochs equal to 50, defined as a complete training cycle that includes the whole training set.

An initial internal validation is performed during the training phase, in order to divide the images into two groups: 80% training and 20% testing (Figure 6.14).

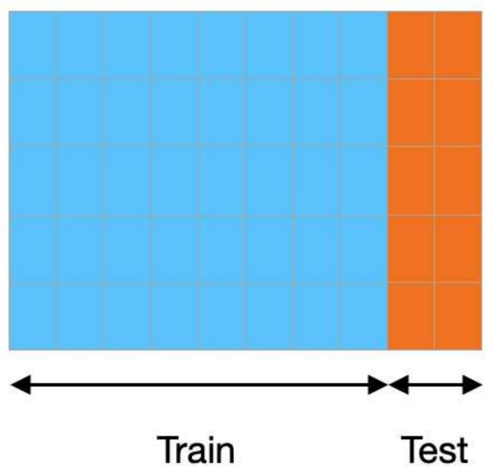


Figure 6.14. The training phase.

6.4.3. <u>Step 3: Test</u>

In the test phase, images are predicted by the network, compared to the classification made by the supervisor (*labeled images*).

For the validation process to be effective, it must be applied to a portion of data that has not been used during the training phase. In fact, the network is turned around and, to obtain the performance of the learning algorithm, the confusion matrix is analyzed: this shows the true positives, true negatives, false positives and false negatives according to a classifier, as shown in Figure 6.15 (Raschka, 2016).

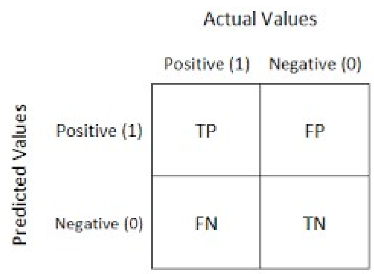
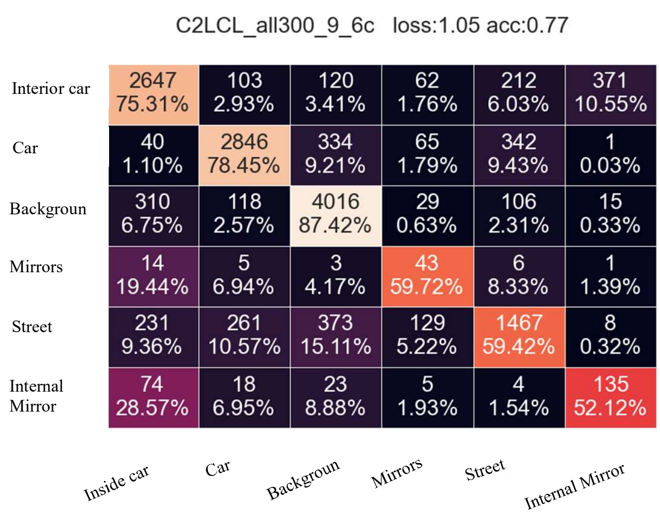
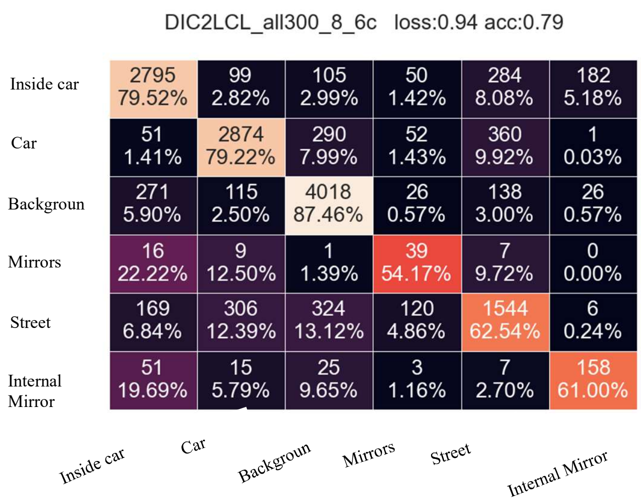


Figure 6.15. Matrix of Confusion.

Note that the sum of the values belonging to the same row returns the elements belonging to a certain class, the analogous operation on the numbers of the same column allows to obtain the portion of the sample contained by a class according to the classification of the network. We show some confusion matrices (Graphs 6.2 and 6.3) related to different models tested during the implementation of the network.



Graph 6.2. Matrix of confusion of the model C2LCL_all300_9_6c.



Graph 6.3.Matrix of confusion of the model DIC2LCL_all300_8_6c.

Graph 6.3 shows the confusion matrix for the C2LCL_all300_9_6c model in which:

- C2L = the name of the network;
- CL = Channel Last, that is the way in which the three-dimensional vectors representing the image data are presented, in this case the last channel indicates the number of colors (3);
- All300 = the maximum amount of frame taken for each class;
- 9 = the test number;
- 6c = the number of classes;

Graphs 6.3 and 6.4 show the results obtained from models respectively C2LCL and DIC2LCL: in the first model was used without the viewfinder, in the second the dual input model (DI) referring to the model with the viewfinder chosen during training.

There is a good level of precision of the network, standing around 78%; note how, to vary the model, the accuracy of the individual classes oscillates in a significant way. In particular, the Car Interior and Interior Mirror classes have increased accuracy with the DIC2LCL model.

The use of the network was accompanied by the figure of a human supervisor. In fact, he had the task of classifying and correcting pre-processed images from the network. The human operator then analyzed the frames processed by the network and modified those classified incorrectly, thus providing the correct frames.

6.4.4. Graphic Interface

In order to make the classification program usable, an interface has been created capable of providing two different analysis modes: Classification and Revision or Revision (Figure 6.16).

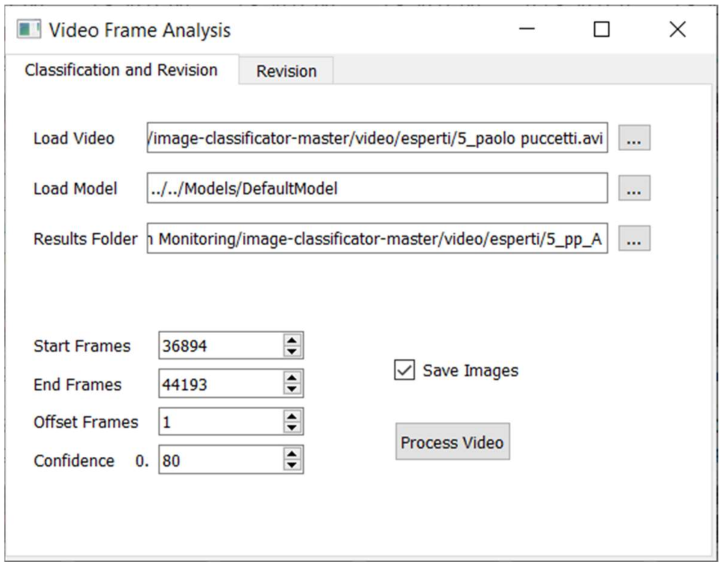


Figure 6.16. Tool of Classification.

6.4.4.1. Classification and revision

The classification and revision mode allows you to choose the video to be classified, indicating the model from a library of models that can be represented in format *json*, which represents the structure of the neural network, or *H5* which defines the weights within it. You also need to designate an output folder where the images will be saved.

The interface shows the initial, final frame and the offset, even defining the confidence level. The latter is considered as the probability value, between 0 and 1, with which the true value of a parameter is considered. The level of confidence is therefore a value that the program assigns to each individual image indicating the "security" with which the frame belongs to the class assigned to it.

At the base of the interface, there is a script that takes into account the Python code. First of all, a class has been created: it is a tool that allows grouping variable programs and functions in a logical and reusable way, facilitating the management of large projects. A class is therefore a system used to model reality so that it can build and manage more or less complex objects. In our case the classes have been identified as those already used in the manual classification phase: 0-Pers; 1-Inside Car; 2-Car; 3-Background 4-Mirrors; 5-Road; 6-Internal mirror.

Later, the different attributes were associated with the classes: to do this, the command inits (initializer) was used, also known as the Builder Method. When creating methods within the Class, consider as the first parameter, the Instance of the class itself, called by convention self. The parameter Self is therefore a variable that indicates the current instance of the class, which allows access to attributes and methods of the object in question.

At this point, by clicking on the "Process Video" button, the program proceeds with the automatic classification of images. The video classification process consists of several steps summarized by the commands shown below.

```
def process_video(self):
    try:
        self.setup_video()
        self.model = self.load_model()
        self.process_frames()
        self.analize_pictures()
```

The video is first loaded and the model selected; in this case the C2LCL_all300_6c.json.

You then enter the central phase of the code: frame process and image analysis.

The software will create a folder in the initially chosen environment with a subdivision by classes, then proceed to insert the selected images into the created folders.

The first step, when processing frames, is to analyze all the pixels to find the red ones pointing to the viewfinder.

The "viewfinder" function allows you to identify the viewfinder: it slides all the pixels of the image vertically and horizontally, stopping when it meets an element whose values meet the thresholds of red (greater than 170), green and blue (both lower than 85). A pixel with these characteristics is identified as a viewfinder (red color "pure") and you proceed by cropping the image in an 80x80, size required by the neural network.

The cropped image is then normalized by dividing all pixels by 255, in such a way as to have only values between 0 and 1. I likewise normalize the x and y coordinates so as to obtain only values between 0 and 1. These operations are intended to facilitate the task of the neural network since data with an order of magnitude very different can slow the learning phase of the network; As a result, the standardisation process makes it easier to assign weights and improves their performance. At this point the prediction of the model takes place: it, in fact, creates a vector for each frame whose elements represent the percentage of belonging to each class and then be moved to the class with the highest percentage. The program proceeds to the realization of the csv inserting a line for every analysed frame (Figure 6.17).

Finally, there is the revision phase: the operator is subjected to all frames with a confidence lower than the established. As shown in figure 6.17, the reviewer simply clicks on the class button corresponding to the frame, which will be given a confidence of 1. He changes the path of the file by moving it to the new folder, by changing the frame data.

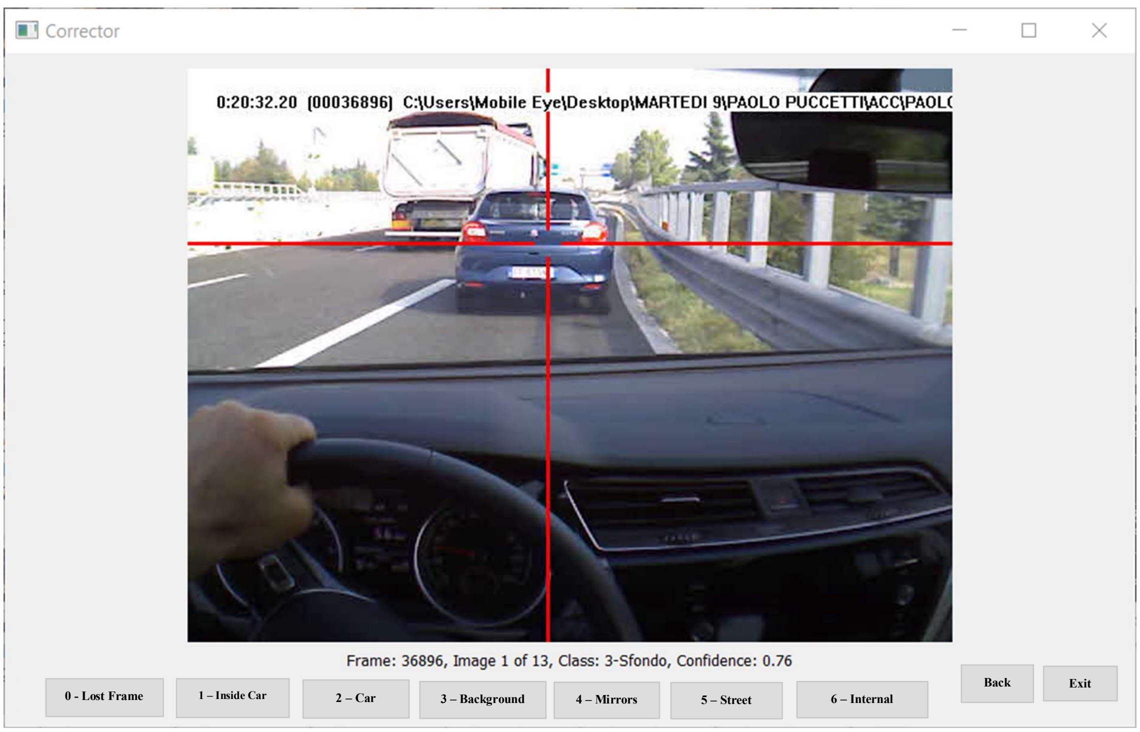


Figure 6.17. Phase of the revision.

6.5. Outcomes

The aim of the research is to assess visual behaviour, in particular the degree of attention paid to drivers by means of state-of-the-art techniques that can facilitate the process of classifying frames. The results obtained were divided into three macro-areas:

- Analysis of the results of the neural network: the performance of the network in the classification phase of the frames obtained from the videos recorded by the Mobile Eye has been evaluated. This operation was performed for each user depending on the classification type (class or macro-class), the confidence of the network, and the state of the system (On/Off). The impact of the adaptive cruise control on the drivers' workload and attention The visual behaviour of the cyclist: the comparison between simulated and real scenario
- Analysis of the user's behavior according to the state of the Adaptive Cruise Control: in this phase all the frames with their relative distribution within the classes and, later, in the macro-classes (Attention and Inattention) were considered also assessing the incidence of lost frames. These are characterized by the impossibility of evaluating the driver's point of view due to the lack of the cursor on the monitor.
- Analysis of kinematic data: in which the tool has been implemented in Python, allowing to associate speed and longitudinal acceleration obtained by the V-Box Pro instrumentation to the frames analyzed in the previous phases. For these kinematic data averages and standard deviations have been calculated. In addition, the timing of perception-reaction and the behavior adopted by users in some critical phases of the experiment, called events, were considered.

6.5.1. Analysis of neural network results

The classification operation was performed with the aid of an implemented artificial neural network. In input were provided frames of the videos recorded by the Mobile Eye of each user and, in output, the network returned the same frames classified according to the following regulation:

0 - Lost: all frames where the displayed element could not be detected;

1 - Car interior: elements present in the interlace in the car (dashboard etc.);

2 - Car: vehicles forming part of road traffic;

3 - Background: everything that is not included in the remaining classes (sky, vegetation, etc.);

4 – Side mirrors;

5 – Road: road paving and safety barriers;

6 – Internal Mirror.

Later, we considered the Macro-Classes:

- Attention: includes all frames classified as car, road and interior mirror. Such a choice considers a full attention of drivers to the task of driving.
- Inattention: encloses the classes Interior, Background and Mirrors and, contrary to the attention, represents moments of time when the user is distracted.

The choice to consider the class mirrors as inattention is due to the object of the study: it wants to investigate the behavior of drivers in relation to the Adaptive Cruise Control and consequently to the longitudinal gear of the vehicle; to drivers, in fact, It has been requested not to make lane changes (if not strictly necessary), for this reason the gaze on the mirrors is to be considered as not appropriate to the longitudinal gear.

The analysis of the results focused on the qualitative evaluation of the work carried out by the network, focusing on the confidence attributed by the network to images.

The calculations were carried out on a small sample belonging to the expert test: among the 26 participating users 13 subjects were selected whose data were qualitatively the best, ie with a small number of frames labelled as lost.

For each user, the network has output two Excel sheets (round trip) with as many rows as frames of the stroke corresponding to the subject. By way of example, Table 6.1 is given in which:

- *Frame:* The frame number of the video recorded by the Mobile Eye.
- *Class e ClassName:* represent the number and name of one of the 7 classes (6 classes plus lost frames) to which the frame in the labeling phase has been assigned.
- *X_line e Y_line:* indicate the coordinates of the viewfinder in the frame.
- *PredClass e PreClassName:* denote the classification performed by the network.
- *Confidence* shows network confidence for that given frame.
- *La colonna 0 Errati:* has been realized with the command Excel SE and it records if the classification carried out from the net coincides with the labellization (1 corrected, 0 otherwise).
- *In Conf. Err.:* Only confidence values corresponding to wrongly classified frames appear.
- *A-D_LAB e A-D_PR:* they perceive frame classification according to macro-classes attention and inattention.

- *ACC_TOT* returns TRUE or FALSE values if, respectively, the classification as a function of the macro-classes has been performed correctly or not.

Column1	FileName	Frame	Class	ClassName	X_line	Y_line	PredClass	PredClassName	Confidence	0 Errati	Conf. Err.	A-D_LAB	A-D_PR	ACC_TOT	A-D_LAB _ER	A-D_PR_ER	ACC_ERRATI
0	4_sb_A_37040.jpg	37040	0	0-Persi	0	0				1							
1	4_sb_A_37041.jpg	37041	0	0-Persi	78	415				1							
2	4_sb_A_37042.jpg	37042	5	5-Strada	149	370	5	5-Strada	0.71	1		0	0	VERO			
3	4_sb_A_37043.jpg	37043	2	2-Macchina	168	373	5	5-Strada	0.73	0	0.73	0	0	VERO	0	0	VERO
4	4_sb_A_37044.jpg	37044	5	5-Strada	172	377	5	5-Strada	0.94	1		0	0	VERO			
5	4_sb_A_37045.jpg	37045	5	5-Strada	173	378	5	5-Strada	0.63	1		0	0	VERO			
6	4_sb_A_37046.jpg	37046	5	5-Strada	177	368	5	5-Strada	0.99	1		0	0	VERO			
7	4_sb_A_37047.jpg	37047	0	0-Persi	0	0				1							
8	4_sb_A_37048.jpg	37048	0	0-Persi	0	0				1							

Table 6.1. Example of excel file.

This file was created for each round trip of the 13 experienced test users and was calculated for both the model without viewfinder (C2L network) and the one with viewfinder (DI network).

The classification performed with the Double Input model has slightly better results (Accuracy of 0.79) so the following analyses will affect the use only such network.

To evaluate the performance of the network, it was decided to investigate the confidence, or trust, that it attributes to the frames being classified. Since confidence varies from 0 to 1, nine intervals have been identified: the first for frames with confidence less than 0,20 and the following with equal amplitude of 0,10 up to 1 (present in the first column of table 6.2). With the command CONTA.SE all the frames have been collected according to the confidence (column Total Frames), then considered only the correct ones (column Corrected) and, consequently, counted the wrong ones (column Frame Errati). Finally, the percentage of incorrect frames on the totals per confidence interval was calculated.

Confidence Range	Tot.	Correct	Cum. Correct	Tot. Cum.	Wrong	Wrong. Cum	% Wrong
c<0,20	0	0	0	0	0	0	0%
0,20<c<0,30	0	0	0	0	0	0	0%
0,30<c<0,40	13	3	3	13	10	10	77%
0,40<c<0,50	67	31	34	80	36	46	54%
0,50<c<0,60	152	68	102	232	84	130	55%
0,60<c<0,70	177	90	192	409	87	217	49%
0,70<c<0,80	236	140	332	645	96	313	41%
0,80<c<0,90	339	218	550	984	121	434	36%
0,90<c<0,99	5049	4775	5325	6033	274	708	5%
Totali	6033				709		12%

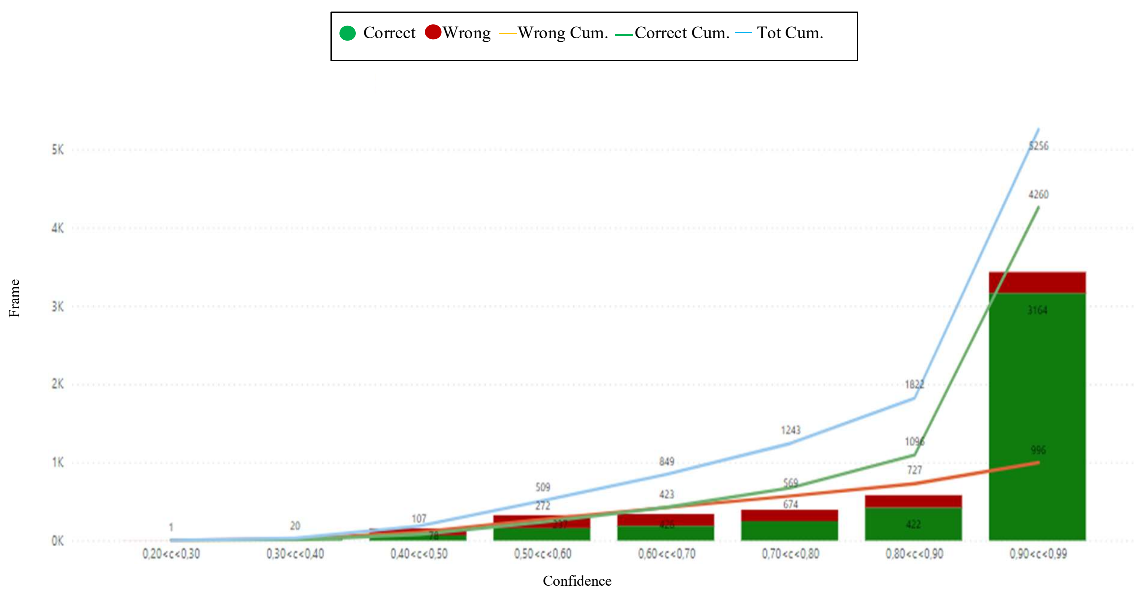
Table 6.2. Frames divided by confidence intervals.

This operation was repeated for each route carried out by the subjects considered in this study; therefore, 26 sheets were made similar to the one shown and, for the final analysis, calculated the arithmetic mean (Table 6.3) and the number of corrected frames.

Model DI	Tot.	Tot. Cum	Correct	Correct Cum.	Wrong	Wrong Cum.	% Wrong
c<0,20	0	0	0	0	0	0	0%
0,20<c<0,30	1	1	0	0	1	1	100%
0,30<c<0,40	30	31	11	11	19	20	64%
0,40<c<0,50	154	185	67	78	87	107	56%
0,50<c<0,60	324	509	159	237	165	272	51%
0,60<c<0,70	340	849	189	426	151	423	45%
0,70<c<0,80	394	1243	248	674	146	569	37%
0,80<c<0,90	579	1822	422	1096	158	727	27%
0,90<c<0,99	3434	5256	3164	4260	269	996	8%
Totali	5256				996		19%

Table 6.3. Average frames divided by confidence interval.

It is possible to make some first considerations: the network usually attributes a high confidence. Most frames, about 65%, have a value greater than 0.90. The percentage of errors decreases as confidence increases; this was predictable. By definition, in fact, as this parameter increases the probability that the network will act correctly. For a better understanding of the data, graphs were made using the Power BI program. Graph 6.4 shows the trend of the number of frames as a function of the confidence interval.



Graph 6.4. Distinction between wrong and correct frames in function of the confusion.

The data used for the purposes of drawing the above graph are average values calculated on the 13 users belonging to the expert test, whose videos have been classified with the model without a viewfinder, called Double Input (DI). Each column represents the totality of frames by confidence ranges, divided into red (wrong) and green (correctly classified). The three lines show the cumulative (orange) corrected (green) total (blue) incorrect frames respectively. Note, by observing the gradient variation of the cumulate strokes, how the wrong frames decrease with respect to the total as confidence increases.

The same operation was also performed by differentiating between Adaptive Cruise Control system on or off (Tables 6.4 and 6.5).

ACC ON - DI	Tot.	Tot. Cum	Correct	Correct Cum.	Wrong	Wrong Cum.	% Wrong
c<0,20	0	0	0	0	0	0	0%
0,20<c<0,30	0	0	0	0	0	0	0%
0,30<c<0,40	30	30	10	11	19	19	65%
0,40<c<0,50	153	183	67	77	86	105	56%
0,50<c<0,60	325	508	160	238	165	270	51%
0,60<c<0,70	339	847	188	426	151	421	45%
0,70<c<0,80	412	1259	258	683	154	575	37%
0,80<c<0,90	605	1864	444	1128	161	736	27%
0,90<c<0,99	3468	5332	3200	4327	268	1005	8%
Totali	5332				1005		19%

Table 6.4. Average of frames for confidence with ACC OFF.

ACC OFF - DI	Tot.	Tot. Cum	Correct	Correct Cum.	Wrong	Wrong Cum.	% Wrong
c<0,20	0	0	0	0	0	0	0%
0,20<c<0,30	1	1	0	0	1	1	100%
0,30<c<0,40	31	32	11	12	19	20	63%
0,40<c<0,50	155	187	67	79	88	108	57%
0,50<c<0,60	323	510	157	236	165	273	51%
0,60<c<0,70	341	850	189	426	151	425	44%
0,70<c<0,80	377	1227	239	664	138	563	37%
0,80<c<0,90	553	1780	399	1063	154	717	28%
0,90<c<0,99	3399	5179	3129	4192	270	987	8%
Totali	5179				987		19%

Table 6.5. Average of frames for confidence with ACC ON.

There are no differences in the performance of the network depending on the system on or off: this testifies to the effectiveness of the network regardless of the state of the system, confirming its strength.

Analysis of confidence by class

To increase the degree of accuracy, the confidence of the images was analysed for each stroke of each user depending on the outcome of the classification. First, the frames were counted according to the predicted class and divided according to the confidence intervals already shown (column 1 of Table 6.6); then the predicted and labelled classes were compared and, if they were equal, frames were defined as correct.

Confidence	Interior car _C	Interior car _E	Car _C	Car _E	Background _C	Background _E	Internal mirror _C	Internal mirror _E	Street _C	Street _E	Mirrors _C	Mirrors _E
c<0.2	0	0	0	0	0	0	0	0	0	0	0	0
0.2<c<0.3	0	0	0	0	0	0	0	0	0	0	0	0
0.3<c<0.4	0	0	1	2	2	4	0	0	0	3	0	1
0.4<c<0.5	0	5	15	7	4	10	1	0	11	14	0	0
0.5<c<0.6	0	8	22	32	6	15	3	0	37	27	0	2
0.6<c<0.7	4	8	29	38	7	9	1	0	49	29	0	3
0.7<c<0.8	6	7	49	35	13	13	3	1	69	38	0	2
0.8<c<0.9	2	10	97	39	14	12	7	0	98	60	0	0
0.9<c<0.99	26	25	3946	113	151	35	79	3	573	89	0	9
Tot	38	63	4159	266	197	98	94	4	837	260	0	17

Table 6.6. Frames classified by class according to the confidence.

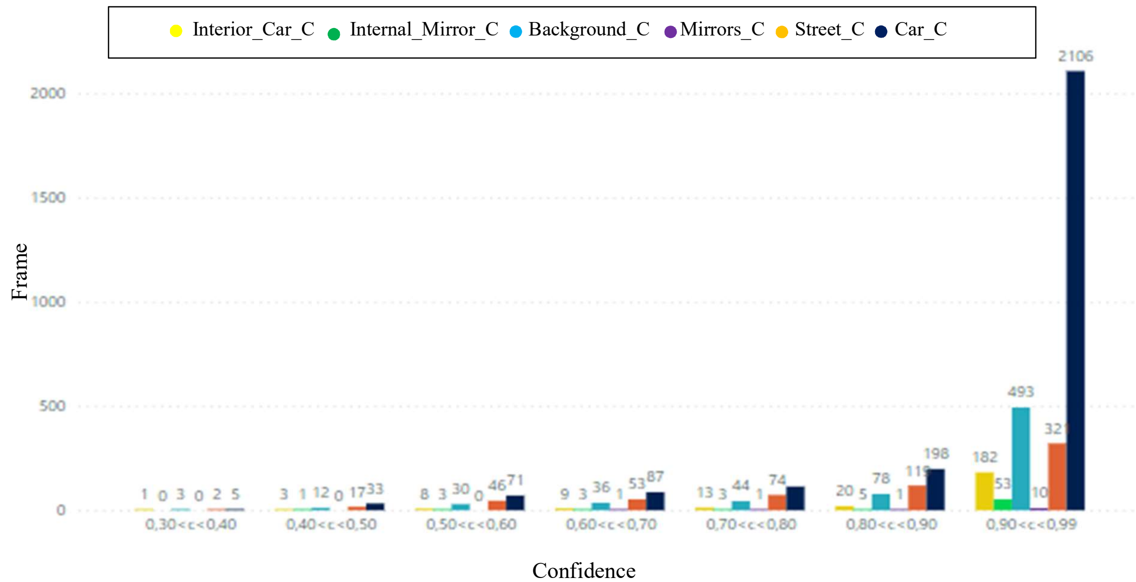
The single box of the above tables encloses the number of frames for a given confidence interval (first column) and for the class indicated in the header row, distinguishing whether the classification has been successful or not (in the first case inserted in the ending column _C, otherwise _E). Also, in this case the averages have been calculated (Table 6.7) considering all the traits.

Confidence	Interior car _C	Interior car _E	Car _C	Car _E	Background _C	Background _E	Internal mirror _C	Internal mirror _E	Street _C	Street _E	Mirrors _C	Mirrors _E
c<0.2	0	0	0	0	0	0	0	0	0	0	0	0
0.2<c<0.3	0	0	0	0	0	0	0	0	0	0	0	0
0.3<c<0.4	1	2	5	4	3	5	0	0	3	6	0	2
0.4<c<0.5	3	6	33	20	12	25	1	1	17	31	0	4
0.5<c<0.6	8	10	71	46	30	42	3	2	46	58	0	7
0.6<c<0.7	9	9	87	42	36	38	3	3	53	53	1	6
0.7<c<0.8	13	10	114	43	44	38	3	3	74	47	1	7
0.8<c<0.9	20	10	198	47	78	42	5	3	119	48	1	7
0.9<c<0.99	182	36	2106	88	493	63	53	16	321	50	10	17
Tot	237	84	2615	289	696	253	68	28	632	293	12	49

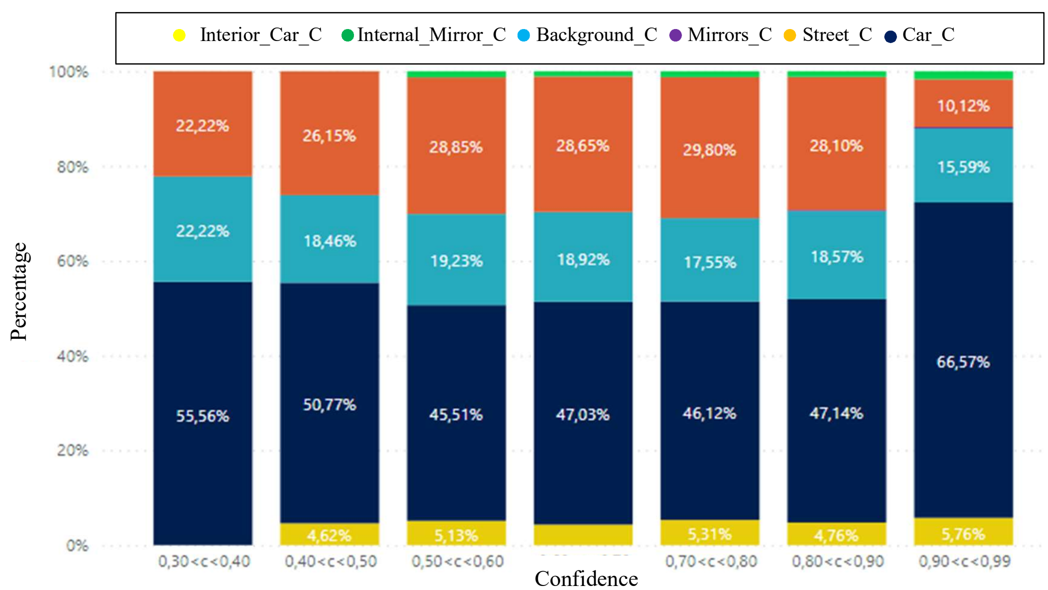
Table 6.7. Frames classified by class according to the confidence.

It is immediate to see the inhomogeneity between classes: *car* is the category that includes most of the images, followed by *background* and *road*, then interior car. The classes Mirror and mirrors contain a small number of images and, often, with a high percentage of errors due to poor training of the network against these categories. The analyses will mainly concern the most represented classes.

Graphs 6.5 and 6.6 show the distribution of frames correctly classified according to the confidence assigned by the network: in the first, you can see the breakdown in percentage of the total in the classes as a function of the confidence interval; the second graph is similarly structured and allows you to perceive the distribution of frames in quantitative terms.

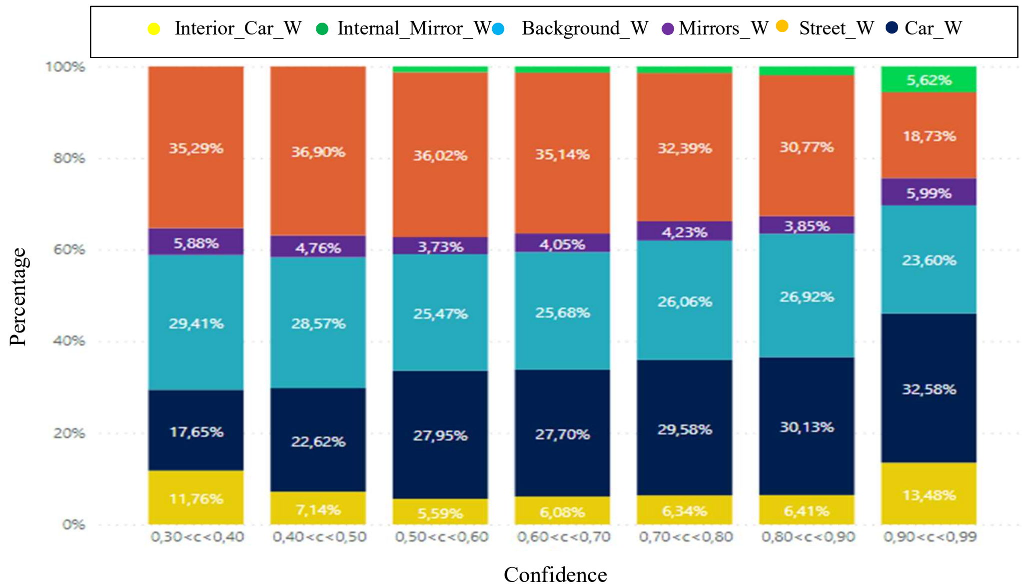


Graph 6.6. Distribution of correct frames (Frame).



Graph 6.5. Distribution of correct frames (Percentage).

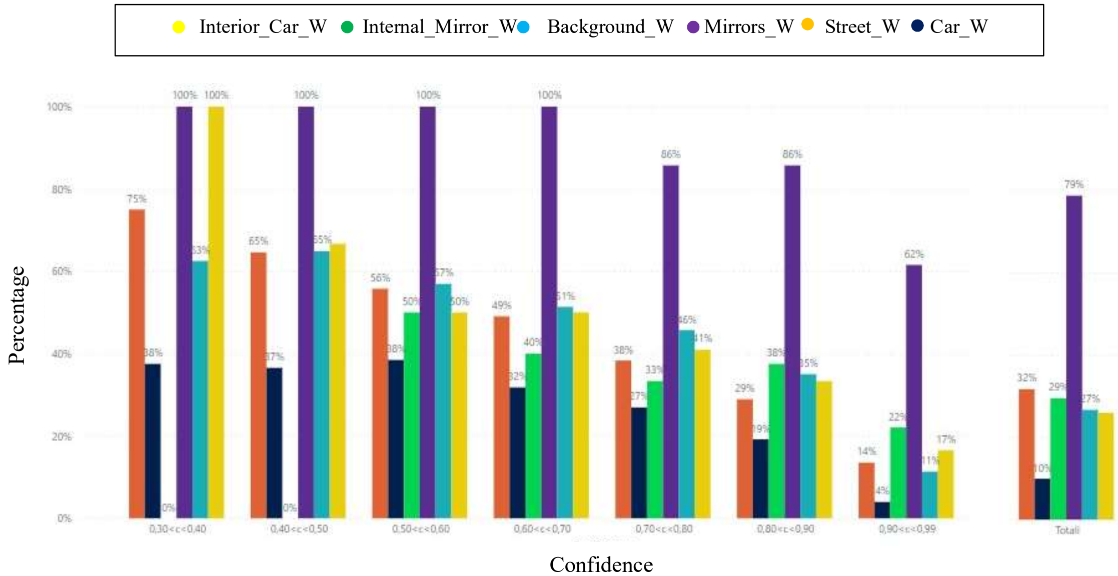
In the case of correctly classified frames, the most interesting data is undoubtedly the significant increase in terms of quantity of the machine and background frames at high confidence (0.9<c<0.99). In this interval, in fact, the network correctly classifies labeled frames as machine and background. There is also growth (modest in percentage but remarkable in quantitative terms) of images classified as internal to high confidence. Graphs 6.7 and 6.8 concern erroneously classified data.



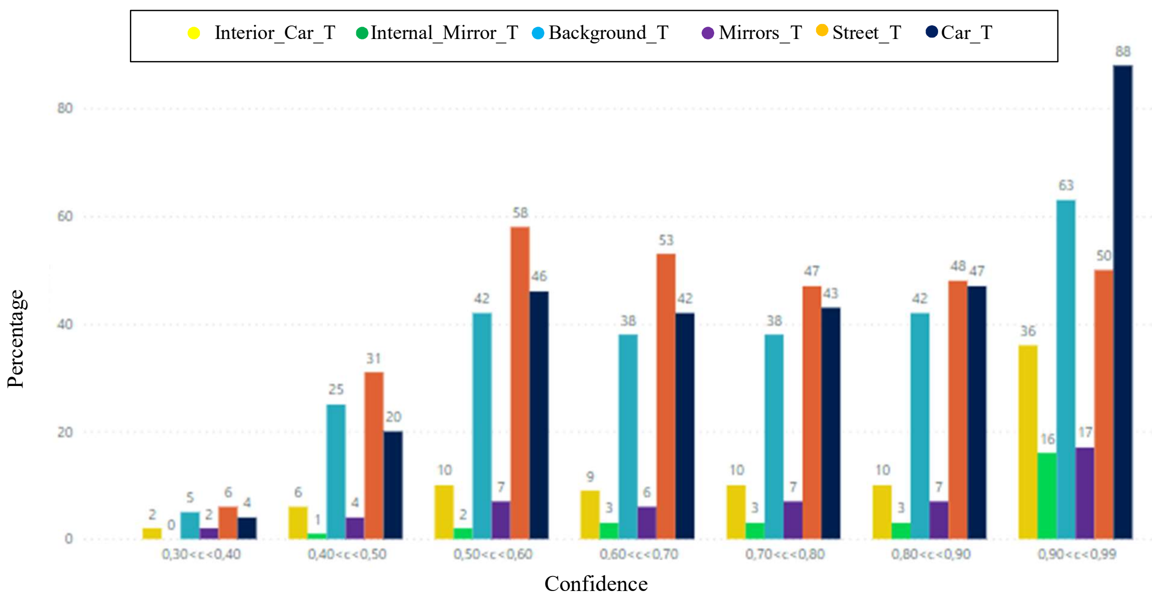
Graph 6.7. Distribution of wrong frames (Percentage).

Different is the case of poorly classified frames: as was to be expected, there is less disparity in quantitative terms between classes. These results evaluate how, considering the wrong frames, the results of the network do not produce a dominant class; note that, excluding the classes mirrors and internal mirror, there is not a significant difference in numerical terms in spite of what we have seen for correctly classified images.

It is important to note, however, that the classes are not homogeneously represented: the images belonging to the machine or background category are much more numerous than mirrors, internal or internal mirrors. To understand the influence of the data-set on the classification quality, look at Graph 6.8 and 6.9, which shows the percentages of incorrect frames on the total for each class as a function of confidence.



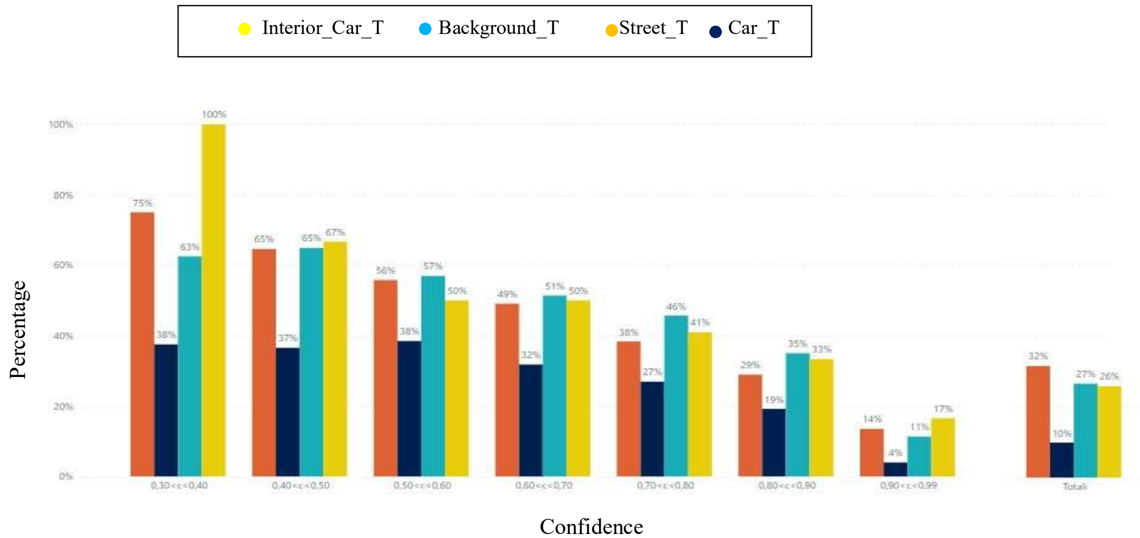
Graph 6.8. Distribution of wrong frames (Percentage).



Graph 6.9. Percentage of frames of the total (Frame).

It should be noted that in graph 6.9 the classes internal mirror and mirrors were excluded, the data of which were not considered relevant for the analysis.

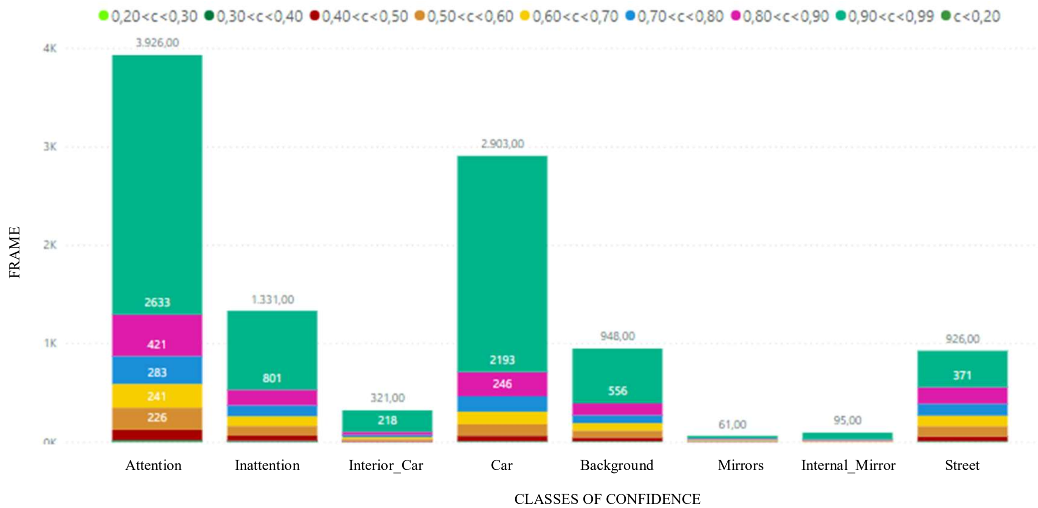
Observe how the percentage of frames wrongly classified decreases with increasing confidence. Pay attention to the trend of the percentage of machine and background frames: although the number of wrong frames seen in graph 6.10 was the highest for the confidence interval 0.9-0.99, the percentage of errors is the lowest in the same range.



Graph 6.10. Distribution of wrong frames of the 4 main classes (Percentage).

The percentages of wrong car and road frames decrease as confidence increases. This leads to confirmation that, for high confidence, the network greatly improves the quality of the classification, especially for classes with a high number of frames. Machine and background are the most represented classes (2192 frames for the first, 556 in the background) and, considering the case of confidence greater than 0.90, have a very low percentage of wrong frames (respectively 4% and 11%) on the total of the analyzed frames. It is immediate to assume the existence of a correlation between the amount of data that the network analyzes and the quality of classification. The high amount of images *car* passed to the network has allowed this to refine the knowledge of this type of object and thus increase the security in classifying it. Keeping the focus on confidence values greater than 0.90 and widening the analysis to all classes results that this range includes 65% of total frames and that errors are only 8%: This means that if you only analyze the images at high confidence you would have a correct result in 92% of cases.

At the same time, analyses were carried out on the impact of confidence intervals on the individual class. In Graph 6.11 we can see the breakdown of confidence intervals in the classes: notice how a machine is characterized by frames having very high confidence (about 84% of which have a value greater than 0.80) and, on the contrary, in the street class there is no clear superiority of a confidence interval over others. These considerations lead to establishing that the network is generally "safe" when ranking machine frames (or, to a lesser extent, background), while it is struggling to predict a frame way.



Graph 6.11. Degree of confidence in classes (Frame).

It is evident, for all classes except street, the dominance of high confidence frames, especially greater than 0.90, testifies to the fact that the network is high confidence.

Attention and inattention analysis

Subsequent analyses concerned the macro-classes Attention and Inattention. To evaluate the attention were added frames belonging to the classes car, road and internal mirror while for the macro-class of Inattention are included images of the remaining car interior, background and mirrors. The following tables show the macro-class data as a function of confidence and the result of classification: corrected C, incorrect E. In Table 6.8 we can observe the data relating to a single user; this calculation was performed for all subjects and then calculated the arithmetic means (Table 6.9).

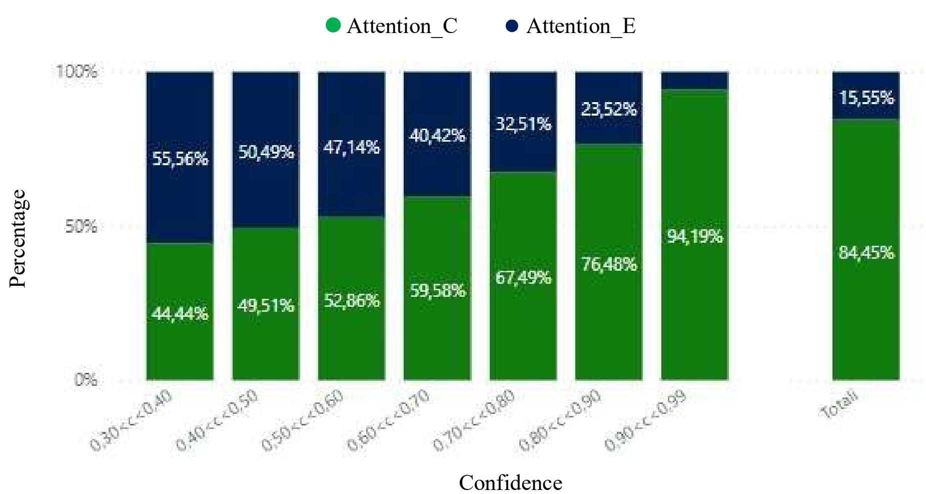
Confidence	Attention_C	Attention_E	Inattention_C	Inattention_E
Confidenza	ATTENZIONE_C	ATTENZIONE_E	DISATTENZIONE_C	DISATTENZIONE_E
c<0,20	0	0	0	0
0,20<c<0,30	0	0	0	0
0,30<c<0,40	1	5	2	5
0,40<c<0,50	27	21	4	15
0,50<c<0,60	62	59	6	25
0,60<c<0,70	79	67	11	20
0,70<c<0,80	121	74	19	22
0,80<c<0,90	202	99	16	22
0,90<c<0,99	4598	205	177	69
Totali	5090	530	235	178

Table 6.8. Example of user 4, the correct and wrong frames according to the Macro-Classes.

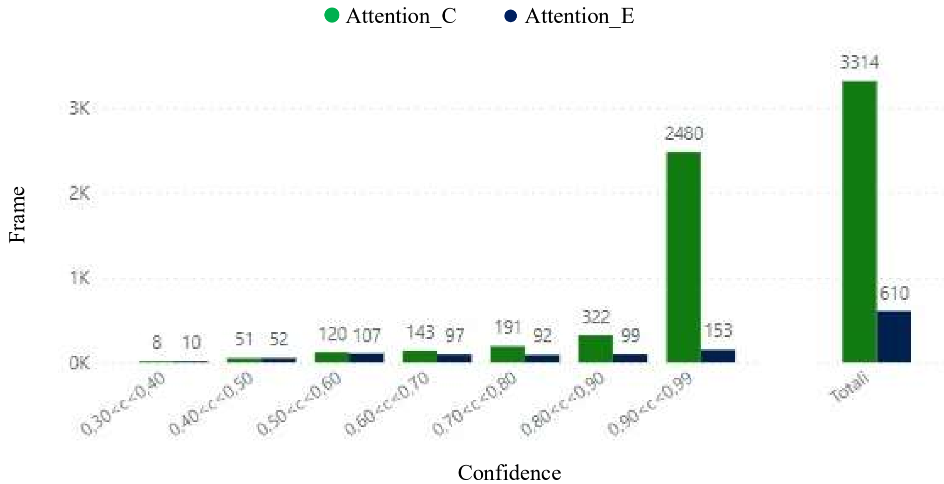
Confidence	Attention_C	Attention_E	Inattention_C	Inattention_E
c<0,20	0	0	0	0
0,20<c<0,30	0	0	0	0
0,30<c<0,40	8	10	3	9
0,40<c<0,50	51	52	16	35
0,50<c<0,60	120	107	39	58
0,60<c<0,70	143	97	45	54
0,70<c<0,80	191	92	58	54
0,80<c<0,90	322	99	100	59
0,90<c<0,99	2480	153	685	116
Totali	3314	610	945	386

Table 6.9. Average of correct and wrong frames according to the Macro-Classes.

Graph 6.12, 6.13 summarizes the values obtained from the averages of the 13 users studied.



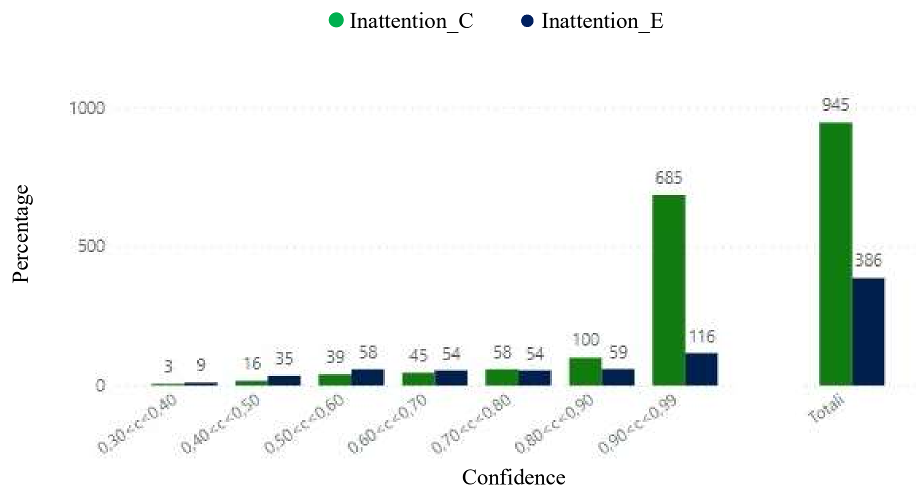
Graph 6.12. Averages of correct and wrong percentage considering the attention (Percentage).



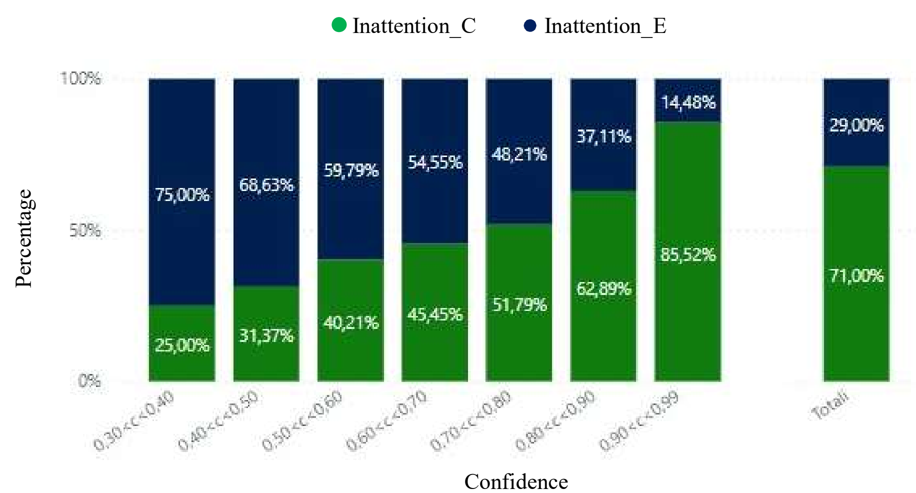
Graph 6.13. Average of correct and wrong frames considering the attention (Frame).

Notice how, as confidence increases, you also increase the percentage of correct images both for attention and inattention. It is important to note that the frames classified as attention are on average three times greater than those of inattention: this difference is motivated by the predominance of camera frames.

The value of 84.45% of frames corrected attention acquires greater importance than the more modest, but acceptable, 71.05% of images of inattention correctly classified. Focusing attention, specifically on images with a confidence greater than 0.90 (two thirds of the total), the results are extremely valid: the network correctly classifies frame attention in 94% of cases. In the case of inattention, however, the same analysis affects 60% of total frames and correctly classifies 85% of images (Graph 6.14 and 6.15).



Graph 6.14. Average of corrent and wrong frames considering the distraction (Frame).



Graph 6.15. Average of correct and wrong percentage considering the distraction (Percentage).

The results just seen refer to the images classified in the 6 classes and then grouped; in this situation, although more precise, frames with predicted class other than labelled but belonging to the same macro-class are considered incorrect. If, on the other hand, we evaluated the performance of the network as a function of a classification performed only on the basis of macro-classes, therefore considering wrong only the images that the network attributes to a class belonging to the macro-class different from the labelled one, the following results would be obtained (Table 6.10,6.11, 6.12).

Confidence	Tot. Frame A-D	Wrong Frame A-D	%Wrong	Correct Frame A-D	%Correct
c<0,20	0	0	0%	0	0%
0,20<c<0,30	1	1	100%	0	0%
0,30<c<0,40	30	12	40%	18	60%
0,40<c<0,50	154	50	33%	104	67%
0,50<c<0,60	324	88	27%	236	73%
0,60<c<0,70	340	80	23%	260	77%
0,70<c<0,80	394	76	19%	318	81%
0,80<c<0,90	579	84	15%	495	85%
0,90<c<0,99	3434	153	4%	3281	96%
Totali	5256	544	10%	4712	90%

Table 6.10. Total average of classification in funcion of macro classes.

Confidence	Tot. Frame A-D	Wrong Frame A-D	%Wrong	Correct Frame A-D	%Correct
c<0,20	0	0	0%	0	0%
0,20<c<0,30	0	0	0%	0	0%
0,30<c<0,40	30	12	40%	18	60%
0,40<c<0,50	153	50	33%	103	67%
0,50<c<0,60	325	87	27%	238	73%
0,60<c<0,70	339	80	24%	259	76%
0,70<c<0,80	412	77	19%	335	81%
0,80<c<0,90	605	82	14%	523	86%
0,90<c<0,99	3468	140	4%	3328	96%
Totali	**5332**	**528**	10%	4804	90%

Table 6.11. Average of frames with ACC ON.

Confidence	Tot. Frame A-D	Wrong Frame A-D	%Wrong	Correct Frame A-D	%Correct
c<0,20	0	0	0%	0	0%
0,20<c<0,30	1	1	100%	0	0%
0,30<c<0,40	31	12	39%	19	61%
0,40<c<0,50	155	50	32%	105	68%
0,50<c<0,60	323	89	27%	234	73%
0,60<c<0,70	341	80	23%	261	77%
0,70<c<0,80	377	75	20%	302	80%
0,80<c<0,90	553	87	16%	466	84%
0,90<c<0,99	3399	166	5%	3233	95%
Totali	5179	559	11%	4620	89%

Table 6.12. Average of frames with ACC OFF.

In these tables have been evaluated, in the confidence intervals present in the first column, the arithmetic average calculated on all users of the total images, incorrect and corrected. In this analysis, however, only those frames that have been labelled in one of the three attention classes but predicted by the network in one of the three classes of Inattention (and vice versa) were considered wrong. In this way the performance of the network has been established in a classification according to macro-classes. The tables differ by means evaluated on all the sections, on the sections with ACC ON and finally on the sections with ACC OFF. As has already been specified, high confidence images (greater than 0.90) are about 2/3 of the total and note how the percentage of errors is between 4% and 5%, sign that the network attributes a frame to the correct macro-class more than 95% of cases, value still above 92%.

6.5.2. Analysis of user behaviour in relation to the ACC system

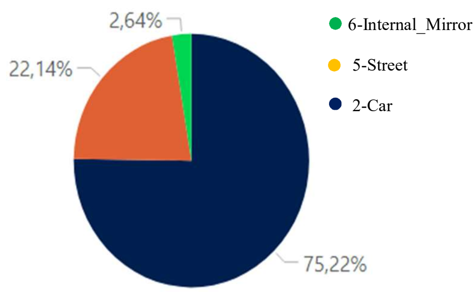
The second phase of the study defined the analysis of the visual behavior of users: using the classified frames it was possible to understand the direction of the users' gaze while driving and to establish the first conclusions on the degree of attention. The Table 6.13 was first produced in which:

- The first column CLASSI lists the possible classification destinations;
- The LAB column indicates the average of the frames of all users for each class labeled by the supervisor;
- The third column evaluates the ratio, in percentage terms, between the class placed in the first column and the macro-class to which it belongs.

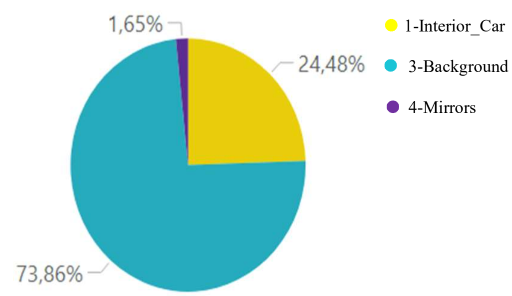
CLASSES	LAB	CL/MACL_LAB
Interior_Car	296	24%
Background	893	74%
Mirrors	20	2%
Lost Frame	1395	
Car	3044	75%
Street	896	22%
Internal_Mirror	107	3%

Table 6.13. Average of labelized data.

The following graphs 6.16 and 6.17 show the distribution, within the macro-classes, of the arithmetic average calculated on all users of the labelled frames.

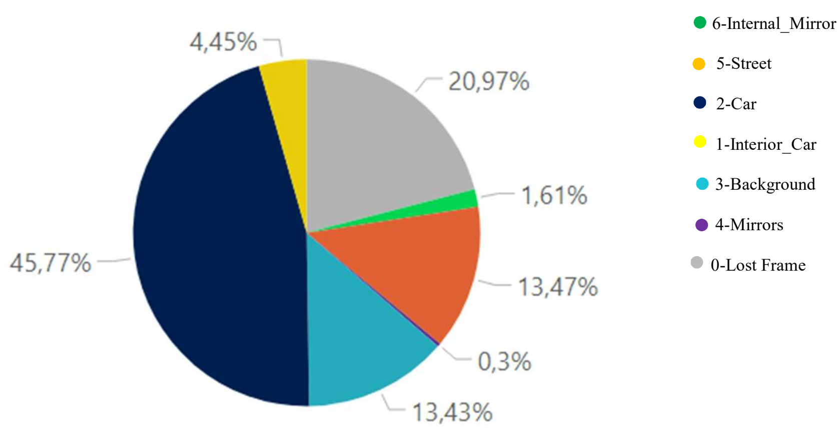


Graph 6.16. Suddivision of attention frames.



Graph 6.17. Suddivision of distraction frames.

In both figures we can see the supremacy of one class over the others: machine for attention, background for inattention; in both cases they occupy about ¾ of the total of the frames of the macro-class of belonging. In contrast, the classes Internal Mirror and Mirrors are too small a sample to be analysed.



Graph 6.18. Suddivision of frames in classes.

Finally, there is an overview of the incidence of individual classes on the total (Graph 6.18), where the greatest number of machine images is evident, while road and background are equivalent.

The analysis described above was also performed by differentiating between ACC system on and off (Table 6.14 and 6.15 respectively).

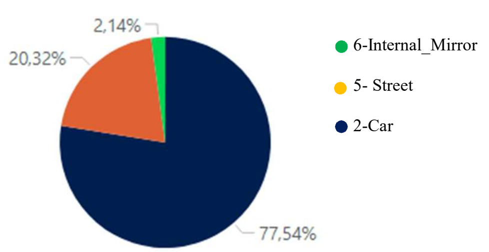
CLASSES ACC ON	LAB	CL/MACL_LAB
Interior_Car	314	25%
Background	918	73%
Mirrors	22	2%
Lost Frame	1348	
Car	2974	73%
Street	975	24%
Internal_Mirror	128	3%

Table 6.14. Average of labellized frame with ACC OFF.

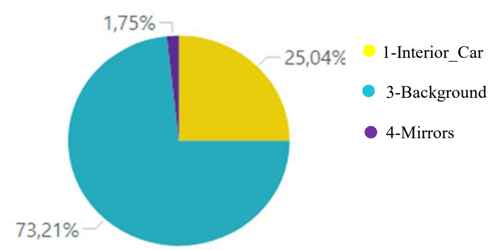
CLASSES ACC OFF	LAB	CL/MACL_LAB
Interior_Car	278	24%
Background	868	75%
Mirrors	18	2%
Lost Frame	1441	
Car	3114	78%
Street	816	20%
Internal_Mirror	86	2%

Table 6.15. Average of labellized frame with ACC ON.

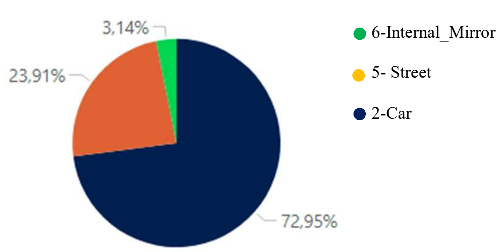
In order to facilitate the understanding of the results, the graphs that represent the distribution of classes within the macro-classes are shown below both for system on (Graph 6.19 and 6.20) and for system off (Graph 6.21 and 6.22).



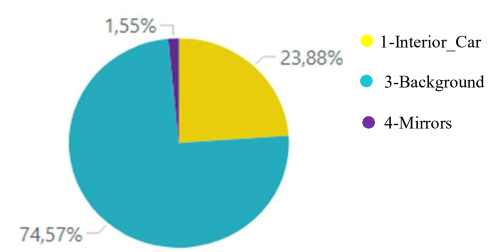
Graph 6.19. Suddivision of frame of attention with ACC ON.



Graph 6.20. Suddivision of frame of distraction with ACC ON.

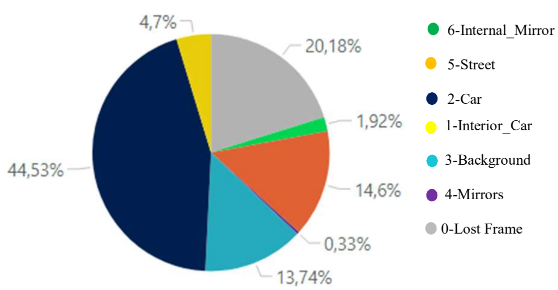


Graph 6.21. Suddivision of frame of attention with ACC OFF.

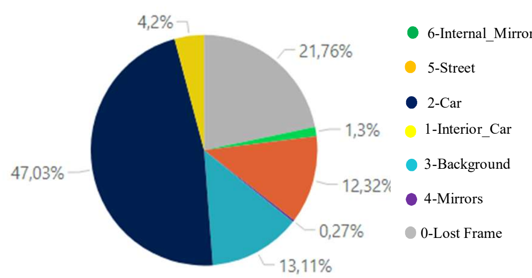


Graph 6.22. Suddivision of frame of distraction with ACC OFF.

In the ON/OFF system comparison there is a difference in the machine frames: these grow within the macro-class Attention in a not negligible in the case of system turned off (from 2974 to 3114). This disparity has led to the conclusion that, with the system switched on, drivers pay less attention to the vehicle in front and in general to the other components of road traffic. Among the images classified as interior cars are also included those in which the user focuses his gaze on the dashboard. In addition, there is an increase in the internal frame in the case of ACC ON, from 278 to 314 (increase of 13 %), a possible indication of a greater propensity to control the operating light of the system in the on-board computer. Note that the mirror and mirror classes are poorly represented and, because they do not reproduce a sufficient sample, they were excluded from the analysis phase. Graphs 6.23 and 6.24 are used to obtain an even more accurate picture of the driver’s visual behaviour.



Graph 6.23. Frame division into classes with ACC ON.



Graph 6.24. Frame division into classes with ACC OFF.

In these graphs the distribution of all classes on the total has been represented: a comparison between the two representations shows how, with the system turned on, the machine class decreases at the expense of a slight increase in the classes of background and internal inattention. These results allow us to assume that the use of the Adaptive Cruise Control system leads to a decrease in the level of attention of drivers while driving.

The subsequent analyses concerned the macro-classes, the data of which are given in Table 6.16.

CLASSES	Average Frames	Average Percetage Frames
Attention_LAB	4046	77%
Inattention_LAB	1210	23%
Total	5256	100%

Table 6.16. Arithmetic means labelled data in all macro-classes.

These values represent the arithmetic means that consider the labeled frames of all the users; it is deduced as the percentage of images belonging to the macro-class Attention are the triple of Inattention. Again, the data were divided into Adaptive Cruise Control system on (Table 6.17) and off (Table 6.18).

CLASSES ACC ON	Average Frames	Average Percetage Frames
Attention_LAB	4077	76%
Inattention_LAB	1255	24%
Total	5332	100%

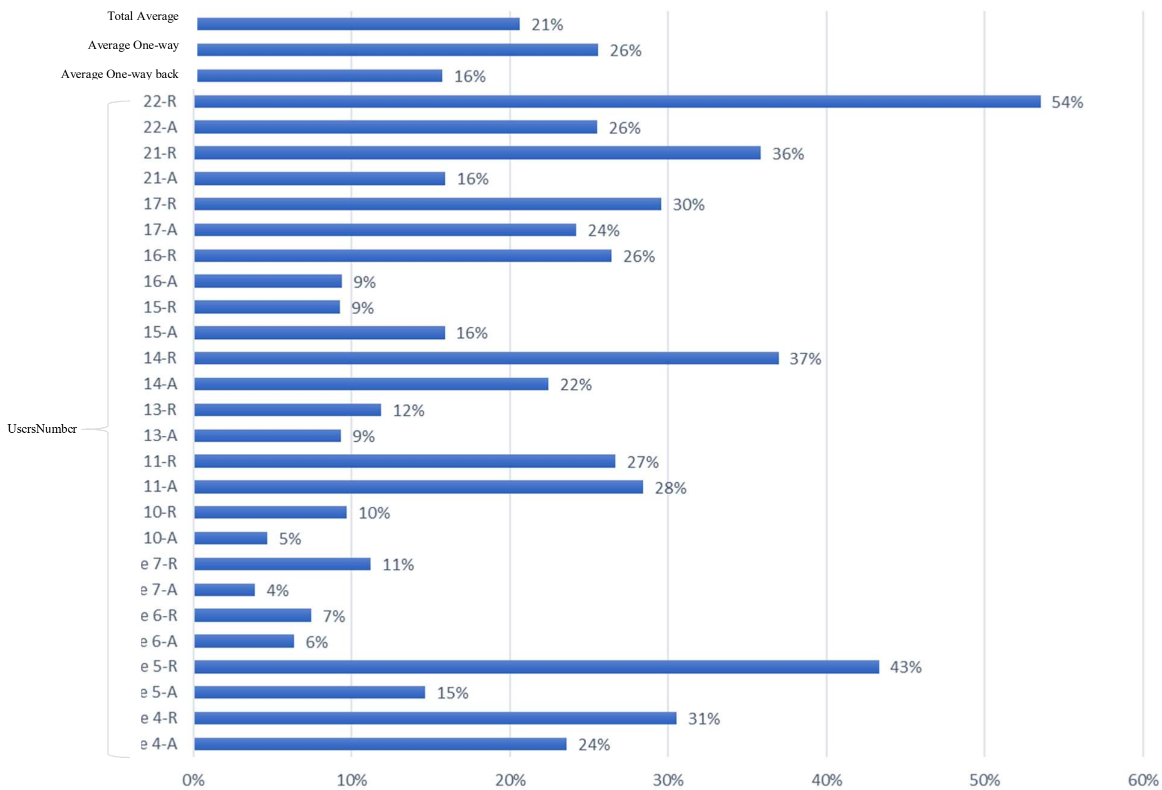
Table 6.17. Arithmetic means labelled data in ACC ON macro-classes.

CLASSES ACC OFF	Average Frames	Average Percetage Frames
Attention_LAB	4016	78%
Inattention_LAB	1164	22%
Total	5179	100%

Table 6.18. Arithmetic means labelled data in ACC OFF macro-classes.

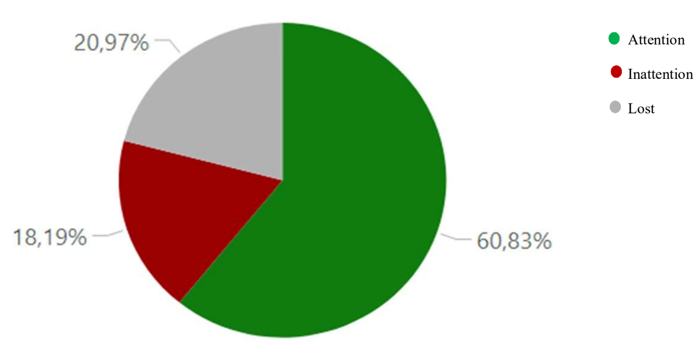
Pay attention to the value of the LAB frames in the ACC ON and OFF tables: notice how users tend to decrease the degree of attention with the On system. In fact, the average percentage of images attention for ACC ON is 76% against 78% of ACC OFF; these results are in line with studies carried out in the past (Cho, et al, 2006; Deng, et al, 2018).

It is also important to note the incidence of frames classified as lost: at the time of labeling, the human operator considered lost all images where the viewfinder was not present in full or the image did not allow a clear representation of the driver's point of view (completely black or white screen). Graph 6.25 shows the incidence of lost frames on the total for each user and for the total.



Graph 6.25. Incidence of lost frames on the total for each user and for the total.

Note that the lost frames are on average 21% for each user, which is not negligible. In graph 6.26, finally, the subdivision of the images is shown highlighting the macro-classes and the lost frames.



Graph 6.26. Subdivision of frames into macro-classes

The above graph confirms the results obtained: the images considered lost are on average 21% of the total and the user focuses on attention classes on average three times as much as those of inattention.

It is therefore understood that drivers, on average, are focused on the driving scene.

6.5.3. Analysis of kinematic data

Chapters 3 and 4 describe the experiments carried out and the equipment used: among the numerous data collected, in this study the longitudinal speeds and accelerations in the section covered for each user were extrapolated and analyzed. The V-Box Pro instrumentation allowed the collection of kinematic data with a sampling period of 0.1 second; speed and acceleration values were associated with each frame: it was necessary to synchronize the videos of the Mobile Eye and the V-Box Pro (recorded with a camera on the dashboard).

During the synchronization phase, each user was asked to look at the operator provided with a device made specifically for the test; Using the VLC Media Player software, the time and number of the frame were recorded the moment the same images were recorded in the video (Figure 6.18).

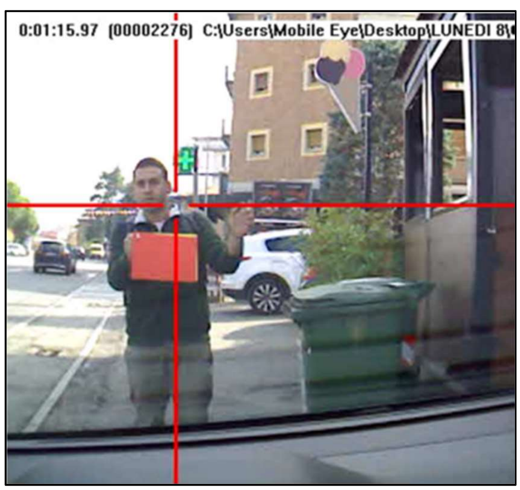


Figure 6.18. Synchronization phase of the movie.

With the software Circuit Tools 2.0 it was possible to extrapolate the kinematic data collected by the V-Box Pro, creating an Excel file (white columns in table 4.18) and then adding a column, named Time ME (yellow background) where the time expressed in seconds has been inserted (for the following instants 1/10 of a second has been added). With the data coming from the V-Box Pro, an Excel file (Table 6.19) has been produced, in which data such as latitude, longitude, speed, distance, acceleration are collected.

Satellites	BrakeTrigger	DGPS	Rtk	WavFile	Time (ME)	Time	Latitude	Longitude	Velocity	Heading	Height	Vertical_velocity	AviFileIndex	AviSyncTime	sampleperiod
9	0	0	0	0		12:57:20.30	44°0028.88172000 N	11°0015.36464400 W	000.086	000.00	+00086.35	000.000	1	17399	00:00:00.10
9	0	0	0	0		12:57:20.40	44°0028.88171400 N	11°0015.36463800 W	000.108	000.00	+00086.35	000.000	1	17499	00:00:00.10
9	0	0	0	0	7.88	12:57:20.50	44°0028.88170800 N	11°0015.36463200 W	000.194	000.00	+00086.33	000.130	1	17599	00:00:00.10
9	0	0	0	0	7.98	12:57:20.60	44°0028.88170200 N	11°0015.36463200 W	000.065	000.00	+00086.33	000.130	1	17699	00:00:00.10
9	0	0	0	0	8.08	12:57:20.70	44°0028.88170200 N	11°0015.36462600 W	000.029	000.00	+00086.32	000.130	1	17799	00:00:00.10
9	0	0	0	0	8.18	12:57:20.80	44°0028.88169600 N	11°0015.36462000 W	000.022	000.00	+00086.32	000.000	1	17899	00:00:00.10
9	0	0	0	0	8.28	12:57:20.90	44°0028.88169000 N	11°0015.36462000 W	000.047	000.00	+00086.31	000.130	1	18033	00:00:00.10
9	0	0	0	0	8.38	12:57:21.00	44°0028.88168400 N	11°0015.36461400 W	000.032	000.00	+00086.31	000.000	1	18099	00:00:00.10
9	0	0	0	0	8.48	12:57:21.10	44°0028.88168400 N	11°0015.36460800 W	000.133	000.00	+00086.30	000.000	1	18199	00:00:00.10
9	0	0	0	0	8.58	12:57:21.20	44°0028.88167800 N	11°0015.36460800 W	000.094	000.00	+00086.29	000.130	1	18299	00:00:00.10
9	0	0	0	0	8.68	12:57:21.30	44°0028.88167200 N	11°0015.36460200 W	000.065	000.00	+00086.29	000.130	1	18399	00:00:00.10
9	0	0	0	0	8.78	12:57:21.40	44°0028.88167200 N	11°0015.36459600 W	000.058	000.00	+00086.28	000.130	1	18499	00:00:00.10
9	0	0	0	0	8.88	12:57:21.50	44°0028.88166600 N	11°0015.36459600 W	000.058	000.00	+00086.27	000.130	1	18599	00:00:00.10
9	0	0	0	0	8.98	12:57:21.60	44°0028.88166600 N	11°0015.36459600 W	000.097	000.00	+00086.27	000.000	1	18699	00:00:00.10
9	0	0	0	0	9.08	12:57:21.70	44°0028.88166000 N	11°0015.36459000 W	000.115	000.00	+00086.26	000.130	1	18799	00:00:00.10
9	0	0	0	0	9.18	12:57:21.80	44°0028.88165400 N	11°0015.36458400 W	000.101	000.00	+00086.26	000.000	1	18899	00:00:00.10
9	0	0	0	0	9.28	12:57:21.90	44°0028.88165400 N	11°0015.36457800 W	000.058	000.00	+00086.25	000.000	1	18999	00:00:00.10
9	0	0	0	0	9.38	12:57:22.00	44°0028.88164800 N	11°0015.36457800 W	000.029	000.00	+00086.25	000.000	1	19099	00:00:00.10
9	0	0	0	0	9.48	12:57:22.10	44°0028.88164200 N	11°0015.36457200 W	000.094	000.00	+00086.23	000.130	1	19199	00:00:00.10
9	0	0	0	0	9.58	12:57:22.20	44°0028.88163600 N	11°0015.36457200 W	000.198	000.00	+00086.23	000.000	1	19299	00:00:00.10
9	0	0	0	0	9.68	12:57:22.30	44°0028.88163000 N	11°0015.36456600 W	000.079	000.00	+00086.22	000.000	1	19399	00:00:00.10
9	0	0	0	0	9.78	12:57:22.40	44°0028.88163000 N	11°0015.36456600 W	000.040	000.00	+00086.21	000.130	1	19499	00:00:00.10
9	0	0	0	0	9.88	12:57:22.50	44°0028.88162400 N	11°0015.36456000 W	000.094	000.00	+00086.20	000.000	1	19599	00:00:00.10
9	0	0	0	0	9.98	12:57:22.60	44°0028.88161800 N	11°0015.36456000 W	000.083	000.00	+00086.19	000.000	1	19699	00:00:00.10
9	0	0	0	0	10.08	12:57:22.70	44°0028.88161200 N	11°0015.36455400 W	000.061	000.00	+00086.18	000.000	1	19799	00:00:00.10
9	0	0	0	0	10.18	12:57:22.80	44°0028.88160600 N	11°0015.36454800 W	000.022	000.00	+00086.18	000.000	1	19899	00:00:00.10
9	0	0	0	0	10.28	12:57:22.90	44°0028.88160000 N	11°0015.36454200 W	000.061	000.00	+00086.17	000.000	1	19999	00:00:00.10
9	0	0	0	0	10.38	12:57:23.00	44°0028.88160000 N	11°0015.36454200 W	000.115	000.00	+00086.17	000.000	1	20099	00:00:00.10
9	0	0	0	0	10.48	12:57:23.10	44°0028.88158800 N	11°0015.36454200 W	000.212	000.00	+00086.16	000.000	1	20199	00:00:00.10
9	0	0	0	0	10.58	12:57:23.20	44°0028.88158800 N	11°0015.36453600 W	000.054	000.00	+00086.15	000.000	1	20299	00:00:00.10
9	0	0	0	0	10.68	12:57:23.30	44°0028.88158200 N	11°0015.36453000 W	000.079	000.00	+00086.14	000.000	1	20399	00:00:00.10
9	0	0	0	0	10.78	12:57:23.40	44°0028.88157600 N	11°0015.36452400 W	000.018	000.00	+00086.14	000.130	1	20499	00:00:00.10

Table 6.19. Output data of V-Box Pro and Time Mobile Eye.

The next step was to isolate the return routes for each user: note the start and end frames, were analyzed videos of the Mobile Eye on VLC and, thanks to the feed frame by frame, The exact times relative to the initial and final frames for each round trip have been extrapolated. These times have been researched in the Time (ME) column to plot the corresponding velocity and acceleration. However, the sampling period of the V-Box Pro is 0.1 second, unlike the Mobile Eye which records a frame every 0.03 seconds. To overcome this discrepancy, the same speed was assumed every 3 frames, making a negligible error. The operation of association given kinematic - frame was realized through a code written in Python that is the one below.

```python
import pandas as pd

csv_data = 'C:\\Users\Michele Paganelli\Desktop\TESI\Dati per Michele\CSV\\4_sb_A_ClassDIC2LCL8.csv'
csv_speed = 'C:\\Users\Michele Paganelli\Desktop\TESI\Dati per Michele\\4A_SPEED.csv'

df_csv_data = pd.read_csv(csv_data)
df_csv_speed = pd.read_csv(csv_speed,';')
df_csv_data.drop(columns=["Unnamed: 0"], inplace=True) #inplace se non funziona drop, oppure riassegna la variabile

count = 0
iterabile = df_csv_speed.iterrows()
element_speed=next(iterabile)

#df_csv_data=df_csv_data.iloc[1: , : ]#prima
#df_csv_data=df_csv_data.iloc[:-1 , : ]#ultima
print(df_csv_speed.head())

for row in df_csv_data.iterrows():

    if count > 2:
        count = 0
        element_speed = next(iterabile)

    df_csv_data.loc[df_csv_data['FileName']==row[1]['FileName'], 'Speed[km/h]'] = element_speed[1]['Velocity']/1000
    df_csv_data.loc[df_csv_data['FileName']==row[1]['FileName'], 'Acceleration[m/s^2]'] = element_speed[1]['LongitudinalAcceleration']*9.81
    count = count + 1

#variabile = input
#df_csv_data.to_csv('C:\\Users\Michele Paganelli\Desktop\TESI\Dati per Michele\speed\\4A_speedkmh.csv')
print(df_csv_data.head())
print(df_csv_speed.head())
```

To make the output functional, the input files (that of the network output and that of the V-Box Pro) have been specified and then provided instructions on the attribution of speed and acceleration data to the corresponding frames (Table 6.20). This implementation allows to add to the files produced by the network containing the classified images the columns Speed (km/h) and Acceleration (m/s2), assuming that these values remain constant for 3 consecutive frames.

FileName	Frame	Class	ClassName	X_line	Y_line	PredClass	PredClassName	Confidence	Speed[km/h]	Acceleration[m/s^2]
4_sb_A_37040.jpg	37040	0	0-Persi	0	0				28.958	0.3924
4_sb_A_37041.jpg	37041	0	0-Persi	78	415				28.958	0.3924
4_sb_A_37042.jpg	37042	5	5-Strada	149	370	5	5-Strada	0.71	28.958	0.3924
4_sb_A_37043.jpg	37043	2	2-Macchina	168	373	5	5-Strada	0.73	29.063	0.2943
4_sb_A_37044.jpg	37044	5	5-Strada	172	377	5	5-Strada	0.94	29.063	0.2943
4_sb_A_37045.jpg	37045	5	5-Strada	173	378	5	5-Strada	0.63	29.063	0.2943
4_sb_A_37046.jpg	37046	5	5-Strada	177	368	5	5-Strada	0.99	29.473	1.1772
4_sb_A_37047.jpg	37047	0	0-Persi	0	0				29.473	1.1772
4_sb_A_37048.jpg	37048	0	0-Persi	0	0				29.473	1.1772
4_sb_A_37049.jpg	37049	0	0-Persi	0	0				30.028	1.5696
4_sb_A_37050.jpg	37050	0	0-Persi	0	0				30.028	1.5696
4_sb_A_37051.jpg	37051	0	0-Persi	0	460				30.028	1.5696
4_sb_A_37052.jpg	37052	0	0-Persi	0	475				29.876	-0.3924
4_sb_A_37053.jpg	37053	0	0-Persi	0	0				29.876	-0.3924
4_sb_A_37054.jpg	37054	0	0-Persi	0	0				29.876	-0.3924
4_sb_A_37055.jpg	37055	0	0-Persi	0	0				30.308	1.1772
4_sb_A_37056.jpg	37056	0	0-Persi	0	472				30.308	1.1772
4_sb_A_37057.jpg	37057	0	0-Persi	0	463				30.308	1.1772
4_sb_A_37058.jpg	37058	0	0-Persi	0	463				30.719	1.1772
4_sb_A_37059.jpg	37059	0	0-Persi	0	460				30.719	1.1772
4_sb_A_37060.jpg	37060	0	0-Persi	0	454				30.719	1.1772
4_sb_A_37061.jpg	37061	0	0-Persi	0	457				30.967	0.6867
4_sb_A_37062.jpg	37062	0	0-Persi	0	455				30.967	0.6867
4_sb_A_37063.jpg	37063	0	0-Persi	0	451				30.967	0.6867
4_sb_A_37064.jpg	37064	0	0-Persi	0	442				31.19	0.5886
4_sb_A_37065.jpg	37065	0	0-Persi	0	0				31.19	0.5886
4_sb_A_37066.jpg	37066	0	0-Persi	0	0				31.19	0.5886
4_sb_A_37067.jpg	37067	0	0-Persi	0	0				31.565	1.0791
4_sb_A_37068.jpg	37068	0	0-Persi	0	0				31.565	1.0791
4_sb_A_37069.jpg	37069	0	0-Persi	0	0				31.565	1.0791
4_sb_A_37070.jpg	37070	0	0-Persi	0	0				32.076	1.3734
4_sb_A_37071.jpg	37071	0	0-Persi	0	0				32.076	1.3734
4_sb_A_37072.jpg	37072	0	0-Persi	0	0				32.076	1.3734
4_sb_A_37073.jpg	37073	0	0-Persi	0	0				32.36	0.7848
4_sb_A_37074.jpg	37074	0	0-Persi	0	0				32.36	0.7848
4_sb_A_37075.jpg	37075	0	0-Persi	0	0				32.36	0.7848

Table 6.20. Kinematic data associated with frames.

At this point you have the values of speed and acceleration for each round-trip frame of each user; the analysis process continues by calculating the average speed in function of the class of the frame creating, for each stroke (Table 6.21).

CLASSES	Total	Average_Speed [km/h]	Dev.St_Speed	Average_Acceleration [m/s^2]	Dev.St_Acceleration
1 - Interior_Car	39	57.45	20.99	0.07	0.67
2 - Car	4447	67.43	13.80	-0.16	0.93
3 - Background	309	65.91	11.90	0.08	0.91
4 - Mirrors	2	27.92	0.00	0.20	0.00
5 - Street	1108	68.28	12.76	0.26	0.70
6 - Internal_Mirror	129	60.00	16.54	0.23	0.74
Lost Frame	1860	64.10	2.79	0.29	0.04
Total	6034	66.56	14.44	0.02	0.90

Table 6.21. Example table user kinematic data 4 Round.

In which:

- Classe refers to the classification performed during labeling;
- Conteggio considers the image count (function CONTA.SE) calculated on all users for each class;
- Vel_Media (km/h) has been calculated with the Microsoft Excel AVERAGE.SE function with which the average of the frame speeds belonging to the same row class has been calculated;
- Dev.St_Vel evaluate the standard deviation of the given speed of the same frames;
- Acc_Media (m/s^2) performs the same calculation of vel_media with the difference that operates with accelerations; same speech with Dev.St_Acc;

After producing this table for each section covered by the 13 expert test drivers, the arithmetic mean of the frames and then the weighted average of the speed and acceleration values were calculated, first considering all the data (Table 6.22), then only those related to the ACC ON system (Table 6.23) and then OFF (Table 6.24).

CLASSES	Average	Average_Speed [km/h]	Dev.St_Speed	Average_Acceleration [m/s^2]	Dev.St_Acceleration
1 - Interior_Car	296	64.64	11.01	0.13	0.78
2 - Car	3044	69.59	13.51	-0.06	0.92
3 - Background	893	71.26	12.88	0.05	0.84
4 - Mirrors	20	56.15	8.83	0.35	0.71
5 - Street	896	70.14	12.50	0.06	0.83
6 - Internal_Mirror	107	64.43	11.90	-0.12	0.93
Lost Frame	4982				
Total	5256	69.53	13.04	-0.01	0.88
Attention	4046	69.57	13.24	-0.04	0.90
Inattention	1210	69.38	12.35	0.07	0.83

Table 6.22. Weighted averages kinematic data.

CLASSES	Average	Average_Speed [km/h]	Dev.St_Speed	Average_Acceleration [m/s^2]	Dev.St_Acceleration
1 - Interior_Car	314	64.76	10.46	0.14	0.79
2 - Car	2974	69.66	12.01	-0.07	0.93
3 - Background	918	72.10	12.13	0.02	0.91
4 - Mirrors	22	56.91	5.73	0.37	0.65
5 - Street	975	69.84	11.55	0.06	0.84
6 - Internal_Mirror	128	63.64	11.18	-0.23	1.01
Total	5332	69.93	11.81	-0.02	0.90
Attention	4077	69.51	11.88	-0.04	0.910.91
Inattention	1255	69.99	11.60	0.06	0.87

Table 6.23. Weighted averages kinematic data ACC ON.

CLASSES	Average	Average_Speed [km/h]	Dev.St_Speed	Average_Acceleration [m/s^2]	Dev.St_Acceleration
1 - Interior_Car	278	64.51	11.63	0.12	0.77
2 - Car	3114	69.52	14.94	-0.05	0.90
3 - Background	868	70.37	13.66	0.08	0.78
4 - Mirrors	18	55.23	12.20	0.32	0.79
5 - Street	816	70.50	13.63	0.05	0.82
6 - Internal_Mirror	86	65.62	12.98	0.04	0.81
Total	5180	69.43	14.30	0.00	0.86
Attention	4016	69.64	14.63	-0.03	0.88
Inattention	1164	68.73	13.15	0.09	0.77

Table 6.24. Weighted averages kinematic data ACC OFF.

In the following analyses, kinematic values for mirror and mirror classes will be omitted, as they are represented marginally. Note how the average acceleration of the car frames is negative, a sign that often the driver looks at the car (especially the prey vehicle) when braking or is near it. There are, however, no substantial differences in longitudinal acceleration between the strokes driven with the system on and off; it is also stressed that the standard deviation is high, always close to the unit. As for speeds, when considering both the outward and return sections, its average is equal to 69.43 km/h, given in line with the travel speeds calculated when users look at the main classes (machine 69,59 km/h, background 71,26 km/h, road 70,14 km/h); there are no particular differences between the average speed relative to macro-class attention and the corresponding data related to inattention.

The comparison between sections with On and Off system has several hints: average speeds with the system on increase slightly for 4 classes out of 6 (except for Road and Mirror interior). What varies most is the standard deviation: you notice a decrease in this parameter for the strokes traveled with ACC On. This decrease is found in all classes. In the total row, a value of 14.30 can be observed with ACC Off and 11.81 for ACC On (a decrease of 17 %). This result leads to deduce that the system, during the journey, produces a lower variability of the speed and consequently an increase of driving comfort, results in line with past studies (Trnros, et al, 2002: Cho, et al, 2006; Hoedemaeker, et al, 1998; Hoedemaeker, 2000). Below are the histograms (Table 6.25, 6.26, 6.27) that summarize the values previously shown in the table.

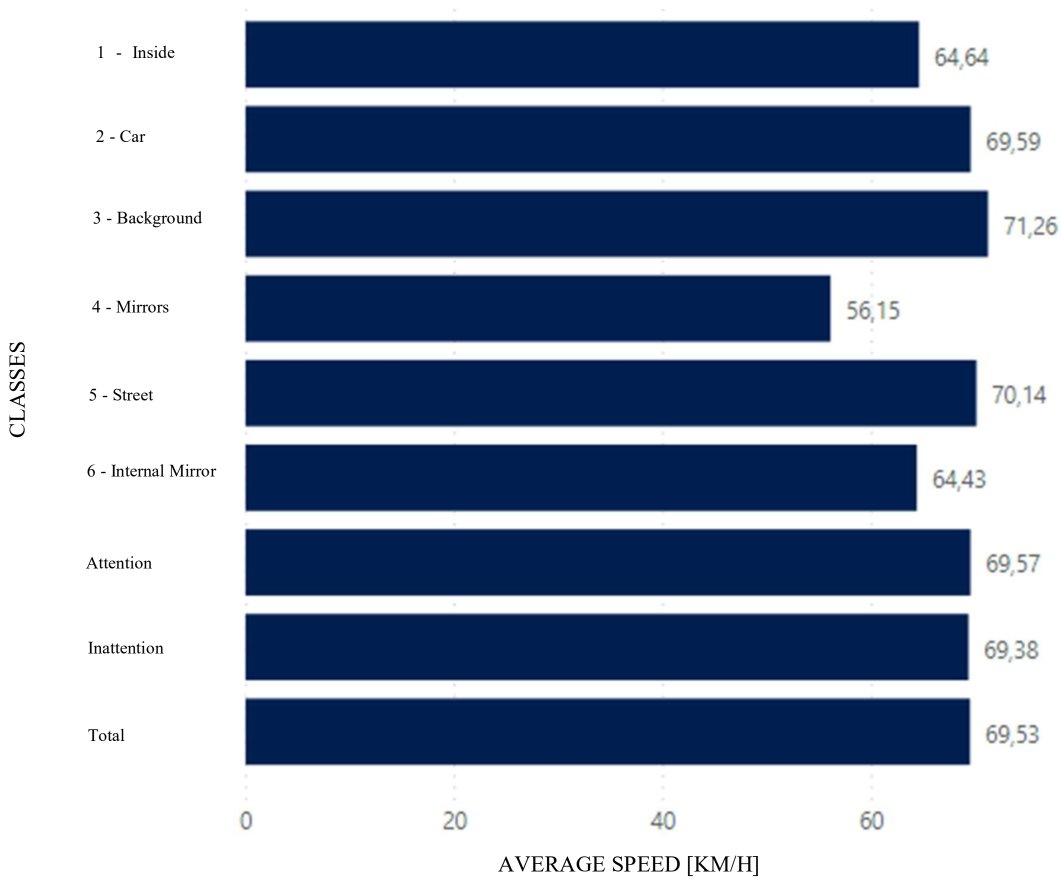


Table 6.25. Average speed with ACC ON.

Table 6.26. Average Speed.

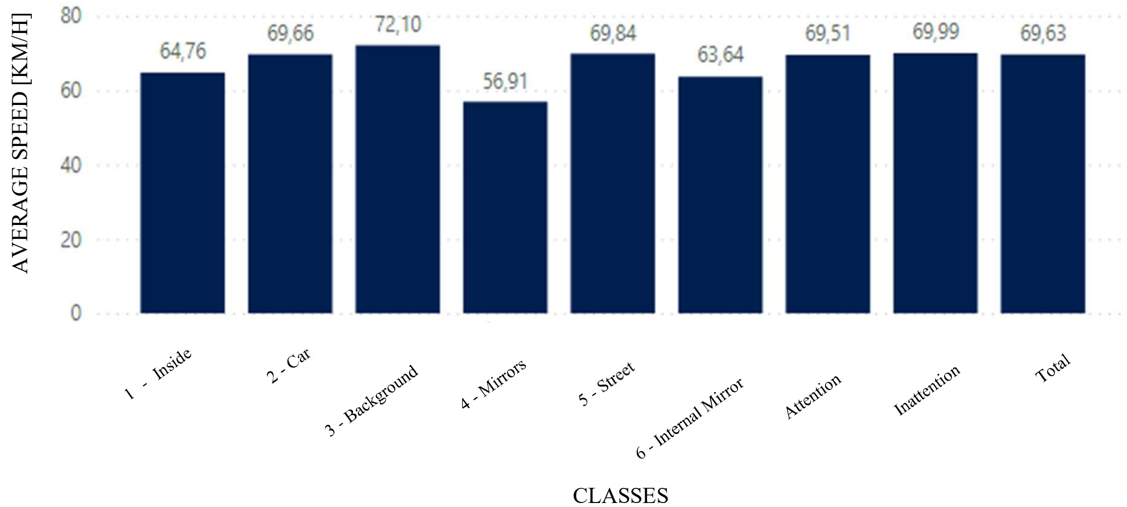


Table 6.27. Average speed with ACC OFF.

In Table 6.28, the maximum and minimum speeds and accelerations during the distances traveled by users were also calculated.

User and state of the system	Data	Speed (km/h)	Situation
4 – One way	Max	86.105	
ACC ON	Min	26.622	
4 – Way back	Max	101.635	Overtaking behind the prey vehicle
ACC OFF	Min	30.668	
5 - One way	Max	86.494	
ACC ON	Min	29.606	
5 - Way back	Max	96.998	Straight section behind the prey vehicle
ACC OFF	Min	40.792	
6 - One way	Max	86.22	
ACC ON	Min	41.443	
6 - Way back	Max	86.67	
ACC OFF	Min	41.332	
7 - One way	Max	86.209	
ACC ON	Min	39.841	
7 - Way back	Max	83.279	
ACC OFF	Min	32.49	
10 - One way	Max	86.209	
ACC ON	Min	45.205	
10 - Way back	Max	83.761	
ACC OFF	Min	43.456	
11 - One way	Max	97.232	Straight section behind the prey vehicle
ACC OFF	Min	1.12	
11 - Way back	Max	96.408	
ACC ON	Min	41.962	

13 - One way	Max	104.332	I pass behind the kill vehicle
ACC OFF	Min	30.794	
13 - Way back	Max	100.343	
ACC ON	Min	40.622	
14 - One way	Max	107.914	I pass behind the kill vehicle
ACC OFF	Min	31.5	
14 - Way back	Max	86.627	
ACC ON	Min	48.355	
15 - One way	Max	95.342	
ACC ON	Min	40.126	
15 - Way back	Max	92.768	
ACC OFF	Min	0.000018	
16 - One way	Max	104.609	I pass behind the kill vehicle
ACC OFF	Min	36.634	
16 - Way back	Max	86.54	
ACC ON	Min	42.156	
17 - One way	Max	90.27	
ACC OFF	Min	39.697	
17 - Way back	Max	98.849	
ACC ON	Min	37.098	
21 - One way	Max	91.681	
ACC OFF	Min	33.559	
21- Way back	Max	90.576	
ACC ON	Min	34.178	
22 - One way	Max	78.253	
ACC ON	Min	33.163	
22 - Way back	Max	90.5	
ACC OFF	Min	40.759	

Table 6.28. Maximum and minimum values of speed and longitudinal acceleration.

Note that in 9 out of 13 cases the maximum speed is higher in the case of ACC Off substantially. Focusing on users 4, 5, 13, 14 and 16, the speed is not only higher than the maximum speed sustained by users in the section with the system on, but also greater than that allowed by the Road Code on the road path (Vollratha, et al, 2011). Exceeding the allowed speed with the system on is due to the maximum limit set by the driver to the system.

More in-depth analysis of the videos of users who have traveled the circuit at high speeds (with ACC OFF) showed how, for users 4, 13, 14 and 16, they have followed the vehicle prey even during lane change (Figure 6.19), this will require an increase in speed.

Figure 6.19. User frame change lane.

Users marked with numbers 5 and 11 reached the maximum speed of 97 km/h during a straight stretch in the lane of the Bologna ring road immediately behind the prey vehicle.

Analysis of kinematic data during events

The degree of attention and inattention of drivers was also analyzed through the study of reaction times during a critical situation, called an event, and of the speeds sustained during this period of time. Perception-Reaction time (PRT) is defined as "the time between the sight of an obstacle and the application by the driver of a braking action" (Olson, et al, 1986). The present study analysed the speeds during the perception-reaction time measured during the test. Dated studies (Törnros, 1995) have observed that reaction times decrease with increasing travel speeds, these results are confirmed by (Jurecki, et al, 2014).

During the experiment, "events" were programmed, situations in which the vehicle was suddenly braking: in the sections with the system off, a braking action by the driver was necessary,in journeys with the system on, subjects were required not to brake and leave control of the vehicle to the system. We studied 100 events distributed among users as per Table 6.29, in which in red the events occurred with ACC OFF and in green those with the system on.

User	Event – One way	Event – Way back	Total
4	6	5	11
5	6	5	11
6	5	4	9
7	4	3	7
10	2	2	4
11	5	5	10
13	4	3	7
14	3	4	7
15	5	4	9
16	4	3	7
17	3	3	6
21	4	4	8
22	2	2	4
Tot ON	30	22	52
Tot OFF	23	25	48
Tot	53	47	100

Table 6.29. Summary table on the event distribution.

The perception/reaction times for each event were evaluated and, subsequently, the travel speeds in this time interval were evaluated. The reaction times were obtained using the Circuit Tools 2.0 software, according to the procedure in Chapter 4.

In Table 6.30 the averages of all the events for every distinct user for system on and off are collected. It is immediate to detect the difference between the perception-reaction times obtained in events with the system on and off: the latter are lower on average about 1 second and in all 13 cases no PRT detected with ACC Off is higher than the same with ACC ON. These results certify that the average driver is more distracted and therefore takes longer to react to a dangerous situation when the system is active. The previous analysis on Visual Behaviour becomes more relevant: to detect the danger during the event it was necessary to focus on the car in front and the driver on average had a greater number of machine frames in the case of the system off.

The further analysis concerned the speed of travel during the above events: tables such as 6.30 were extracted for each event of all the sections traveled by 13 experienced users, in which velocities and longitudinal acceleration of the frames belonging to the time interval defined as PRT and weighted averages and standard deviations have been collected.

CLASSES	Tot	Average_Speed [km/h]	Average_Acceleration [m/s^2]	Dev.St_Speed	Dev.St_Acceleration
1 - Interior_Car	0	0.00	0.00	0.00	0.00
2 - Car	78	81.91	-0.66	2.07	0.94
3 - Background	0	0.00	0.00	0.00	0.00
4 - Mirrors	0	0.00	0.00	0.00	0.00
5 - Street	0	0.00	0.00	0.00	0.00
6 - Internal_Mirror	0	0.00	0.00	0.00	0.00
0 – Lost Frame	24	82.55	0.26	0.22	0.66
Total	102	82.06	-0.45	1.64	0.88

Table 6.30. Kinematic data of the generic event

This data processing was carried out for each subject: in Table 6.31 the analyses concerned all users, while Tables 6.32 and 6.33 were obtained by considering only the events in the ACC On and Off sections respectively; in the first column the sum of the frames of the corresponding class has been calculated. Figures 6.27, 6.28 and 6.29 show the distributions of the classes in percentage terms by considering respectively all events (Graph 6.27), only ACC ON (Graph 6.28) and only ACC OFF (Graph 6.29).

CLASSES	Tot	% of Tot	Average_Speed [km/h]	Average_Acceleration [m/s^2]	Dev.St_Speed	Dev.St_Acceleration
1 - Interior_Car	240	2%	77.30	-0.23	0.98	0.67
2 - Car	5476	52%	82.07	-0.32	1.47	0.80
3 - Background	1576	15%	82.35	-0.32	1.24	0.65
4 - Mirrors	16	0%	82.58	0.35	0.16	0.58
5 - Street	1275	12%	82.83	-0.28	1.31	0.62
6 - Internal_Mirror	117	1%	79.91	-0.77	0.70	0.62
0 – Lost Frame	1831	17%				
Attention	6868	65%	81.81	-0.31	1.22	0.63
Inattention	1832	17%	81.69	-0.30	1.20	0.66
Total	10531	100%	82.08	-0.31	1.38	0.74

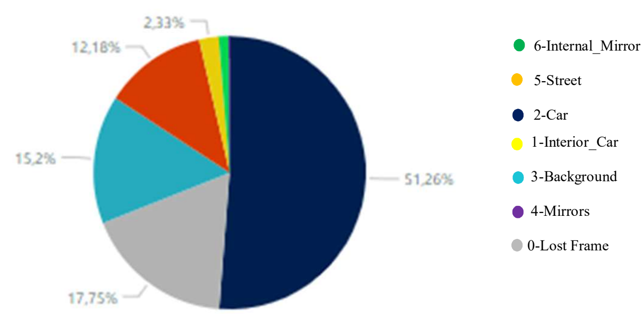
Table 6.31. Kinematic data for all users.

CLASSES	Tot	% of Tot	Average_Speed [km/h]	Average_Acceleration [m/s^2]	Dev.St_Speed	Dev.St_Acceleration
1 - Interior_Car	112	2%	80.40	-0.32	1.38	0.80
2 - Car	3068	51%	82.36	-0.28	1.29	0.66
3 - Background	998	17%	82.85	-0.39	1.48	0.74
4 - Mirrors	16	0%	82.58	0.35	0.16	0.58
5 - Street	796	13%	81.61	-0.22	1.42	0.68
6 - Internal_Mirror	48	1%	74.92	-1.31	1.18	0.58
0 – Lost Frame	998	17%				
Attention	3912	65%	81.13	-0.28	1.40	0.69
Inattention	1126	19%	82.61	-0.37	1.45	0.74
Total	6036	100%	82.23	-0.30	1.35	0.68

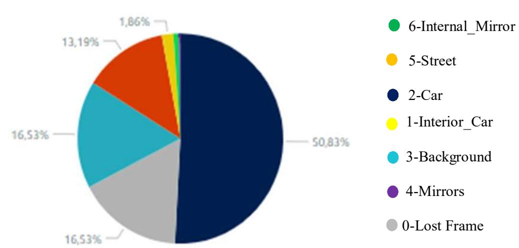
Table 6.32.Kinematic data ACC ON.

CLASSES	Tot	% of Tot	Average_Speed [km/h]	Average_Acceleration [m/s^2]	Dev.St_Speed	Dev.St_Acceleration
1 - Interior_Car	128	3%	74.58	-0.15	0.64	0.57
2 - Car	2408	54%	81.71	-0.36	1.23	0.72
3 - Background	578	13%	81.49	-0.14	0.49	0.50
4 - Mirrors	0	0%	0.00	0.00	0.00	0.00
5 - Street	479	11%	84.87	-0.38	1.14	0.53
6 - Internal_Mirror	69	2%	83.38	-0.39	0.36	0.65
0 – Lost Frame	833	19%				
Attention	2956	66%	82.77	-0.34	0.96	0.55
Inattention	706	16%	80.24	-0.14	0.52	0.51
Total	4495	100%	81.87	-0.32	1.06	0.65

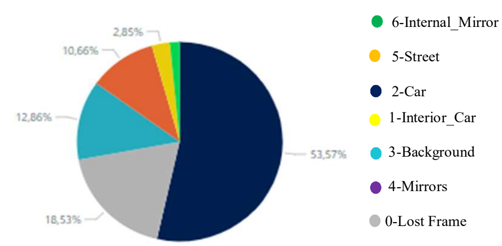
Table 6.33. Kinematic data ACC OFF.



Graph 6.27. Percentage of total by classes.



Graph 6.28. Percentage for classes with ACC ON



Graph 6.29. Percentage for classes with ACC OFF

From these analyses it is possible to know the user’s behavior in a situation defined as "critical": the analyzed frames are in fact collected in a time interval in which the driver notices the sudden braking of the vehicle in front and, therefore, it perceives a situation of danger or alarm anyway. Note how, during events, more than half of the frames are ranked machine and that about 17% are lost. The results related to macro-classes are in line with those already obtained with the totality of the images: attention encloses about three times the frame of inattention.

Note the average speeds distinguished by macro-classes: in the case ACC ON a lower average speed during frame attention has been obtained than those of inattention, the latter is run at a higher speed even of the analogues with OFF system.

The accelerations, as was to be expected, are slightly below zero and negative since a time interval is being analysed where the system (or the driver) releases the accelerator to prepare to act on the brake. However, there is a lower mean acceleration value for the off system; this is evidence of the fact that entrusting longitudinal control to the vehicle results in an average acceleration closer to zero and therefore also greater comfort for users on board the vehicle.

Finally, there is a summary table (Table 6.34) in which the averages of the perception-reaction times are calculated considering all the events of each user are collected, the same calculation has been performed to obtain the average speeds.

USER	ON [s]	Average_Speed ON [km/h]	OFF [s]	Average_Speed OFF [km/h]
4	4	83.96	3.60	81.73
5	3.45	80.49	3.00	83.23
6	3.64	82.41	2.53	78.93
7	3.95	81.24	2.40	74.68
10	3.25	79.09	2.70	77.84
11	2.82	87.52	2.78	82.58
13	2.67	88.75	2.47	85.10
14	4.30	79.89	3.00	100.40
15	4.52	86.39	3.80	79.82
16	7.43	81.87	4.38	77.35
17	3.33	84.53	2.57	87.44
21	3.78	76.22	3.08	79.38
22	2.8	65.00	2.60	75.84
AVERAGE	3.84	81.33	2.99	81.87

Table 6.34. Average of PRT and speed.

The considerations relating to the disparity of PRTs have already been discussed, now the focus on average speeds: in only 4 cases out of the 13 total analyzed travel speeds during PRTs with the system off are higher than the homologues with the system on.

6.6. Conclusion

The analyses carried out have led to important results considering neural networks, visual behaviour and driving behaviour.

The performance in the classification phase of the neural network operating with the Double Input model was evaluated from the videos recorded by the Mobile Eye Tracker. The analysis involved 13 users, the arithmetic average was calculated according to the type of classification (class or macro-class), the confidence of the network, and the state of the system (On/Off). The network has proven to be highly reliable and robust, as 65% of the images are classified with over 0.90 confidence and are not affected by the system (on/off) status. Considering only frames with confidence above 0.90, the most represented classes such as Machine and Background have a small percentage of wrong frames (4% and 11%) Internal mirror and mirrors were excluded from all analysis because they were poorly represented. In fact, in neural networks there is a relationship between the amount of data subjected to the network and the quality of classification: the high number of frames belonging to the two classes mentioned above has allowed to refine the criteria for classification of the network, which gives such images a high confidence.

The analysis carried out on the results of the network has allowed to establish that, if we consider only the frames having a confidence greater than 0.90, this set has a corrected percentage of 92% and contains 65% of the total frames. By grouping the classes within the macro-classes Attention and Inattention it was observed that the network correctly classifies the attention frames with a percentage greater than 84% and inattention with a value of 71% and that the first ones are on average triple the seconds. Considering only images with a confidence greater than 0.90, the results are excellent: attention has a percentage of corrected 94%, while inattention of 85%. Finally, the performance of the network was determined following a different classification based on macro-classes: evaluating wrong only images labeled in one of the three attention classes but predicted by the network in one of the three of Inattention (and vice versa). In this analysis, considering all frames with confidence greater than 0.90, they are corrected in 95% of cases, concluding that the network classifies most of the images in the correct macro-class with excellent results. The results then showed that it is possible to automate a large part of the image classification procedure, otherwise done manually by an operator.

The second phase of the study was to analyse the influence of the ACC system on the visual behaviour of users. By studying the frames classified by the human operator, the direction of the gaze was detected, and the degree of attention and possible correlations with the driving process were evaluated. The comparison showed that, with ACC ON, the percentage of images attention is 76%, against 78% of the ACC OFF case; this confirms the classification made by the network, that on average the images attention are triple those of inattention. It is concluded that the system affects users by decreasing the degree of attention while driving (results confirmed by studies in the literature).

The third and final phase involved kinematic data (driving behaviour) collected during the test with the Video V-Box Pro instrumentation. The weighted averages of travel speed and longitudinal acceleration of each user have been calculated by means of a code in Python specially developed to associate the values of the V-Box to the frames classified. The standard deviation in the case of ACC ON is 17% lower, highlighting how the system reduces the variability of the speed and increases the comfort of travel; moreover in 9 cases out of 13 the maximum speed is higher in the case of ACC OFF. The analysis of events has affected the perception-reaction time (PRT): this has always been lower with the system turned off, confirming that the system decreases the attention of drivers, as already highlighted in previous analyses. Finally, the study of kinematic data produced lower mean deceleration values with the system running, further test of the difference in driving due to the ACC system.

7. CONCLUSIONS

The three years of PhD have led to the realization of research of technological innovation. Nowadays, the development of driving automation is becoming impactful on the road environment. The vehicle, thanks to the new features became a different entity than in the past. The introduction of new mechanisms to assist the driver while driving establishes new criteria for vehicle control and management. This, therefore, entails a simultaneous change in the principles of road safety.

By focusing on visual behaviour, it is possible to evaluate how the use of Adaptive Cruise Control does not increase attention while driving. On the contrary, the mechanism causes the user to be particularly pointed towards the dashboard, as it turns out intrigued. As a result, the frame rate related to inattention is high. The main motivation lies in the driver's willingness to check the correct functioning of the system, constantly looking at the dashboard. It is no coincidence that he repeatedly observes the indicator lamp on the dashboard to determine whether the ACC has detected the vehicle in front and whether, consequently, the speed is modulated according to the distance.

The examination carried out for the Events, in addition to confirming the trend evaluated in the entire path for both users ACC user and no-user, highlights how, for the attention, the category with the highest frame percentage concerns the led light. In fact, when the user is attentive, he looks at the vehicle in front, trying to evaluate the possible future maneuvers. The focus on the stop light is high but, decreases when the ACC is on, precisely because the user trusts the system to manage the vehicle.

Considering driving behaviour, the first relevant data was provided by traffic precisely to assess the level of service present in the roads under study. According to the data collected, it has been possible to consider it as belonging to LOS A. Not surprisingly, the traffic recorded in the logs is homogeneous, so it does not lead to significant problems in terms of traffic. In fact, it presents free flow conditions with total absence of conditioning between vehicles, also because the width of the lanes is always constant.

The kinematic data obtained from the use of the V-Box allowed the recording of the average speed for both experienced and inexperienced users. In both cases, the recorded speeds were below the limit amounts from the highway code, both with the system on and off. On the other hand, the reaction time was relevant. Although it may be thought that the response times of human drivers are longer than those of the ACC system, there has been a reversal of the trend. Not surprisingly, for both experienced and inexperienced users, the reaction times are considerably greater when the ACC is switched on. This is a further factor that excludes the possibility of an increase in road safety with the use of the driver assistance system.

The workload, another key parameter in the driving behaviour, considers that the user has better performance when the system is on. The evaluation of the mental path has emphasized that, in fact, the workload to the system on is greater than that one that is recorded to system off. These values, however, have a small gap. The driver, therefore, is more mentally engaged with the system on, but not too much precisely because the workload is about equal between the two conditions. The action of the system, therefore, does not produce substantial variations in the workload of the driver.

As a result, the use of the system has led drivers to feel a lower mental workload when the system is on, because it does not run into the concern that the system may have malfunctions, thus leading to collision with the vehicle it takes.

The questionnaires, however, showed that the subject considered that the task to be performed was not particularly difficult. The system, according to the extrapolated assessments, intervened when necessary and at the most appropriate time. The champion adapted well to the system and immediately understood the mechanism that distinguished him, despite being inexperienced. The guide was simple and the user was able to maintain high attention. The sample trusted the system while not always checking its operation. It was also found that it worked well in emergency situations. Only 1 user out of 26 total did not feel comfortable with the system.

Thanks to this analysis, however, it was possible to encounter problems related to the high post-processing times of data. Frame-by-frame analysis, in fact, defines the most objective analysis possible in relation to the driver's point of view, but at the same time requires long periods of data analysis, as you have to manually analyze each frame, and then categorize it and attribute it to the context of attention or inattention. For this reason, an automatic tool has been devised, output regulated thanks to neural networks. This element made it possible to carry out both a check of the manually categorized data and the possibility of interpolating the visual data with the kinematic ones. It was in fact possible to consider frames related to attention and inattention, in relation to the kinematic parameters of the vehicle.

Finally, in order to quickly and efficiently manage the large volume of data, an artificial neural network has been implemented to classify the images recorded by the Mobile Eye Tracker. Artificial intelligence and machine learning represent the new frontier of information processing, able to improve step-by-step learning from the analyzed data. The network used in this study has produced excellent results in the automation of the classification process, classifying more than two thirds of the total images with a percentage of corrected more than 90%;

This study demonstrated the advantages of using artificial neural networks in image classification, with the intention of being a starting point for future road safety applications. In fact, the analysis methodology, followed by the inclusion of a graphical interface that allows users to automatically count the fixing frames, represents a breakthrough in road safety. In particular, the possibility to apply this innovation to other road contexts and to widen the field of available results is an important milestone in the critical study of automation.

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