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DESIGN AND CHARACTERIZATION OF AUTOMATED AGRICULTURAL
VEHICLE SYSTEMS

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“Se volete trovare qualcosa, non c’è niente di meglio che cercare.”

J.R.R. Tolkien

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Abstract

Nowadays, technological advancements have brought industry and research towards the automation of various processes. Automation brings a reduction in costs and an improvement in product quality. For this reason, companies are pushing research to investigate new technologies and possibilities. The agriculture industry has always looked towards automating various production processes, from product processing to storage. In the last years, the automation of harvest and cultivation phases also has become attractive, pushed by the advancement of autonomous driving. ADAS systems are the core of the automation revolution. Nevertheless, autonomous driving is not enough. Merging different technologies will be the solution to obtain total automation of agriculture processes, such as the harvest. For example, sensors that estimate the physical and chemical properties of products can be used to evaluate the maturation level of fruit. Therefore, the fusion of these technologies has a key role in industrial process automation.

In this dissertation, ADAS systems and sensors for precision agriculture will be both treated. In this thesis work, several measurement procedures for characterizing commercial 3D LiDARs will be proposed and tested to cope with the growing need for comparison tools. Axial errors and transversal errors have been investigated. Moreover, a measurement method and setup for evaluating the fog effect on 3D LiDARs will be proposed. Each presented measurement procedure has been tested. The obtained results highlight the versatility and the goodness of the proposed approaches. Regarding the precision agriculture sensors, in this thesis, a measurement approach for the Moisture Content and density estimation of crop directly on the field is presented. The approach regards the employment of a Near Infrared spectrometer jointly with Partial Least Square statistical analysis. The approach and the model will be described together with a first laboratory prototype used to evaluate the NIRS approach. Finally, a prototype for on the field analysis is realized and tested. The test results are promising, evidencing that the proposed approach is suitable for Moisture Content and density estimation.

Riassunto

Al giorno d'oggi, i progressi tecnologici hanno portato l'industria e la ricerca verso l'automazione di vari processi. L'automazione comporta una riduzione dei costi e un miglioramento della qualità del prodotto. Per questo motivo, le aziende stanno spingendo la ricerca a indagare nuove tecnologie e possibilità. L'industria agricola ha sempre cercato di automatizzare i vari processi di produzione, dalla lavorazione del prodotto allo stoccaggio. Negli ultimi anni anche l'automazione delle fasi di raccolta e coltivazione è diventata attraente, spinta dall'avanzamento della guida autonoma. I sistemi ADAS sono il cuore della rivoluzione dell'automazione. Tuttavia, la guida autonoma non è sufficiente. La fusione di diverse tecnologie sarà la soluzione per ottenere l'automazione totale dei processi agricoli, come il raccolto. Ad esempio, i sensori che stimano le proprietà fisiche e chimiche dei prodotti possono essere utilizzati per valutare il livello di maturazione della frutta. Pertanto, la fusione di queste tecnologie ha un ruolo chiave nell'automazione dei processi industriali. In questa tesi, i sistemi ADAS e i sensori per l'agricoltura di precisione saranno entrambi trattati. In questo lavoro di tesi, saranno proposte e testate diverse procedure di misurazione per caratterizzare LiDARs 3D commerciali, per affrontare la crescente necessità di strumenti di confronto. Sono stati studiati errori assiali ed errori trasversali. Inoltre, verranno proposti un metodo di misurazione e una configurazione per valutare l'effetto nebbia sui LiDARs 3D. Le procedure di misurazione proposte sono state testate. I risultati ottenuti evidenziano la versatilità e la bontà degli approcci proposti. Per quanto riguarda i sensori per l'agricoltura di precisione, in questa tesi viene presentato un approccio di misurazione per il contenuto di umidità e la stima della densità delle colture direttamente sul campo. L'approccio riguarda l'impiego di uno spettrometro Near Infrared insieme all'analisi statistica Partial Least Square. L'approccio e il modello saranno descritti insieme ad un primo prototipo di laboratorio utilizzato per valutare l'approccio NIRS. Infine viene realizzato e testato un prototipo per l'analisi sul campo. I risultati dei test sono molto promettenti, dimostrando che l'approccio proposto è adatto per il contenuto di umidità e la stima della densità.

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Chapter 1

Introduction

The technological evolution of recent years has brought the industry to look more and more towards full automation of many industrial processes to improve their products and reduce costs. Automation is currently a major goal for a wide range of industries, including manufacturing, logistics, and biomedical. With the increasing complexity of the processes being automated, research is looking towards finding new technologies to achieve full automation in a secure and safe manner. The automotive industry has followed this path by automatizing the production of automobiles and industrial vehicles and successively moving towards autonomous driving, considered a game changer for the future [1, 2]. The possibility of improving driving comfort and safety and reducing traffic on roads stimulates the development of autonomous driving systems. Also, the agricultural and agrifood industry has been pushing for the automation of various phases of cultivation and harvesting. The agriculture industry was a pioneer in the research on autonomous driving, developing tractors and machines able to accomplish operations such as sowing, irrigation, harvesting and crop monitoring in a quasi-autonomous manner.

The constantly raising demand of Advanced Driver-Assistance Systems (ADAS) have pushed the research in the development and improvement of sensors able to provide the environmental sensing essential for autonomous driving. Consequently, in recent years, RADARs, Imaging systems, and LiDARs have seen a sharp increase in their performances and importance. Particularly, LiDAR (Light Detection and Ranging) systems emerge, among the various sensors, thanks to their high precision in distance estimation and significant measurement range. The increase of performance and the parallel reduction of costs of LiDARs, brought a multitude of new sensors available on the market. The huge variability in performances, characteristics and technologies of commercial LiDARs raises the demand of benchmarking tools that may help to disentangle the wide range of LiDARs available.

Autonomous driving will be part of the future of the automotive industry, but only

the fusion of different technologies can achieve complete automation. For instance, ADAS systems are not enough to achieve complete autonomous driving, but other technologies such as health monitoring and drowsiness [3] are required. Considering agriculture, the need of integration between ADAS systems and other technologies is more evident. Let's consider harvesting; the automation of this process can be reached by adopting ADAS systems for the harvesting machine and by including sensors that can evaluate the quality of the product to be collected directly on the tractor, avoiding waste of time and products. For example, wheat must be collected when it reaches a specific level of maturation. Usually, the techniques used for wheat analysis are destructive and required to collect samples. Performing these analyses in a non-destructive manner and directly on the machine will result in less time, money and product waste while also allowing automation of the harvesting process. There are several examples of agriculture machines that reach quasi-complete automation. For example, the Agrobot E-series by Agrobot shown in Fig. 1.1 is an automatic machine able to harvest strawberries which are reached the correct maturation level [4, 5]. This machine exploits an imaging system to correctly move its arms e find the strawberries. A camera and infrared depth sensors collect strawberry information used to determine the maturation state of the fruit. These data are elaborated through AI to respect real-time requirements. The machine is equipped with ADAS systems, in the specific LiDARs, to accurately move without ruining the cultivation and to respect the safety of on-field workers.



Figure 1.1: Photo of the Agrobot E-Series by Agrobot [4].

Merging autonomous driving technique and crop analysis techniques will brought agriculture industry to a new level. To reach that target is fundamental the development and investigation of new sensors and new measurement techniques. This is the starting point of my PhD program, during which I have investigated the performances and the behaviour of commercial LiDARs, designing benchmark setups and

methods, and studying the limits of applicability of such instruments. In parallel, I worked on the design and realization of a instrument for estimating the moisture level of crop directly on the field. The instrument is based on Near-Infrared Spectrum (NIRS) analysis, one of the most promising non-destructive analysis technologies. The estimation is achieved by employing a statistical PLS model developed on alfalfa grass sample spectra.

1.1 LiDAR Basic Characteristics

LiDARs are instruments for remote sensing that exploits visible light to estimate distances [6, 7]. In the previous century, LiDARs were born for satellite ranging and tracking, and the main applications were related to the aerospace and military areas. For example, NASA used a LiDAR to map the moon's surface during the APOLLO 15 mission and exploited that technology in other missions. The capability of environmental sensing of LiDARs has been exploited in a multitude of areas ranging from Oceanography to Archaeology (3D mapping archaeological sites). For example, Fig. 1.2 shows a map of the coast of Lynnhaven Inlet, Virginia, captured through a LiDAR by the National Oceanic and Atmospheric Administration.

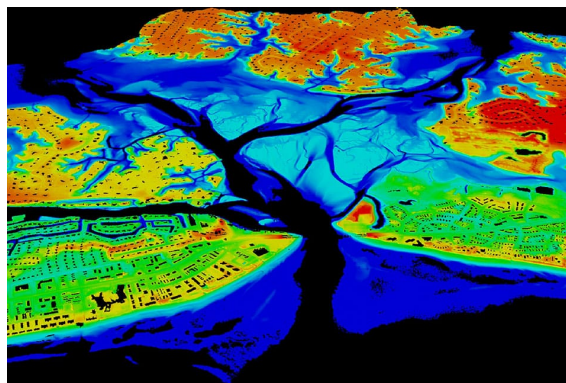


Figure 1.2: A LiDAR map of Lynnhaven Inlet, Virginia, property of National Oceanic and Atmospheric Administration [8]

These systems have been also used to probe pollution of the atmosphere. At the turn of the '900s and 2000s, the cost of production of LiDARs started to decrease, making such sensors more attractive for other markets like automotive. Agriculture has started to look at LiDARs for mapping agriculture fields, successively moving towards the autonomous control of drones and tractors. Autonomous driving for agriculture machines can bring many advantages, from the possibility of working on the field in a continuous way, even during the night, to performing certain operations more accurately, such as sowing. Fig. 1.3 shows the concept of an autonomous drive tractor produced by CNH Industrial.



Figure 1.3: A concept of autonomous tractor produced by CNH Industrial.

Nowadays, LiDARs exploit different technologies to estimate the distance of an object and 3D map an environment, from Phase Array to Flash LiDAR [1, 9]. Pulsed Time of Flight (ToF) LiDARs are the most used in automotive and autonomous driving applications [2]. Since only Pulsed Time of Flight (ToF) 3D Spinning LiDARs have been treated in this work, the following is a brief recall of the main working principles of such systems. The basic working principle of Pulsed ToF LiDARs, as described by Donati in [10] and represented in Fig. 1.4, is based on measuring the time a light pulse emitted by the instrument employs to travel towards a target and come back. The pulse travel at the speed c/n in the propagation medium, with c being the speed of the light in the vacuum and n the refractive index of the propagation medium. Since the pulse travels at the light speed c/n , it is possible to retrieve the distance of an object as:

$$d = \frac{t}{2} \cdot \frac{c}{n}. \quad (1.1)$$

The pulse is emitted from a light source, typically a laser with a wavelength ranging from 700 nm to 1100 nm. After the pulse is back-reflected by an object, it is collected by optics and read by a photodetector. The light source and the collector are placed both inside the instrument. To provide a 3D map, in 3D Spinning LiDARs, the light source and the detector rotate with a rotation period T_R . During the rotation, the LiDAR emits pulses and collects the respective echoes coming from the environment, giving as an output a Point Cloud (PC), thus a 3D approximation of the surrounding. Fig. 1.5(a) shows a schematic example of the operation of a spinning LiDAR, and Fig. 1.5(b) shows an example of Point Cloud acquired along a road.

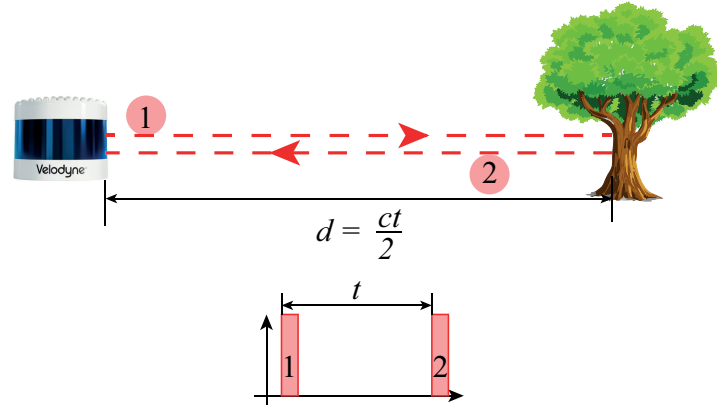
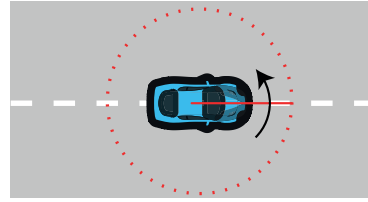


Figure 1.4: Schematically representation of the Time of Flight LiDAR working principle. The pulse emitted by the LiDAR (1) travels until it hits a target and is back reflected (2). The distance is estimated from the travel time t and knowing the speed of light in the propagation medium c/n .



(a) 3D Spinning Sampling



(b) Point Cloud

Figure 1.5: Schematically representation of the working principle of a 3D Spinning LiDAR. The source of the instrument rotates, emitting pulses along a circumference. By collecting the echoes is possible to reconstruct the environment as in Fig. 1.5(b)

3D LiDARs usually have been characterized by the following parameters:

1. The measurement range.
2. The resolution of Point Cloud point position.
3. The spot divergence.
4. The Point Cloud density.
5. Robustness to noise.

In the following a brief description about these metrics.

LiDAR Measurement Range

A significant parameter for a LiDAR is the measurement range, i.e. the minimum and the maximum distance the instrument can measure. The lower limits may

depend on two main factors related to optics and read electronics. In the case the instrument is designed with two separated optics, one for the source and one for the detector, depending on the optics' reciprocal distance, the measurement has a dead zone, as in Fig. 1.6. In fact, the field of view of the receiver and the field of illumination of the transmitter coincide only after a distance that depends on the optics and the reciprocal distance between the optical axes of the source and detector.

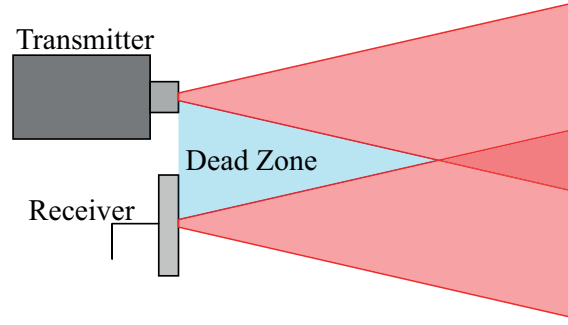


Figure 1.6: Schematic representation of the dead zone problem of LiDAR. Depending on the optics and the position of the transmitter and receiver, the field of view and illumination (the red areas) do not coincide for a distance shorter than a threshold, generating a dead zone (the light blue area).

Regarding the electronic, the minimum distance depends on the minimum measurable time T_{min} . In general, that parameter depends on how fast is the read-out electronics, and it imposes the minimum distance as:

$$L_{min} = \frac{c \cdot T_{min}}{2} \quad (1.2)$$

The range upper limit is theoretically given by the ambiguity problem, typically of laser telemeters. In pulsed ToF LiDAR, there is an ambiguity when the repetition time T_R is shorter than the time T the pulse employs to reach the target and travel back to the receiver. In the case $T_R < T$, the LiDAR sends a pulse in the same position before the first pulse has been detected. Fig. 1.7 schematically shown the NAR problem.

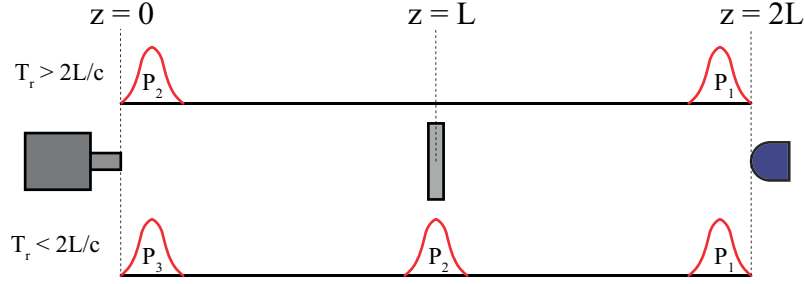


Figure 1.7: Schematic representation of the NAR problem. If the repetition period $T_r > 2L/c$, the pulse P2 is emitted only when the pulse P1 has been collected. In case $T_r < 2L/c$, P2 is emitted before P1 has been collected, generating an ambiguity in detection.

To avoid any errors due to this ambiguity, it is required to impose a condition on the maximum measurable distance. From the 1.1:

$$L_{max} \leq \frac{c \cdot T_r}{2}. \quad (1.3)$$

In automotive applications, the repetition rate f_r goes from some Hertz to tens of Hertz, and, as a result, L_{max} will be in the order of thousands of km, thus higher than what is required by the application. However, the receiver requires a minimum optical power to detect the echo $P_r \geq P_{min}$ and the received power P_r decreases with the square of the target distance L . Accordingly, the maximum distance L_{max} depends on P_{min} , as will be discussed in Section 2.5. Additionally, P_r depends on the optical properties of the target, in particular on its reflectance. Indeed, the LiDAR manufacturers define the maximum working distance concerning the reflectance of the target in percentage. Usually, commercial LiDARs for automotive purposes have a maximum working distance L_{max} ranging from tens of meters to hundred meters.

LiDAR Scanning Resolution

According to the basic working principle of a 3D spinning LiDAR, the instrument rotates at a specific frequency while the source emits pulses and the receiver collects the echoes. The mapping of the environment, thus, takes place sequentially by knowing the current steering direction and measuring the relative axial distance d . 3-D LiDARs only measure the range; the position of each point of the PC is estimated knowing, or supposing, the direction (elevation (ϕ) and azimuth (θ) angles) from which the reflection comes. The elevation angle is usually defined by the manufacturer by fixing the vertical directions of the laser sources. Differently, the azimuth can be measured, e.g. recording the motor position by an encoder, or assumed, e.g. knowing the firing frequency of the laser with respect to the revolution position of the laser source. In general, a commercial Spinning LiDAR samples the environment along fixed directions. Thus, the PC is represented in polar coordinates

with the origin, which is the LiDAR. Consequently, the PC of a ToF 3D spinning LiDAR is characterized by three different resolutions, one for each polar direction: i) axial distance resolution, ii) azimuth resolution $\Delta\theta$ (the horizontal angular distance between two points) and iii) elevation resolution $\Delta\phi$ (the vertical angular distance between two points). In Fig. 1.8 schematically shown the azimuth and elevation resolution. The azimuth and elevation resolutions give the angular resolution on the polar position of the points, differently the axial distance resolution is minimum variation in the axial distance measurement.

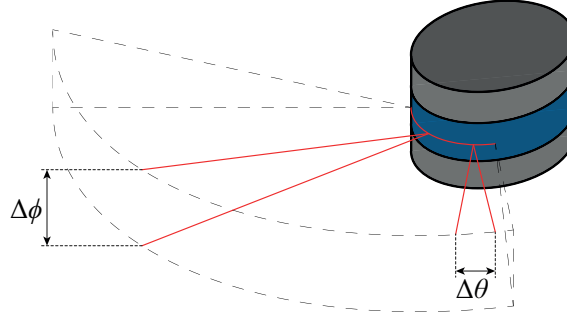


Figure 1.8: In this figure, the azimuth resolution θ_r and elevation resolution ϕ_r are represented. θ_r is the angular distance between two adjacent points on the same channel. ϕ_r is the angular distance between two points emitted at the same time but on two different elevation channels.

Beam Divergence

The divergence of the laser beam must be considered when choosing a LiDAR. As the distance L increases, the laser beam diverges, and consequently, the size of the laser spot on the surface of an object. Note that the optical power of a single pulse is spread over the entire spot, so the bigger the spot, the lower the optical power per area. Let's now consider an object smaller than the spot at a specific distance L ; the object may not be detected or confused with the background, depending on its optical properties. Hence, minimum detectable object size depends on spot divergence and spot size.

Concerning the spot, also the shape is a parameter that characterizes the LiDAR. Even though each beam is represented in the PC as a point, the single spot can be designed with different shapes, such as vertical lines and multiple dots. The choice of shape is usually about the manufacturer, and rarely, such information is fully provided in the datasheet. As an example, Fig. 1.9 shows the single spot of an MRS 1000 captured with a CCD camera [11]; in this case, the single spot is composed of three dots placed at the vertices of an equilateral triangle.

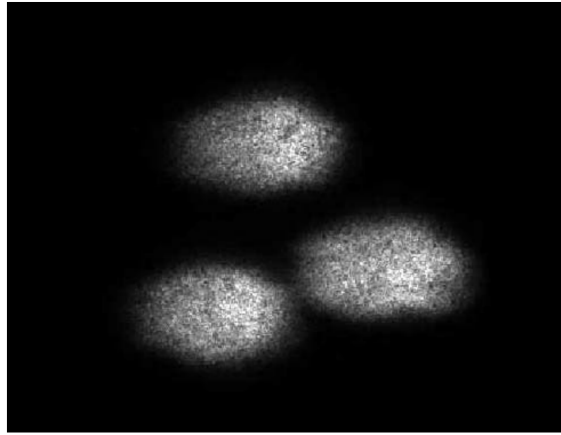


Figure 1.9: Example of an actual elementary spot of a commercial LiDAR — MRS 1000 by Sick. The single spot is composed by three dots placed on the vertices of a triangle.

Point Cloud Density

A LiDAR can be used not only for measuring the distance of a target but also for detecting objects. This application is a direct consequence of the environmental mapping capability. The higher the number of points in which the LiDAR samples an object, i.e. the Point Cloud density, the higher the detection capability. The PC density depends on three main factors: i) the angular resolution, ii) the spot size divergence, and iii) the computational power of the LiDAR. In fact, getting the beam closer and reducing the divergence through better optics design increases the density of the points. The demand for target detection is pushing LiDAR manufacturers to raise the azimuth resolution, i.e. the horizontal angular distance between two adjacent points of the Point Cloud (PC), as much as possible. The density of PCs has reached a high value, making possible a very accurate reconstruction of the environment and, therefore, the recognition of objects. Despite a higher azimuth resolution and better environmental sensing, increasing the PC density too much may result in unwanted effects that may degrade the performance. Hence, PC density is a parameter of considerable interest.

Robustness

Another important parameter that characterizes the performances of a LiDAR is the robustness to noise. There are different sources of noise that may affect the behaviour of an instrument, ranging from electronic noise to environmental noise. Regarding automotive and agriculture applications, the robustness against environmental light (sun, street light etc.), other infrared sources, unwanted echo reflections and adverse weather is fundamental. For example, to limit issues due to rain, the wavelength of the laser source is a wavelength with a minimum water light absorp-

tion. Manufacturers have found different solutions to increase the robustness of LiDARs. For example, certain instruments emit multiple beams for a single position, evaluating the travel time of multiple echoes to retrieve the object's distance. This operation is implemented selecting an "echo filter" mode, that select the echo from which estimate the target distance.

As previously introduced, nowadays, LiDARs have gained further relevance in many application areas resulting in a significant rise in available products. All these parameters compete to define the performances of such instruments; however, such information is not usually directly provided, and the actual behaviour of LiDARs in particular conditions is not always predictable. These factors raise the need for tools and methods capable of characterizing and comparing LiDARs performances, starting from the main parameters to more complex analyses. Characterization studies are fundamental in this sense to understand the limits of applicability of these instruments and provide benchmark tools that allow performing repeatable comparisons on commercial devices.

I started from these needs, studying possible measurement methods that allow the investigation of several critical parameters of commercial LiDARs. This work aims to design measurement setups and methods that enable an accurate and repeatable comparison between different instruments, exploring various parameters. In this work, I report the description and results of the following analysis:

1. Warm-Up/Stability.
2. Error in the estimation of distance of extended target.
3. Axial Error
4. Robustness to Target Reflectance.
5. Transversal Errors and Detection Probability

This work starts from the study of possible errors in the estimation of the axial distance to arrive at the study of transversal errors (on x and y axes) that can therefore affect detection recognition.

These analyses regard the characterization of the static characteristics of the LiDARs. Successively, the behaviour in real world is explored, analysing the performances of these systems in adverse weather conditions. In particular the robustness of the distance measurement in fog is investigated.

For each analysis, a scalable setup and measurement procedure were designed and experimentally tested using commercial LiDARs. In the specific, in this work, three LiDARs have been characterized: a VLP 16 by Velodyne, an MRS 1000 and an

MRS 6000 by Sick. These instruments are all ToF 3D spinning LiDARs with similar characteristics that will be better described in successive sections.

1.2 Near Infrared Spectroscopy for Precision Agriculture

The agricultural industry is constantly looking for new technologies that can allow an enhancement of the production process and the final product itself. As introduced in Section 1.1, on one side, autonomous driving agriculture machines can considerably improve the efficiency of various processes such as sowing and harvesting. However, to reach complete automation, autonomous driving must be supported by other technologies, such as systems for crop monitoring that can be mounted directly on agriculture vehicles. In precision agriculture, to assess the quality of products, it is fundamental to investigate their physical properties [12, 13, 14]. Conventional techniques are often destructive and can not be performed directly on the field, requiring specific laboratories. Differently, optical techniques are usually non-destructive, contactless, and fast and allow the investigation of various physical properties, such as the sugar content of fruits, the protein content of grain or the moisture level of the crops, which is the focus of my work, mainly considering alfalfa.



Figure 1.10: Bale of alfalfa grass. Before the bale can be sold, it must be dried, until it reaches the optimal water content.

The quality and, obviously, the cost of a hay bale are strictly linked to the moisture content (MC); the perfect moisture level is about 10-15 %. The crop sample is heterogeneously composed of stems, leaves, and air interstices. Therefore, the information of interest is the total moisture which includes the water content in the solid part of the sample and the humidity deposited on it. The traditional technique for evaluating the moisture content of a bale of hay is destructive and slow. In fact, it is necessary to collect a alfalfa sample from the bale, weigh that sample, dry it

and weigh it again to measure the water content that has been dried [15].

As previously introduced, optical techniques can study the water content avoiding the destruction of a sample directly in the field. Among other techniques, Near-Infrared Spectroscopy (NIRS) is considered very promising [16, 17]. In particular, the MC can be investigated by exploiting the absorption peaks present in the near-infrared region [18]. Moreover, density is another crucial parameter that influences the quality and especially the cost of a bale, and that can be estimated by exploiting the NIRS technique.

Spectroscopy is the study of the interaction between matter and electromagnetic radiation. A spectrometer is thus a instrument that allow to investigate the composition, structure, and properties of a material by analyzing the way it absorbs, emits, or scatters light. A general NIR spectrometer is usually composed these elements:

- The light source. The source can be a lamp or a laser emitting light with a specific spectrum — in the NIRS case, the source must emit light in the NIR range.
- The Monochromator. This device is able to separate the light into its individual wavelength components. Thus, it is possible to analyse the sample response to a single wavelength at a time.
- The Detector. A detector is required to collect the transmitted/reflected light by the sample and convert it into an electric signal.
- The Data Processing system. To obtain the spectrum of a sample, an element able to process the collected signal is required.
- Optics. A spectrometer usually presents some optical elements improving the performance of the spectrometer, such as a filter or focusing lenses.

There are various types of spectrometers, depending on the working principle. For example, the three classic types of spectrometers are:

- Transmittance Spectrometer: the sample is interposed between the light source and the detector. The spectrometer measures the transmittance, i.e. the ratio between the light passing through the sample and the light incident on the sample.
- Reflectance Spectrometer: the source and the detector are both on the same side of the sample. The instrument calculate the reflectance, thus the ratio between the light incident on the sample and the back-scattered light.

- Absorbance Spectrometer: the instrument estimates the light absorbed by the sample. The absorbance can be estimated through the transmittance by computing the logarithm of the ratio between the light passing through the sample and the light incident on the sample. Nevertheless, to obtain a more accurate estimate, the reflected component must be also considered. To collect both the reflected and transmitted components, it is possible to insert the sample in an integrating sphere using a fiber spectrometer.

The schematic representation of these three different spectrometers is shown in Fig. 1.11

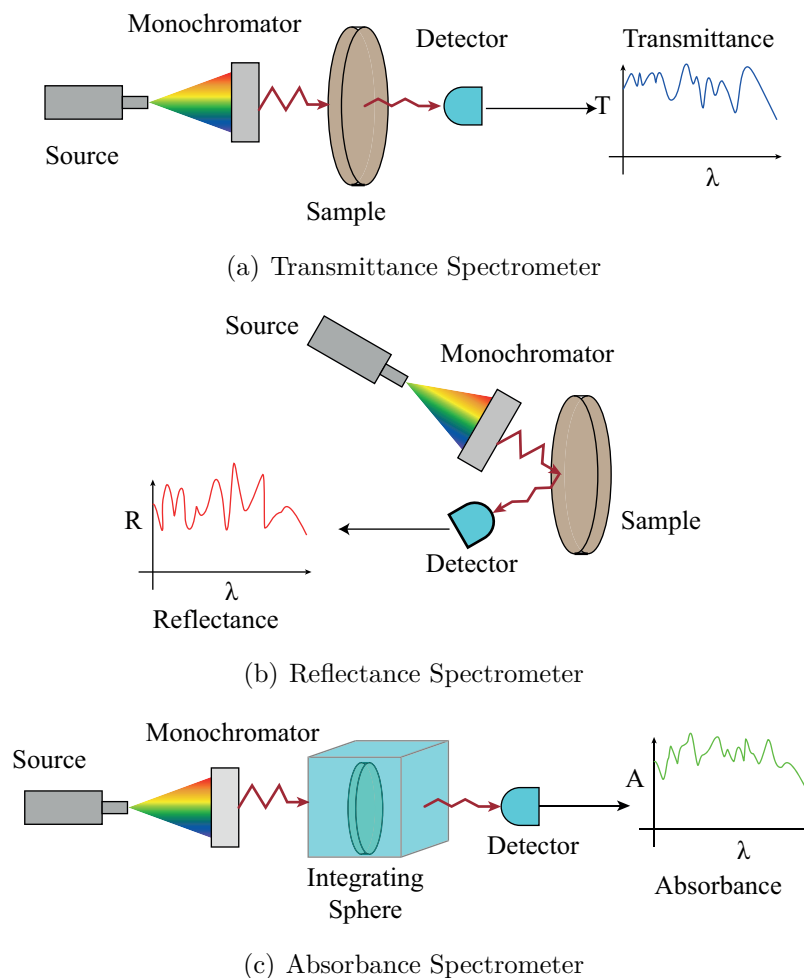


Figure 1.11: Schematic representation of typical spectrometers. The source emits light at different wavelengths that hit the sample. A detector measures the light intensity after the target for each wavelength producing the sample spectrum. The spectrometer can work in transmission measuring the transmittance T (top figure), in reflection measuring the reflectance R (middle figure) or measuring absorbance A (bottom figure). In the bottom figure, an integrating sphere allow to collect all the light that is not absorbed by the sample.

NIR spectral region typically includes wavelengths from 780 nm to 2500 nm.

The NIRS approach brings several advantages to the analysis of sample chemical and physical composition, that can be exploited for analysis directly on the field. First of all, thanks to its high penetration depth in biological tissues, NIRS can be used to provide information on organic samples [19, 20]. This characteristic makes NIRS widely spread in biomedical applications, in which, for example, this technique is used to search for particular molecules, such as glucose or oxygen, in the blood. Also, the agrifood sector has started to be interested in such technology, and, as already introduced, NIRS technology is of great interest for the study of crop MC. In fact, NIRS is particularly useful for in situ sample analysis, as it does not require sample preparation, such as shredding or solubilization, and can be used directly on the field. Moreover, NIRS can analyze a wide range of compounds, including carbohydrates, proteins, fats, minerals and chemical compounds. Indeed, the NIR spectrum includes absorption bands associated with overtones and combinations of fundamental vibrations of functional groups like -CH, -NH, -OH, and -SH. This property makes it useful for analyzing organic substances, such as cereals, fodder, food, feed, dairy products, meat and human tissues. In addition, it can be used for the analysis of environmental samples such as soils, water and sediment; thus, NIRS is very suited to evaluate the water content of crop [21]. In general, the NIRS approach for organic samples analysis directly in the field is fast, economical and non-destructive, making it very interesting for the agri-food sector. In Section 5.1, a more comprehensive analysis of such approach will be reported.

Unfortunately, the relationship between the NIRS spectrum of crop and moisture can be affected by several quantities, whose most important are density and the variability of crop depending on the harvesting point. Density is not only a parameter which affect the MC estimation, but its variability strongly affects the cost of the bale and must be controlled. Also, the variability of the sample affects the NIRS spectrum; different harvesting points offer crops with different characteristics, e.g., in terms of leaf-to-stem ratio, due to different soil compositions or sun exposures. This variability translates into spectrum variability. To face these critical aspects, a model for the MC and density estimation must be defined starting from numerous samples and tests and a statistical model.

Our work focused on the collection of crop spectra and the design of a statistical model able to correlate the collected spectra with the MC, and that can be implemented on an instrument that works directly on the machine. The choice of the model falls on a Partial Least Square (PLS) regressor. Multivariate statistics is considered a suitable tool for spectrum analysis [22, 23, 24], and among the numerous techniques, PLS regression represents a promising approach to analysing the acquired NIR spectra. As better described in Chapter 5, this technique can be used

to find the best correlation between two matrices, even if the regressor predictor matrices are noisy.

I decided to merge the NIR spectroscopy and the PLS regression to design a statistical model for the moisture and the estimation of crop density. In this work, the data pre-treatment and the model will be described and evaluated with experimental data acquired on grass samples.

Chapter 2

LiDAR Static Characteristics

In this chapter, the characterizations performed on commercial LiDARs will be described, starting from the market's needs and of the requests of LiDAR users, which push researchers to study certain aspects of LiDAR behaviour. Before focusing on the measurement methods and the analysis carried out on commercial LiDARs, it is significant to point out the importance of characterization.

As noted in Chapter 1, in the last decades, a multitude of new LiDARs, different in optical designs, measurement principles, and technologies, has been launched on the market. The increasing interest in LiDARs brought to several studies proposing new design techniques [25, 26, 27, 28, 29, 30]. Manufacturers usually provide basic information about LiDARs, often limited to those described in Section 1.1, and, thus, it is not trivial a comparison between such instruments. In addition, for parameters such as axial error or spot divergence, the measurement procedure and the conditions under which these parameters are extrapolated are not usually specified. Characterization processes play a relevant role in this respect, proposing measurement procedures that can allow the comparison between different systems under the same conditions. These analyses allow an end user to choose the best instrument for a specific application. In last years, to fulfill the need for assessing and benchmarking the various new sensors, International Standard have been proposed [31, 32] and many scientific articles have been published [1, 2, 9, 33, 34, 35, 36, 37, 38].

There are many conditions and phenomena that may affect the performances of commercial LiDARs that are not usually treated in instruments' manuals and datasheets. For example, according to [36], there are several sources of offsets, eccentricities and tilts that may produce errors in the measured coordinates; it is, therefore, significant to investigate such errors. The size, shape and optical properties of a target may also affect the performances of LiDARs, and it is essential to propose characterization methods to point out the influences these properties may have on environmental sensing. In conclusion, the reduction of costs of LiDAR has opened the doors of this

technology to other applications, such as object recognition. LiDARs applicability to this topic is very interesting, however it is important to study the limits of the applicability of such instruments and the possible issues that may affect the object recognition.

The following chapter describes the measurement methods and setup designed to characterize LiDARs. Successively, in Chapter 3, I present the results of the tests we performed to evaluate the proposed methods and investigate popular commercial LiDARs – a VLP 16 by Velodyne, an MRS 1000, and an MRS 6000 by Sick. For each analysis, the following points will be described:

1. The motivation pushing for such analysis.
2. The theoretical background on which the measurement is based.
3. The measurement setup design for the characterization.
4. The measurement method.

2.1 Warm-up and Stability

The first characterization that must be performed on any instrument is the warm-up and stability analysis. Warm-up time can be defined as the amount of time it takes for the sensor to attain its highest accuracy or performance level once it is turned on or similarly the time the instrument takes to measure something with a certain accuracy with a certain probability. Stability refers the ability of a measurement system produces the same values over time while measuring the same sample, thus maintain the same metrological properties over the time. The importance of such analysis is two-folded. Warm-up and stability are significant parameters for LiDARs application areas, and clearly also for automotive. It is crucial to understand the warm-up time and the maximum error performed by the LiDAR until the instrument is ready to correctly operate. At the same time, the stability in the measurement must be investigated, mainly considering long-period operations. Both analysis are obviously crucial for the safety in civil autonomous driving. In addition, these analyses are of great importance also because all the other characterizations are based on warm-up time and stability parameters. Other types of characterization may take a long time to execute, and thus, the warm-up and stability must be investigated first to ensure that the instrument under test (IUT) is stably mounted, that there is minimal thermal and mechanical drift, and that the IUT is regularly working. These tests were designed to retrieve information crucial for all the other characterizations and to ensure the validity of the analysis that will be presented in successive sections.

2.1.1 Measurement Setup

The warm-up and stability analysis has been achieved by exploiting a particular setup designed and realized in our laboratory as described in [39, 40]. The setup must be scalable and easy to mount to make it suitable for different characterizations with few modifications. Actually, this setup is the basis for the setups used for the other characterizations will be discussed in the following sections. The core of the setup is a rail system realized with aluminium extrusion profiles. The track is a 21 m long monorail at one side of which is placed the IUT. The IUT is mounted on a multi-axis stage, allowing the correct alignment of the IUT with a target placed on a sliding carriage that can move along the track. The rail is fixed to the ground through H-shape adjustable supports, which allows setting the track parallel to the optical axis of the IUT, even if the floor is not perfectly even. As a target, it is possible to use several objects varying in size, shape and optical properties, depending on the requirements of the analysis. For the warm-up and stability analysis, the target must be larger enough to be hit by at least a beam of the IUT, considering the beam divergence and the maximum measurement distance. For this analysis, a 24" $\times$ 24" hardboard (model TB4 by Thorlabs) whose spectral reflectance at the common commercial LiDARs wavelength (850 nm - 950 nm) is about 70 %, as shown in Fig. 2.1.

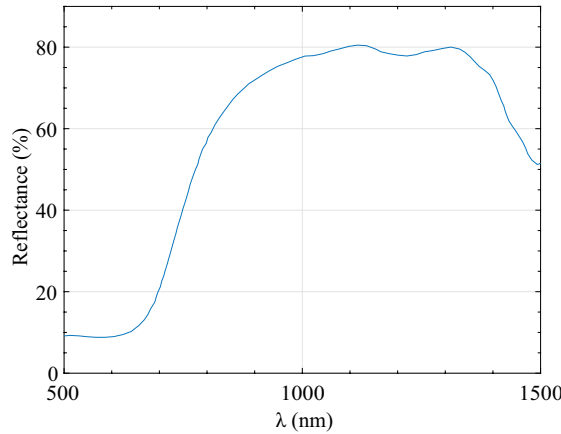


Figure 2.1: Spectral reflectance of the target (model TB4 by Thorlabs) declared by the manufacturer.

The target size is larger enough to ensure at least one full beam can hit the target at L_{MAX} , considering the divergence of commercial LiDARs. To avoid environmental influences, the setup is placed in a room with controlled light and temperature. Fig. 2.2 shows a schematic representation of the setup used for this characterization.

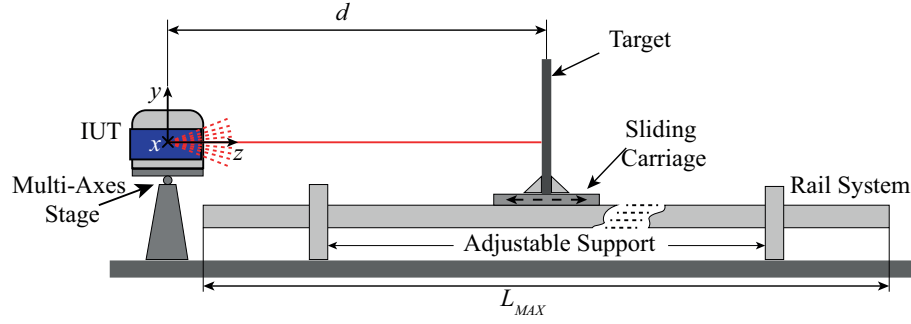


Figure 2.2: On the left of the figure, the IUT is mounted on a multi-axes support that allows alignment with the track and the target. The rail system is long $L_{MAX} = 21$ m. The target can move along the track through a sliding carriage that can be translated by modifying the measurement distance d . The adjustable supports and the Multi-Axes Stage allow a correct alignment depending on the analysis of interest.

2.1.2 Measurement Procedure

The warm-up and stability have been investigated following the measurement and analysis procedure described in this section. The LiDAR was kept off for at least twelve hours before starting the measurement to avoid influences due to past operations. The measurement procedure, thus, consists of placing a target in front of the IUT at a known distance d and acquiring Point Clouds of that target for a time T at a frequency of f_c . Therefore, after having predisposed the setup, fixing the target, and aligning it with the IUT, the LiDAR was turned on, starting the acquisition of $N_{TOT} = T \cdot f_a$ PCs. After the measurement, each PC was manually segmented to keep only the points falling on the target, extracting a set of points $P(t)$, where t is the acquisition time. The cardinality N_t of the set $P(t)$ depends on the angular resolution of the LiDAR, i.e. on the PC density, so it is a variable quantity. Note, that each point of the PC is a four-dimensional array containing the Cartesian coordinates (x, y, z) of the point and the intensity I , of the detected signal. To analyse the estimated target distance d , for each time instant, the mean and the standard deviation of the mean of the distance z and of the intensity I were

computed over the points of the set $P(t)$:

$$\begin{aligned}
 \bar{z}(t) &= \frac{1}{N_t} \cdot \sum_{i=1}^{N_t} z_i(t) \\
 \bar{I}(t) &= \frac{1}{N_t} \cdot \sum_{i=1}^{N_t} I_i(t) \\
 s_{\bar{z}}(t) &= \sqrt{\frac{1}{N_t(N_t - 1)} \sum_{i=1}^{N_t} [z_i(t) - \bar{z}(t)]^2} \\
 s_{\bar{I}}(t) &= \sqrt{\frac{1}{N_t(N_t - 1)} \sum_{i=1}^{N_t} [I_i(t) - \bar{I}(t)]^2},
 \end{aligned} \tag{2.1}$$

where N_t is the cardinality of $P(t)$, $z(i)$ is the axial distance of a single point of the set $P(t)$, and $I(t)$ is the detected intensity of a single point of the set $P(t)$. It is possible to investigate the warm-up by analysing the time the mean measured parameter employs to stay in a specific tolerance interval TI . This interval is defined by upper (T_U) and lower (T_L) tolerance limits. However, if the standard deviation is not negligible concerning the mean, TI can not be applied. Hence, it is possible to estimate the warm-up time upper limit time applying a rule similar to the “guarded acceptance” rule used in conformity assessment according to JCGM 106:2012 [41]. Two guard bands centered in T_U and T_L were defined. The bands have an amplitude that is two times the standard deviation of the mean $s(t)$ of the parameter of interest $-2 \cdot s_{\bar{z}(t)}$ for the estimated distance. With the introduction of these bands, it is possible to estimate a warm-up upper limit t_{warm-U} as the time the mean measured value employs to stay within the upper tolerance interval $UTI = [T_L + s(t), T_U - s(t)]$, obtained reducing TI of $2 \cdot s(t)$. Similarly, the lower limit of the warm-up time t_{warm-L} is defined following a decision rule similar to “guarded rejection” rule as defined in JCGM 106:2012. t_{warm-L} evaluated as the time the mean measured value takes to stay into the lower tolerance limit $LTI = [T_L - s(t), T_U + s(t)]$. Fig. 2.3 represents the decision rules applied to investigate the warm-up time, showing the intervals TI , UTI , and LTI .

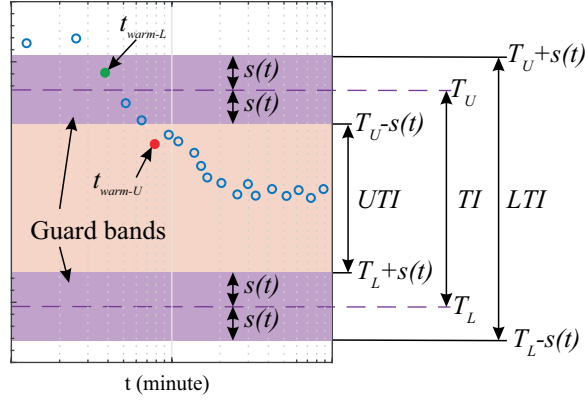


Figure 2.3: Decision rules employed in the analysis of warm-up time interval. TI is the tolerance interval, defined by the tolerance limits T_U and T_L , highlighted by the dashed line (---). The guard bands (violet regions), with an amplitude of $2 \cdot s(t)$, are centred in the tolerance limits. The t_{warm-L} (●) is the time the measured value takes to stay within the interval LTI. Similarly, t_{warm-U} (●) is the time the measured value takes to stay within the interval UTI.

After determining the warm-up time, it is possible to quantify the stability. Considering t_{warm-U} , it is possible to assume that the warm-up ends after firsts, respectively, n_{w-z} or n_{w-I} of n_{TOT} acquisitions. Thus, the stability can be investigated in terms of experimental standard deviation of the mean calculated after the warm-up time.

$$\begin{aligned}
 s_{\bar{z}steady} &= \sqrt{\frac{1}{n_{TOT} - n_{w-z} - 1} \sum_{i=n_{w-z}}^{n_{TOT}} [\bar{z}(i) - \bar{z}_{steady}]^2} \\
 s_{\bar{I}steady} &= \sqrt{\frac{1}{n_{TOT} - n_{w-I} - 1} \sum_{i=n_{w-I}}^{n_{TOT}} [\bar{I}(i) - \bar{I}_{steady}]^2},
 \end{aligned} \tag{2.2}$$

where $\bar{z}_{steady}$ and $\bar{I}_{steady}$ are the mean value of the estimated distance and intensity computed after the $n - w$ samples.

$$\begin{aligned}
 \bar{z}_{steady} &= \frac{1}{n_{TOT} - n_{w-z}} \sum_{i=n_{w-z}}^{n_{TOT}} \bar{z}(i) \\
 \bar{I}_{steady} &= \frac{1}{n_{TOT} - n_{w-I}} \sum_{i=n_{w-I}}^{n_{TOT}} \bar{I}(i).
 \end{aligned} \tag{2.3}$$

2.2 Error in Distance Estimation

LiDARs rely their environmental sensing ability on their accuracy in estimating distances. Therefore, it is very significant to investigate the error in distance estimation and even more important to allow a customer to compare the performance of LiDARs in this regard. Error in distance estimation depends on the design parameters of the instrument, such as the photosensitive elements, the read-out electronics, the discriminator and the processing algorithm. Distance estimation is also affected by issues external to LiDAR. Optical properties of the target and environmental weather may severely affect the ranging ability of the LiDAR. These effects will be discussed in next sections, while in the following I pose the focus on the error due to the LiDAR itself. Thus, the aim is design a setup and a procedure that allow to compare the error in distance estimation in the same optimal conditions — good visibility, high reflectance target, static measurement. To quantify the error, it is necessary to compare the estimated distance of the LiDAR with a reference instrument. This instrument must provide highly accurate measurements, which can be assumed as the actual values of distance. Thus, I compare the estimate provided by the IUT with the measurement provided by an absolute interferometer (model HP5527A by HP).

2.2.1 Measurement Setup

The analysis of the error has been achieved comparing the estimate of the IUT with the reference distance measured with an interferometer. This characterization setup and procedure is presented in [39, 40]. This instrument, exploiting an interferometric signal, allows to detect of relative movements with a resolution down to nanometers [42], thus can be used as reference. The interferometer used for this test is a HP5527A by HP, that is a single-axis linear interferometer with a nominal fundamental optical resolution 316.5 nm [43]. The distance error characterization is performed on the setup shown in Fig. 2.4. This setup is an evolution of the one presented in Section 2.1.1 and used for the characterization of the warm-up and stability. The basis is the same aluminium rail system with a sliding carriage allowing the movement of a target, varying the distance d between target and the IUT. For this characterization, the interferometer (INT) is placed on the same side of the IUT, and a corner cube (model M-BBR 1-II by Newport) is fixed on the sliding carriage at a distance d_{INT} , measured by the INT. The target must be large enough to be hit at least by a beam at the maximum measurement distance. Specifically, for this analysis, the same target used for warm-up is adopted, i.e. the 24" $\times$ 24" hardboard (model TB4 by Thorlabs). The interferometer can only measure relative distances

with respect to the initial interferometric signal, and thus it is crucial to correctly align the INT and the corner cube to avoid missing the interferometric signal during the measurement. Since the IUT and the INT are two separate and independent instruments, each minimum misalignment between them and the target will result in a difference in the measured distances. To correctly align the setup, it is required to act on the multi-axes stage, where the IUT is fixed. The z -axis of the IUT must be set parallel to the track, to the z -axis of the INT, and perpendicular to the target plane. The complete alignment procedure is described in Appendix A.

In Fig. 2.4, it is possible to note that there is an offset between the distance d_{INT} — INT to corner cube — and d — IUT to target —. This offset is due to two sources: i) the known difference between the plane of the target and the corner cube (d'_{offset}) and ii) the unknown distance between the origin of the axis of IUT and INT (d''_{offset}). Thus, even excluding the known distance target-corner cube and although the setup is correctly aligned, there may be a potential offset between the LiDAR estimate of d and the reference d_{INT} . Therefore, the total d_{offset} must be investigated to compensate for it. In the following section, the offset compensation technique will be described.

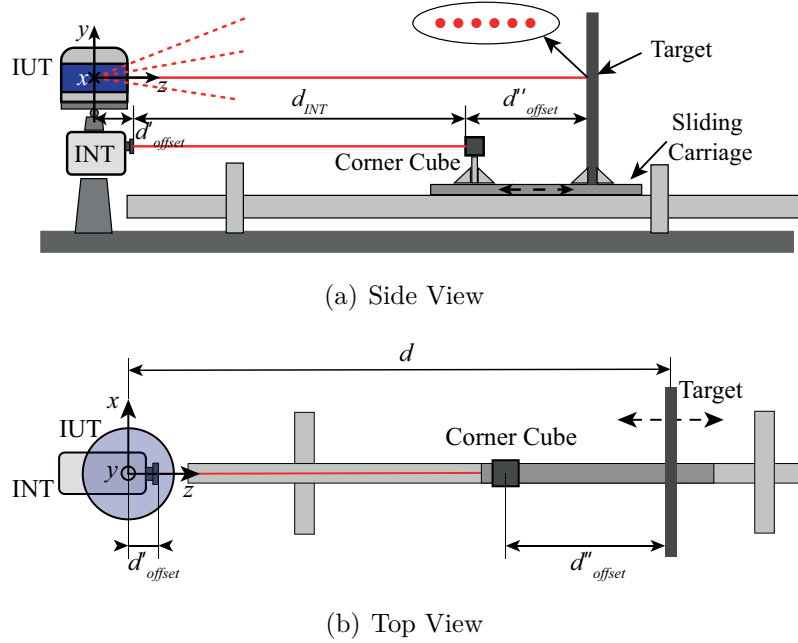


Figure 2.4: Schematic representation of the side and top view of the setup used for the characterization of the error of the IUT respect to an interferometer. Moving the carriage along the rail, it is possible to modify the IUT to target distance, d . The corner-cube fixed to the carriage is used by the interferometer INT to measure distance d_{INT} . The origin of the Cartesian system, x, y, z coincides with the IUT origin. Acting on the multi-axis stage, the IUT is aligned to the rail so that the z -axis is parallel to it. d'_{offset} is the difference between the plane of the target and the corner cube, while d''_{offset} is the distance between the origins of the interferometer and the IUT along the z -axis.

A photo of the actual setup used is shown in Fig. 2.5.

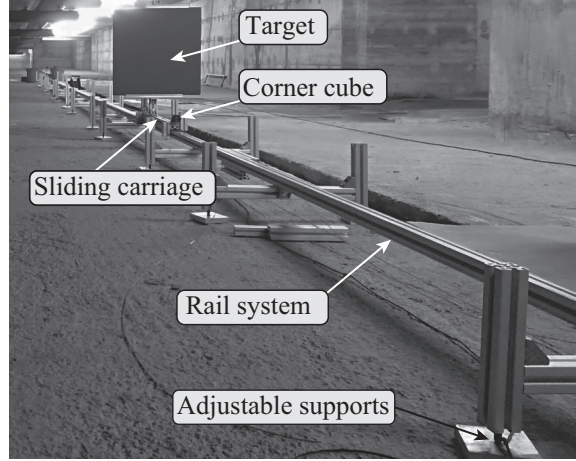


Figure 2.5: Photo of the realized setup. In the photo are recognizable all the main element of the rail-system.

2.2.2 Measurement Procedure

The analysis of the error in distance estimation is performed following the measurement and analysis procedure described in this section, using the setup in Fig. 2.4. The IUT, INT, rail and target were aligned as described in Appendix A, placing the target at a distance d from the IUT. After waiting for the warm-up time t_{warm-U} , estimated as in Section 2.1, the measurement started. The characterization is performed by varying the distance d between the IUT and the target moving the sliding carriage along the rail system. For each distance d , I have acquired a PC of the IUT and the measured distance $d_{INT}(d)$ by the INT. At the end of the measurements, as for the warm-up analysis, the PC points falling on the target were manually segmented. Thus, the set of points $P(d)$ was extracted for each target distance. Assuming $z_i(d)$ the distance along the z -axis associated with each point of the set $P(d)$ for a single measurement distance, I computed the mean value of $z_i(d)$ and its standard deviation, for each distance:

$$\begin{aligned}\bar{z}(d) &= \frac{1}{N_d} \sum_{i=1}^{N_d} z_i(d) \\ s_{\bar{z}(d)} &= \sqrt{\frac{1}{N_d(N_d-1)} \sum_{i=1}^{N_d} [z_i(d) - \bar{z}(d)]^2},\end{aligned}\tag{2.4}$$

where N_d is the number of points composing each $P(d)$. Note that, as previously introduced, as the distance d increases, the number of points on the target decreases. N_d must be chosen considering the number of points falling on the target at the maximum measurement distance. Hence, to observe the same angular field of view

of the IUT, the same N_d points (same angular coordinates) have been analysed for each target distance d .

As shown in the previous section, there is a fixed and unknown offset between the IUT and the INT origins. To correctly investigate the error of the IUT with respect to the INT, this d_{offset} must be quantified. Hence, d_{offset} was estimated as the intercept of the linear interpolation between $\bar{z}(d)$ and $d_{INT}(d)$. Then, for each target position d , was computed as:

$$Error(d) = d_{INT}(d) + d_{offset} - \bar{z}(d) . \quad (2.5)$$

Estimating d_{offset} from the linear interpolation between $\bar{z}(d)$ and $d_{INT}(d)$, the measurement is compensated for any constant offset error affecting the IUT. Thus, eq. (2.5) represents the “best case” error.

2.3 Axial Error and Environment Approximations

In Chapter 1 sharp increase in LiDAR performances and importance has been highlighted. On one side, the LiDARs hardware has been improved, majorly reducing the cost of such instruments. Moreover, rendering software and point cloud post-processing algorithms have also been enhanced. Although LiDARs are distinguished by good accuracy in distance estimation, the approximate nature of the 3D LiDAR measurement principle must be considered. Nonetheless, as described in more detail in the next section, pulsed 3-D LiDARs — the leading technology in automotive [2] — map the environment by sampling it on concentric spheres, which differ in their radii by Δr , the axial distance quantum. This sampling of the surrounding, thus, translates in approximation and deformation on a fixed set of spheres. For example, flat surfaces are bent on spherical domes whose radii differ by Δr . Given that, depending on the commercial system, Δr may be in the order of centimetres or millimetres. The value of the space quanta may thus significantly affect the distance estimation introducing deformation that alters the actual shape of an object. This issue is mainly present in applications such as object detection. This section aims to describe the characterization analysis designed to point out the approximation intrinsic to 3D LiDARs and, thus, the limits of these systems. Specifically, the focus is posed on axial distance measurement and, thus, on one of the main sources of uncertainty in ToF distance estimation. The presented analysis differs from other studies [38, 44, 45] on axial distance error because it proposes a thorough procedure to estimate this error by analyzing the effect of quantization respect to other error sources. This work was presented in [46]. The characterization of axial error due to quantization was performed by analyzing the distribution of the points of a Point Cloud in the different concentric spheres. In the following, the theoretical background related to the approximation due to LiDAR nature is described before describing the measurement procedure adopted for this analysis.

2.3.1 Theoretical Background: Approximation intrinsic to 3D LiDAR

As introduced in Section 1.1, LiDARs are able to estimate the axial distance of a target. The 3D mapping of the environment is achieved through two techniques: scanning and flash. In this work, only the scanning technology is treated, but also flash LiDAR suffers from approximation issues. In both cases, the instrument is only able to measure the axial distance of a target, while the position is estimated by knowing, or supposing, the direction (azimuth and elevation angle) from which the back-reflected echo comes. The receiving optics can be assumed as point-like, since

its size is negligible than the surrounding. Hence, both scanning and flash LiDARs analyze the surrounding space by “sampling” it on concentric spheres, which point density depends on the azimuth and elevation resolution Section 1.1. Note that all 3D LiDARs approximate the surrounding in concentric spheres, As previously introduced, these concentric spheres radii differs by a Δr , which depends on the axial distance resolution. Fig. 2.6 shows a schematic representation of the environmental sampling of a 3D LiDAR.

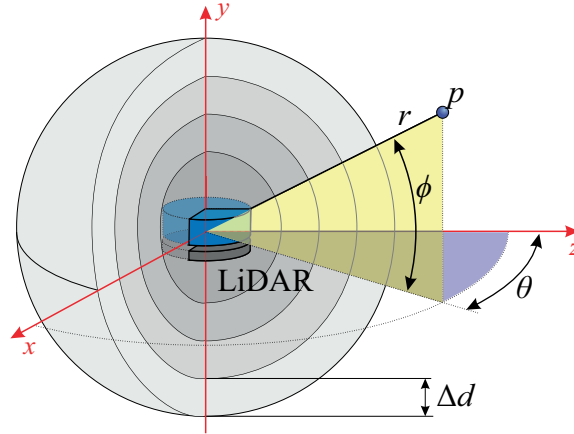


Figure 2.6: Schematic representation of the environmental sampling of a 3D LiDAR. The figure shows the concentric sphere approximation of the environment. A generic point p is represented by its polar coordinate radius r , azimuth θ and elevation ϕ . (θ, ϕ) are pre-determined and usually fixed by knowing the direction of the collected echo. The creation of the point cloud is achieved by converting the original polar coordinates into Cartesian coordinates (x, y, z) .

The axial distance resolution, and as a consequence Δr , depends on the technology adopted for the LiDAR. As previously described and shown in Fig. 1.4, ToF Pulsed LiDARs measure the travel time of a pulse that hits a target and comes back to the instrument to estimate the target distance. Therefore, the quantization in the distance is a consequence of the quantization in time:

$$\Delta r = \frac{c}{n} \cdot \frac{\delta t}{2}, \quad (2.6)$$

where δt is the time quantum. The quantization, and the axial resolution, are thus mainly due to the least significant bit (LSB) of the time to digital converter (TDC), i.e. the electronics at the receiver measuring the travel time [10, 47, 48].

As shown in Fig. 2.6, a single point p can be represented in polar coordinates as $p = (r, \theta, \phi)$. Moreover, Section 1.1 introduced the definition of azimuth resolution, $\Delta \theta$, and elevation resolution $\Delta \phi$ of a 3D Spinning LiDAR. These angular resolutions are the angular distances between adjacent points and, thus, the angular quanta. In 3D Spinning LiDARs, the elevation quantum is fixed and usually depends on the inclination of the laser that generated the pulse. Also, the azimuth quantum is

generally fixed or assumed fixed, and depends on the firing frequency of the laser source. Therefore, the azimuth angle is generally estimated by exploiting an encoder in closed-loop feedback control. Thus, the environmental mapping takes place on a finite and often fixed set of angular directions. Therefore, it is possible to say that all the polar coordinates of the single point p are quantized and can assume only a finite set of allowed values. It is significant to underline that all 3D LiDARs, not only ToF Spinning, introduce quantization of the Point Cloud, even though the angular and axial resolution depends on other factors. For example, Flash LiDAR does not emit beams but a single flash and acquires the echoes through a matrix of photodetectors. Hence, for Flash LiDAR, the angular quantization comes from the line of sight of each photodetector in the matrix. Consider a single elevation represented by the coordinates ϕ_i . On that channel, the point along the beam propagation direction can assume values that belong to concentric circumferences whose radii differ by Δr . Each circumference constitutes a bin B in which the environment is quantized. Moreover, on this circumference, the points on the azimuth plane can assume only fixed values which are equally spaced by $\Delta\theta$. Fig. 2.7 shows the quantization of PC points on azimuth plane and on the propagation direction for a single elevation channel (CH) ϕ_i .

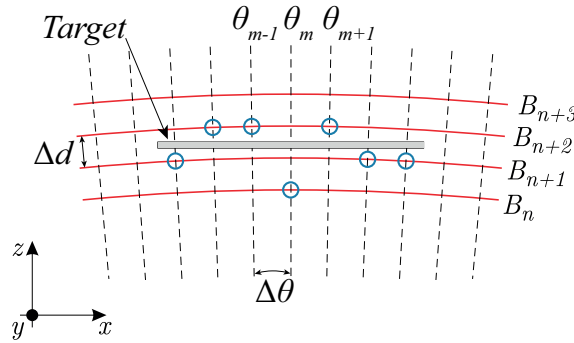


Figure 2.7: Schematic representation of how a single CH ϕ_i of a pulsed LiDAR scans its surroundings. The “almost vertical” dashed lines (---) represent the beams of the pulses sequentially emitted by the LiDAR (scanning mode) or the lines of sight of the receivers composing a single channel (flash mode). The “horizontal” sections of circumferences (—) represent the quantization in the distance estimate. Each of such semicircles constitutes a bin, for example, B_n , and its radius differs by Δr from the adjacent semicircles. The circles (○) represent the result of the sampling of the target by the LiDAR channel. Due to quantization and measurement errors, the samples (○) are distributed over several bins.

Note that although the quantization in the angles is clear and generally explicitly declared by the manufacturer, that relating to the axial measurement is normally not.

2.3.2 Measurement Procedure and Setup

The analysis of the axial error was performed by exploiting the same setup presented in Fig. 2.4, thus using the sliding carriage to change the IUT-target distance d and verify that distance through the interferometer. Note also that the proposed setup can be applied to different characterizations, showing flexibility being adaptable for various analyses. This is a very important point of the work, as the goal is to provide scalable and simple benchmarking tools. Also, for this analysis, the offset distance d_{offset} between the IUT-target distance and the INT-corner cube distance is considered. The target is, thus, the 24" $\times$ 24" hardboard model TB4, by Thorlabs. The procedure involves the analysis of the PC at different target distances d . In contrast to the previous characterization, for axial error analysis, the distance d must be modified both in fine steps — shorter than the axial quantum Δr — and in large steps able to highlight the various contributions of uncertainty. The proposed method thus involves acquiring and analyzing multiple PCs for each target position. Then, statistical analysis of how the points are distributed among the various bins is performed. In the following, the proposed procedure is described in detail.

After aligning the IUT, the INT and the target and waiting for the warm-up time, the target was placed at the first distance d . As described in the following, this characterization involves the analysis of a single point of the PC. Thus, the warm-up must be investigated differently than in Section 2.1. The single point warm-up analysis will be described at the end of this section. When the target wasn't fixed at its first distance d , the analysis can start, and n_{PC} PCs and d_{INT} were acquired. To study more than one echo filter mode of the IUT, n_{PC} PCs must be acquired for each mode, to provide the same acquisition conditions. Then, the target was translated by a "fine" step d_{step} that must be lower than the distance quantum Δr . Such a procedure has to be repeated for n_d distances. n_d must be large enough to allow analyzing more bins — the fine step multiplied by n_d must be at least of the order of some Δr .

Moreover, the same procedure must be repeated by moving the target by "large" steps, thus varying the initial distance d . For example, the results will be presented in Section 3.3 were acquired initially placing the target at $d \approx 1.4$ m and $d \approx 6.8$ m. The optical power of the echo reflected by a target at 7 m is about 1/20 of the power when the target is at 1.4 m. Therefore, such distances allow obtaining an estimate, albeit rough, of the effect due to a variation in the power of the received echo (e.g., due to a different target reflectance). This analysis aims to roughly study how the target reflectance influences the axial error due to quantization and, thus, affects the axial resolution. In the Section 2.4 a more rigorous procedure to evaluate the effect of target reflectance is presented.

After the acquisition phase, each PC was analyzed. The axial error was investigated by analyzing a single point p for each of the acquired PCs. The procedure involves the analysis of how such p point is distributed among the various bins within the n_{PC} measurements and how such distribution varied as the actual position d of the target varied. Since the polar coordinates are quantized and predetermined, it is possible to select the same point over all the acquired PCs, by fixing the coordinates. The single point is chosen to be the point with the minimum geometrical distance from the target, thus defined by polar coordinates $\phi_t = 0^\circ$ and $\theta_t = 0^\circ$. Hence, defining $\Psi_{PC}(n, d)$, $n \in [1, n_{PC}]$, as the set of all points composing the n -th PC acquired at distance d , the analyzed points was:

$$p(n, d) = \Psi_{PC}(n, d) | (\phi_t = 0^\circ, \theta_t = 0^\circ) . \quad (2.7)$$

Each point, p , was therefore defined by the value of its radius, and such a value, r_p , is a discrete random variable that can only assume the values corresponding to the radii of the IUT bins — the concentric circumferences. To evaluate how that random variable distributes among the different bins at different distances, the empirical probability density function Γ was evaluated by analyzing the number of times that the p point fell into each bin for each distance d . Defining $\Lambda(d)$ as the set of n_{PC} single points p acquired at the distance d , Γ was calculated as:

$$\Gamma(d, r_{bin}) = \frac{\mathbf{card}[\Lambda(d) | r_p = r_{bin}]}{\mathbf{card}[\Lambda(d)]} , \quad (2.8)$$

where $\mathbf{card}[\dots]$ is the cardinality, r_{bin} is the value of the radius of the considered bin, and $\mathbf{card}[\Lambda(d)] = n_{PC}$. For each position d , the mean distance estimated by the IUT, d_{IUT} , and its experimental standard deviation of the mean were computed as:

$$\begin{aligned} \overline{d_{IUT}}(d) &= \frac{1}{n_{PC}} \cdot \sum_{n=1}^{n_{PC}} r_p(n, d) \\ s_{\overline{d_{IUT}}}(d) &= \sqrt{\frac{\sum_{n=1}^{n_{PC}} [r_p(n, d) - \overline{d_{IUT}}(d)]^2}{n_{PC} \cdot (n_{PC} - 1)}} . \end{aligned} \quad (2.9)$$

In addition, the error $e(n, d)$, relative for each single point p , and the mean error, $\bar{e}(d)$, computed over the n_{PC} PCs respect with d_{INT} were computed. According to eq. (2.5) and taking into account d_{offset} the errors were computed as:

$$\begin{aligned} e(n, d) &= d_{INT} + d_{offset} - r_p(n, d) \\ \bar{e}(d) &= d_{INT} + d_{offset} - \overline{d_{IUT}}(d) \end{aligned} \quad (2.10)$$

Single Point Warm-up

In Section 2.1, I described the procedure to characterize the warm-up time of a commercial LiDAR considering the mean distance of a target and the mean intensity

of the reflected echo. Since in classic applications, it is significant to consider several points of a PC to observe an object with an extended size, the previous analysis regards the mean value of several points falling on the target. Nevertheless, for the analysis of the axial error, a single point of the PC must be analyzed. Hence the previous definition and analysis are not suitable for this analysis, but it is required to adapt the procedure to a single point. The measurement procedure follows what is described in Section 2.1, acquiring a PC at a minute for 15 hours. The analysis is related to the single point $p(t)$ with polar coordinates $(\phi_t = 0, \theta_t = 0)$. As described above, p can only take a finite number of values. Therefore, the warm-up analysis examined how p distributed in the various bins as time t changed and, in particular, analyzed it with movable windows having a width equal to n_{PC} . Defining $\Omega(n)$ as the set of all the p points acquired up to the n -th sampling instant t_n , if $p(t)$ is stationary, the expected value of the ratio:

$$\Xi(n + n_{PC}/2, r_{bin}) = \frac{\mathbf{card}[\Omega(n + n_{PC} - 1)|r_p = r_{bin}] - \mathbf{card}\Omega(n)|r_p = r_{bin}]}{n_{PC}}, \quad (2.11)$$

calculated at the distance d coincides with the expected value of $\Gamma(d, r_{bin})$. Since r_p is a random variable, to study the warm-up time t_w of a single point is possible to observe when the distribution of that random variable stabilizes. The warm-up and stability were thus investigated by analysing the expected value of $\Gamma(d, r_{bin})$ and so of $\Xi(n, r_{bin})$.

2.4 Effect of Target Reflectance and Multiple Echoes

As introduced in Chapter 1, one of the reasons for the strong growth in the automotive market for LiDAR systems is the ability to use them for distance measurements, environmental sensing, and object recognition. Autonomous driving requires ADAS systems that must recognize different elements on the road, including other vehicles, pedestrians, traffic signals and rubble or grit on the road surface. Considering agriculture automotive, the requirements are different. Depending on the applications, ADAS systems must detect holes in the ground, obstructions, rows of seeds and fruits or vegetables to be harvested. Moreover, for example, in agriculture, it is often required to recognize small objects with a large background behind them, e.g. detecting a stalk of wheat in a field, collecting multiple echoes for the same pulse. It is clear that all these objects are totally different in shape and size but also in optical properties, which may affect the estimation of the LiDAR. Materials with different reflectances, for example, can be seen differently by a LiDAR.

The significant role of target reflectance is well-known by manufacturers and researchers. As mentioned in Section 1.1, the measurement range of a LiDAR is determined on the reflectance of the target to be detected. In this regard, there have been proposals for studies that report on the reflectance of typical objects found in the automotive field in order to optimize the selection of ADAS systems [34]. Additionally, a recent study has found that targets placed at the same distance may no longer be detectable if their reflectance falls below a certain value [49]. Furthermore, difference in target reflectance, or the presence of multiple echoes coming from different target may result not only in the miss detection of objects but also in error in axial distance estimate. Thus, an ADAS system must be robust against the difference in target reflectance to avoid erroneous distance estimation or deformation of the object.

In the previous section, the characterization of the axial error due to quantization has been treated, also exploring the possible difference in target reflectance. As successively presented in Section 3.3, the axial error distribution does not depends on the target reflectance. However, depending on the characteristics of the LiDAR — mainly the echo discriminator — the reflectance may affect the uncertainty in the distance estimation. In this section, according to the work presented in [50], a simple measurement method for studying the target reflectance effect is presented. The method allows for the evaluation of both the impact of single target reflectance (target wider than the cross-section of LiDAR beam) and the effect of the reflectances of multiple targets in the case of multiple echoes.

2.4.1 Reflectance Effect

It is trivial that the optical properties of objects have great importance for optical measurement techniques. LiDAR performances may be affected by the reflectance characteristics of targets. Since this work deals with ToF LiDARs, the focus is on the effect that the difference in reflectance of a target can have on the distance estimate of that target. In particular, the difference in the target reflectance results in different waveforms of the back-reflected echo.

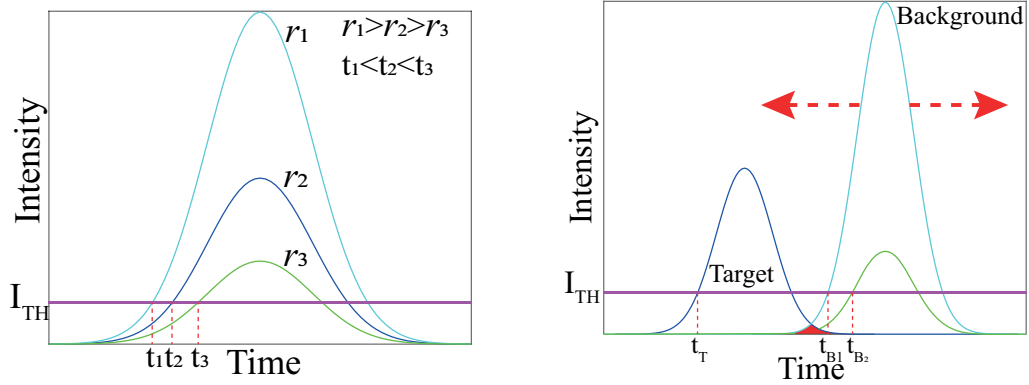
The proposed analysis regards two different scenarios: i) Single Echo and ii) Multiple Echo.

The first simple scenario involves the presence of a flat target large enough to completely intercept the LiDAR beam (as for the characterization presented in previous sections). In this case, the back-reflected echo is a single pulse whose amplitude depends only on the target surface reflectance and its distance from the LiDAR. The second scenario is more complex. In fact, if the target has an angular extension smaller than the width of the beam at the target surface, the target does not completely intercept the beam. The beam can overcome the target and hit other objects behind the target, the background, at different distances and with different reflectance. In this case, the echo waveform collected by the LiDAR depends on the reflectance of the target but also on the distance between the target and the background and on the background reflectance. The resulting echo waveform could be complicated, and the determination of the main Target distance could be non-trivial.

To better introduce the problem of target reflectance, Fig. 2.6 schematizes the two possible scenarios applied to a simple case. Let's assume the waveform of the LiDAR beam is purely Gaussian and that the Target distance is estimated by measuring the instant in which the back-reflected echo signal crosses an intensity threshold I_{TH} , i.e. leading-edge discriminator. Fig. 2.8(a) represents the simplest scenario. The target intercepts the entire beam generated by the LiDAR, and assuming the target is orthogonal to the propagation direction, the echo remains Gaussian. Therefore, the echo waveform depends on the reflectance of the target surface. In the figure it is possible to observe that the higher the reflectance, the higher the intensity. Assuming the discriminator as leading-edge, the reflectance influences the distance estimation. In fact, the higher the intensity the shorter the time required to the echo to cross the intensity threshold. The echo arrival time is inversely proportional to the reflectance, thus the higher the reflectance the lower the estimated distance. Fig. 2.8(b) schematizes the multiple echo scenario according to which the beam is only partially intercepted by the beam. To simplify the description, let's assume there is a single object behind the target, the background (BG), able to completely

intercept the remaining part of the beam. The BG generates a second echo, whose waveform depends on the reflectance of the BG, that may overlap with the main echo. The superimposition of the echoes may generate a distortion of the Gaussian shape of the echo, resulting in possible multiple echoes at the receiver side and in an error in the distance estimation. Furthermore, the echoes superimposition depends on the reflectance of the BG and the distance between the target and BG. So the error in the estimated distance could depend on these factors. Note that if behind the object are present more than one object able to reflect the beam, the echo waveform will result more complex.

The characterization of the reflectance effect is thus crucial to understand the limit of applicability of a commercial system, for example, for object recognition. I designed a setup and a characterization procedure to investigate the LiDAR behaviour in both scenarios. This measurement procedure can be used to compare the performances of different LiDARs, providing a fast tool for such analysis.



(a) Single Echo: Targets with different reflectance. (b) Multiple Echoes: Target and Background

Figure 2.8: Fig. 2.8 shows the theoretical waveform of three echoes reflected by the target with different reflectances $\rho_1 = 2\rho_2$, $\rho_2 = 2\rho_3$ and ρ_3 . In these simplified scenarios, the echo is assumed as Gaussian. The higher the reflectance ρ , the higher the echo intensity and, as a consequence, the shorter the time arrival t , in which the echoes overcome the intensity threshold I_{TH} .

Fig. 2.8(b) shows the theoretical behaviour of a single beam impinging a target not able to completely intercept the beam. If there is a background behind the object, the LiDAR collects an echo composed by the superimposition of at least two echoes. These echoes, having different arrival times t_T and t_B , may generate an error in the estimation of target distance. Note that the instant t_B depends on the reflectance of the background. The red area highlights the overlap between the echoes.

2.4.2 Measurement Procedure and Setup

The two possible scenarios have been investigated separately. The setup adopted is different for the two scenarios, but is based on the rail-system proposed for the other characterizations. For each scenario the setup and the measurement method will be described.

Single Echo

The setup used for the first analysis is represented in Fig. 2.9. The IUT was aligned to a rail system 4 m long. The alignment was achieved through the translating stage by Thorlab. The target is fixed on a sliding carriage enables varying the distance of the target d_T . For this analysis a particular set of target have been chosen. To ensure a correct characterization of the effect of target reflectance a set of Standard reflectance Targets. Specifically, the targets are 4 circular NIST certified reflectance standard with radius 1 in (Spectralon® Diffuse Reflectance Standards, by Labsphere LABSPHERE® Inc., North Sutton, NH, USA). The certified reflectance of the Targets in the spectral range $[250, 2500]$ nm are: $\rho_1 = 2\%$, $\rho_2 = 50\%$, $\rho_3 = 75\%$ and $\rho_4 = 99\%$.

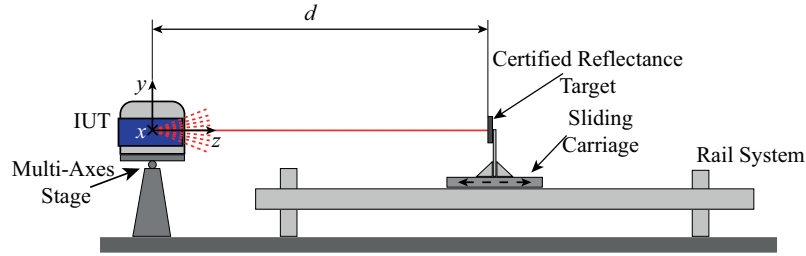


Figure 2.9: Schematic representation of the the measurement setup used for the single echo analysis. IUT and Target are aligned along a rail system. The Target can be moved along the system, toward and backward the IUT, increasing or decreasing d .

The measurement involves analyzing the estimated distance of the target at different distances while changing the reflectance of the target. For this analysis, a single optical beam emitted by the IUT must be studied. It is possible to exploit the fact that 3D LiDARs emit beams along fixed polar directions, as discussed in Section 2.3.1, to analyse the same beam by fixing the polar coordinates θ_t, ϕ_t . For this analysis, the beam must be completely intercepted by the target. Thus, the maximum measurement distance depends on the target size and angular aperture of the IUT emitted beam.

After waiting for the warm-up time for a single beam, the analysis can be started by placing a reference target at a known distance d_T and acquiring N_{rep} PCs of the

IUT at this distance. Then, the target was changed to modify the reflectance, and the acquisition was repeated for each reference target. Successively, this procedure was repeated at N_{dist} target distances. To evaluate the possible effect of drift in the measurement, the acquisition with the first target was repeated at the end of the test.

The analysis of the acquisition was performed by extracting the estimated target distance of the single beam with polar coordinates ($\theta_t = 0^\circ, \phi_t = 0^\circ$) from each PC. As described in the previous section, the estimated distance of a single beam is a random variable that can assume a value among discrete bins whose width represents the IUT axial quantum Δr . Therefore, having fixed the distance d_T of the Target with known reflectance ρ , the mean value of the Target distance is estimated as the mean distance of the i -th distance $d_{T_i}^r$, the radius value of the point related to the beam ($\theta_t = 0^\circ, \phi_t = 0^\circ$) for each n_{rep} PCs.

$$\bar{d}_T^r = \frac{1}{N_{rep}} \sum_i^{N_{rep}} d_{T_i}^r . \quad (2.12)$$

Considering the IUT spatial resolution R reported in the datasheet of commercial LiDARs, type B standard uncertainty can be estimated assuming a uniform probability density function within the single bin:

$$u_B(d^r) = \frac{R}{\sqrt{12}} . \quad (2.13)$$

To evaluate how the reflectance of the target affects the target distance estimation the behaviour of the mean estimated distance $\bar{d}_T^r$ was studied, considering the uncertainty type B.

Multiple Echoes

The multiple echoes analysis requires the presence of a second disturbing echo. To simulate the presence of a disturbing echo, the experimental setup consists of a thin target that allows a portion of the beam to pass through and a background located behind the target that is able to intercept the remaining part of the beam. The analysis is performed considering only the horizontal dimension, but it is possible to rotate the IUT by 90° and adapt the setup to study multiple echos considering the vertical dimension.

That setup is shown in Fig. 2.10. The IUT is aligned with a target, with a small horizontal size, fixed at a distance d_T along the track. d_T must be chosen to have a beam horizontal size $W_b(d_T)$ wider than the horizontal size of the target W_T , considering the divergence of the spot α . Assuming $W_b(d_T) > W_T$, only a part of the beam is intercepted by the target, while the remaining part is intercepted by a

larger background BG at $d_T + d_{T-B}$. BG is placed on a sliding carriage allowing to change the mutual distance between the target and BG d_{T-B} and, thus, study the effect of the BG position on the target distance estimation. The BG was made with a Spectralon® Diffuse Reflectance Standards to verify the dependence of the measured Target position on BG reflectance ρ .

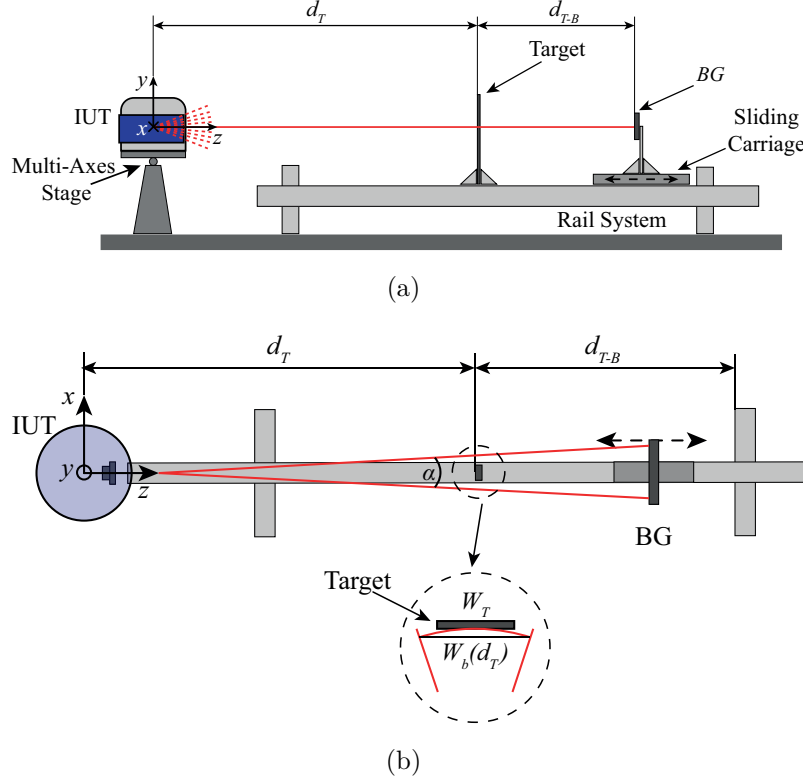


Figure 2.10: Schematic not in scale representation of the measurement setup for Multiple echoes analysis. The IUT is aligned with the background and the Target along the rail system. The Target is fixed at d_T , while the background can move in a range changing the distance d_{T-B} . The red lines represent the beam with a horizontal divergence α . In the zoomed area the detail of the beam at the target surface. The Target size W_T has to be smaller than the beam section $W_b(d_T)$.

Once the IUT ended the warm-up, the first BG was placed at an initial d_{T-B}^{start} distance from the target. N_{rep} PCs have been acquired with the BG at this position. Then, the BG was moved from d_{T-B}^{start} to d_{T-B}^{stop} for a total of N_{dist} different d_{T-B} distances. The complete procedure was repeated with all the backgrounds with reflectance ρ known. As in the case of a single echo, a single optical beam must be studied. The effects on the target estimated distance have been evaluated by studying the trend of the mean estimated target distance according to eq. (2.12). The uncertainty type B on mean distance was computed from the resolution R of the IUT as in eq. (2.13).

The results of both analyses will be shown in Section 3.4.

2.5 Transversal errors and Detection Probability

The great importance of LiDARs in recent years is due to their ability to perceive their surroundings. This ability is expressed not only by estimating the distance of obstacles but also in 3D object perception. For example, let's consider a vehicle that mounts a 3D LiDAR for autonomous driving; generally, object recognition is achieved through imaging systems such as cameras and stereo cameras, used to recognize objects of interest for a specific application: traffic signals or pedestrians for civil automotive and harvesting products for agriculture. Nevertheless, LiDAR can be used as a redundant system, increasing detection accuracy.

Object recognition depends on two main factors: i) the object detection probability and ii) the possible object deformation introduced in the PC representation. Object detection and object deformation depend on LiDAR characteristics, and thus the study of such information is of considerable importance. This information is not usually provided by LiDAR manufacturers, thus it is of great relevance to have characterization tools to investigate the object detection ability of a commercial LiDAR and object deformation introduced by the instrument itself. In this section, a measurement method is proposed to investigate these aspects. Moreover, a characterization example of the MRS 6000 is presented to evaluate the proposed approach in Section 3.5.

Recalling Section 1.1, a 3D-LiDAR senses the surrounding by analyzing the echoes generated by the emitted beams after being back-reflected by the environment. Depending on the LiDAR technology, the coordinates of the points in the Point Cloud have been determined in different ways. However, all the 3D-LiDARs represent the points in the PC in polar coordinates $p = (r, \theta, \phi)$. It is known that environment sampling is achieved along a set of predefined and discrete beams with different angular directions that differ by the horizontal (azimuth) angular resolution $\Delta\theta$ on the horizontal plane and by the vertical (elevation) angular resolution $\Delta\phi$ on the vertical plane. Thus, the PC representation of the surrounding is angular quantized. From the Section 2.3.1, the axial distance is also quantized, and the radius can assume only a finite number of values, i.e. bins, that differ by the axial quantum Δr , that is the difference in the radius. Regardless of where the object that created the received echo is, PC points can only be found along a finite set of diverging straight lines, the rays. The quantized nature of the PC can affect object detection and especially deform an object. In this section, the study of the error introduced by the quantized nature of 3D LiDARs is extended to errors in the plane orthogonal to the beam propagating axis. Hence, errors in the polar position of a PC point are investigated instead of in the distance from the IUT.

The study of these errors is strictly linked to the object detection capability of the

LiDAR and to the point placement in the Point Cloud. To better understand this concept, focus on what a PC point represents. A point p may represent a target or a portion of a target having the centre in the polar coordinates of p , (θ_t, ϕ_t) , having the angular extension $\pm\Delta\phi/2$ and the azimuth angular extension $\pm\Delta\theta/2$. The angular quantization can thus generate three different errors that are schematically shown in Fig. 2.11, concerning the azimuth plane:

- **type 1: Enlargement.** Although a target does not fully cover the angular sector of a specific point of the PC, that point is still inserted in the PC. In this scenario, the target appears larger, and its angular representation in the PC is broader than in real life (e.g. target $\mathbf{T}_1$ and $\mathbf{T}_2$).
- **type 2: Shrinkage.** Although the target has an angular extension wider than the angular sector of a specific point (that is, the target extends in the sectors of more than one point), it is affected with at least one point less than the affected ones. The angular extension in the PC is lower than in the reality (e.g. target $\mathbf{T}_3$).
- **type 3: Shift.** The target is represented in the PC with a point or a set of points whose center is located at different angular coordinates to those of the target center (e.g. target $\mathbf{T}_1$, $\mathbf{T}_2$ and $\mathbf{T}_3$).

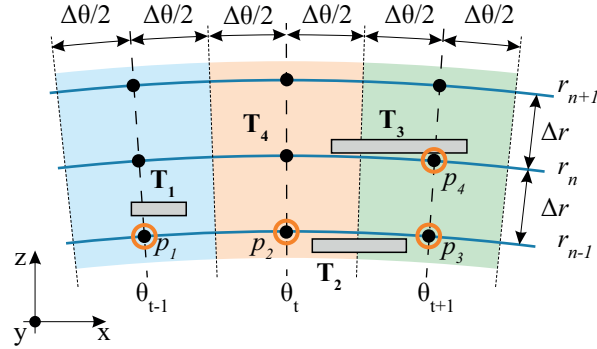


Figure 2.11: Schematic representation of quantization transversal errors introduced by 3D LiDARs. The figure shows the azimuth-distance plane of a PC (elevation channel ϕ_t fixed). The three dashed lines represent three rays propagating axis respectively at angular position θ_{k-1} , θ_k and θ_{k+1} . The rays are equispaced by $\Delta\theta$, i.e. the horizontal angular resolution. The blue lines (—) represent the circumferences in which the axial distance is quantized (the bins) equispaced by the axial quantum Δr . The dots represent the possible value that the points in the PC can assume. The dots with the orange circle (○) represent the points actually inserted in the PC by the LiDAR. Target $\mathbf{T}_1$ is approximated with the point p_1 . Since a point p represents a target or a portion of a target with a horizontal angular extension $\pm\Delta\theta/2$, $\mathbf{T}_1$ is both enlarged and shifted (its actual center does not coincide with p_1). Target $\mathbf{T}_2$ is hit by two rays; thus, it is enlarged and shifted. Target $\mathbf{T}_3$ represents the opposite case of $\mathbf{T}_2$. $\mathbf{T}_3$ is hit by two rays, but it is represented in the PC by a single point p_4 , so it is shrunk.

The representation in Fig. 2.11 regards only the errors on the horizontal plane. Nevertheless, it is possible to extend the same representation to the vertical plane. As easy to verify, type 3 error is always less than half the angular sampling period. Type 1 and 2 errors have a maximum value of less than the angular sampling period for each of the target sides (overall horizontal and vertical errors are always less than twice the respective angular sampling period). Furthermore, type 1 and 2 errors generally imply a type 3 error as well.

In addition to these errors, it is possible to observe a fourth error, that is, **type 4: cross-talk**. Let's consider scanning 3D LiDAR. For example, if the beam cross-section has an actual angular extension wider than $\Delta\theta$, the same target portion can be sampled from several adjacent beams. In this scenario, the target is represented by more points being represented larger than in reality, as in Fig. 2.12. The type 4 error can also occur in flash LiDARs if adjacent pixels collect the echo coming from the same target portion. For example, this issue can be due to optical aberrations or distortions. Note that the cross-talk error on each side of the target may be larger than the angular resolution $\Delta\theta$, instead of types 1,2 and 3 that are, by definition, lower than $\Delta\theta$.

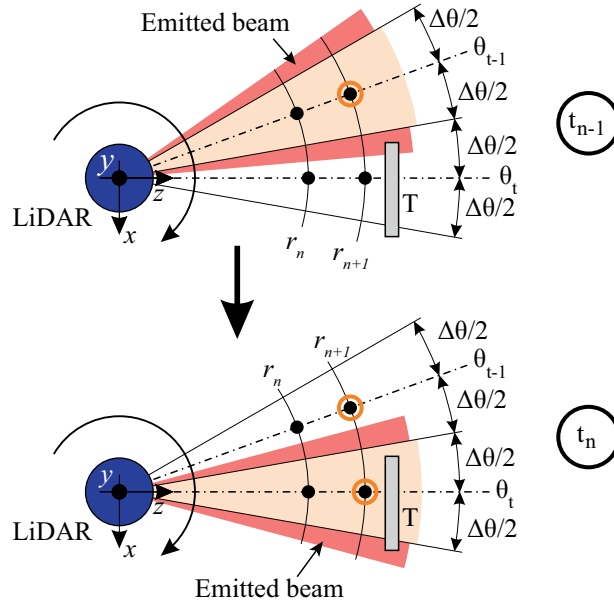


Figure 2.12: Schematic representation of Cross Talk in scanning LiDARs. At the instant t_{n-1} the LiDAR emits a beam centered at θ_{t-1} , which nominally covers the angular sector $[\theta_{t-1} - \Delta\theta/2, \theta_{t-1} + \Delta\theta/2]$. If at the target (T) distance, the beam has an angular extension wider than the nominal angular resolution $\Delta\theta$, the LiDAR can receive an echo from this target, adding a point p_1 in PC. At the successive instant t_n , the LiDAR emits a beam with azimuth position θ_t . Since the target (T) is present in the angular sector $[\theta_t - \Delta\theta/2, \theta_t + \Delta\theta/2]$, the LiDAR adds point p_2 to the PC.

Finally, if the target involves more rays, depending on the target and on the

propagating medium, “internal” points may be missing in the PC creating some holes or voids (**type 5: voids**).

The proposed measurement method aims to provide a tool to quantify the magnitude and the probability of all transversal errors. According to this approach, these errors can be evaluated the single ray empirical detection probability is investigated — the probability that a single ray, with polar coordinated (θ_t, ϕ_t) detects the target by adding a point in the PC .

Optical Power and Detection Probability

As will be described in more detail in the next section, the study of the error due to quantization can be achieved by evaluating the single ray detection probability. Thus, it is important to understand which factors influence that probability. Among the various elements, the optical power of the received echo plays a relevant role [6, 7]. The optical power of the received echo Φ_R is defined as:

$$\Phi_R = \int_{A_T} \int_{A_D} L \cdot \frac{da_T \cos \gamma_T da_D \cos \gamma_D}{l^2} , \quad (2.14)$$

where A_D is the area of the detector, da_D the infinitesimal element of the area A_D , A_T is the area of the target illuminated by the beam and da_T the infinitesimal element of the area A_T . L is the radiance of the echo at da_T , and γ_T and γ_D represent the angles formed by the direction of the flux in relation to the target and detector surfaces respectively. Furthermore, the received power Φ_R depends on various factors, including the power emitted by the beam Φ_L , the beam’s angular divergence, the attenuation of the propagating medium, and the optical properties of the target, i.e. angular dispersion and surface reflectance ρ_T . Assuming the LiDAR beam is a flat-top and the target surface reflectance is Lambertian, the power that reaches the detector can be estimated by using the formula in eq. (2.15).

$$\Phi_R = \rho_T \cdot \frac{\Phi_L}{\sigma} \cdot \frac{1}{\pi} \cdot A_T \cdot \frac{A_D}{r^2} \cdot \eta_{atm}^2 \cdot \eta_{sys} , \quad (2.15)$$

Fig. 2.13 schematically represents the beam impinging on a target with surface reflectance ρ_T and with a cross-sectional area of the beam at the target surface σ . Assuming the beam is a flat-top, the irradiance reaching the target is $\eta_{atm} \Phi_L / \sigma$, and the radiance of the echo reflected is $\eta_{atm} \rho_T \Phi_L / (\sigma \pi)$, in case of a Lambertian target. A_T is the target area illuminated by the beam, and A_D / r^2 is the solid angle under which the LiDAR detector sees the target. Thus, the total received optical power at the detector is $\eta_{atm}^2 \rho_T \Phi_L A_T A_D / (\sigma \pi r^2)$ — η_{atm} is the single pass attenuation coefficient thus it must be considered two times. Finally, η_{sys} is the optical efficiency of the receiver, which determines the actual optical power read by the

LiDAR.

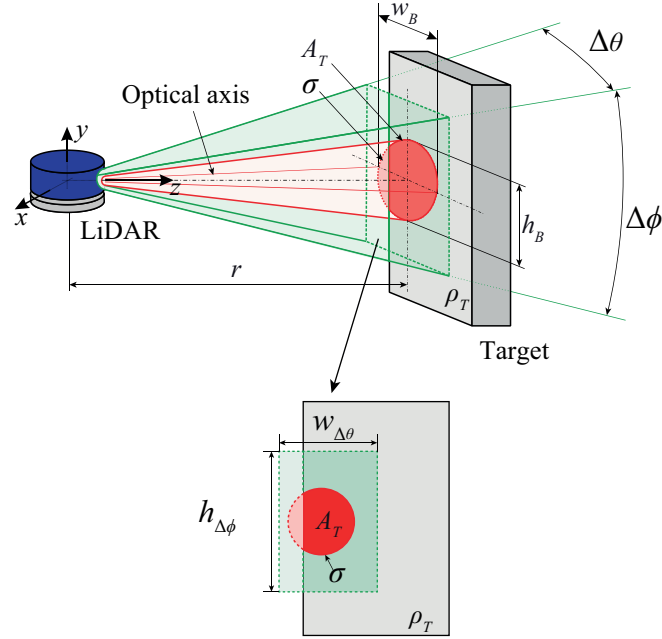


Figure 2.13: Schematic representation of a LiDAR beam impinging on a flat target with surface reflectance ρ_T . The red area is the cross-section σ of the emitted beam at the target surface. σ has a maximum height h_b and a maximum width w_B . A_T is the portion of the target illuminated by the beam ($A_T \leq \sigma$). The green rectangle is the projection at the target surface of the angular sector represented by the considered ray. This area has a width $w_{\Delta\theta}$ and height $h_{\Delta\phi}$, projection of $\Delta\theta$ and $\Delta\phi$.

From eq. (2.15), it is, thus, possible to observe that the received power depends on the illuminated area of the target and the cross-sectional area of the beam at the target surface. According to this consideration, it is possible to study the detection probability varying the target area illuminated by the beam and observe what happens to the distance estimated by that beam. A measurement approach that recalls the knife-edge method will be described in the following sections.

2.5.1 Measurement Setup

As introduced in previous section, to study the transversal errors due to quantization, the single ray detection probability was analyzed. The proposed measurement method employs the setup presented in Fig. 2.14. Note that the presented setup is based on the original setup for the error estimation, highlighting the flexibility of such a facility. The proposed method recalls the knife-edge method used for measuring the divergence of a laser beam. In fact, a thin slab, i.e. the “knife”, is placed in front of the IUT; the knife is translated along a direction orthogonal to the single

beam axis, and the estimated distance of the ray is analyzed for each horizontal knife position. The single ray detection probability is evaluated by analyzing how the point, related to the beam (θ_t, ϕ_t) , distributes among the various bin — placing the point in the knife bins or in the background bins.

The setup is a rail system with a sliding carriage allowing movement on the z-axis, thus varying the distance knife-IUT d_k . Differently, d_{bg} is the distance between the IUT and the background. Since the single ray detection probability is retrieved by observing the PCs, in which the knife is estimated at the correct position, it is crucial to distinguish the knife from the background. Thus, the distance knife-background d_{off} must be large enough depending on the IUT characteristics. Theoretically, d_{off} must be higher than the maximum axial error of the IUT. However, the presence of the background may affect the knife estimation distance as described in Section 2.4. Thus, it is convenient to have the background at a distance much higher than the error and not comparable to the knife distance (a higher order of magnitude). The knife is mounted on a linear translation stage allowing the horizontal movement. A variation δx in the knife position results in a variation in the azimuth angle of the IUT of $\delta\theta$. Since the analysis aims to investigate the presence and the effect of Cross Talk, the scanned area must be wider than $[\theta_t - \Delta\theta/2, \theta_t + \Delta\theta/2]$ range. To cover the correct angular interval, a stack of three motorized linear translation stages (model Z825B by Thorlabs) is used. The knife width w_k and height h_k play a relevant role in the analysis; the choice of the target size must be performed accurately as better described in Section 2.5.2. The knife thickness must be thinner than w_k to reduce the impact caused by the tilt of the knife away from the direction orthogonal to the beam radius. Note that for simplicity, this work considers only the azimuth quantization $\Delta\theta$, thus investigating the detection probability only on the horizontal axis (the method can be easily replicated on the vertical (elevation) axis by rotating the IUT).

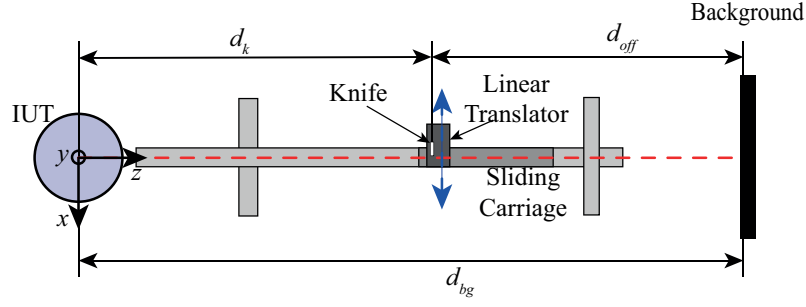


Figure 2.14: Schematic representation of the setup used for the detection probability analysis. The knife is mounted on a line translation stage that allow the x-axis movement. d_k is the distance between the knife and the IUT and it can be varied moving the sliding carriage along the rail system. d_{bg} is the distance between the background and the IUT and d_{off} is the distance between the knife and the background. The blue dashed arrow (- - -) represents the movement of the stage.

2.5.2 Measurement Procedure

The analysis regards the evaluation of the single ray detection probability of the knife at different horizontal positions at a fixed distance between the IUT and the target. The measurement require to evaluate the radius estimated by a single ray of the IUT, when a knife is perpendicularly moved into the ray. As the knife enters the illumination field of the beam, the illuminated area of the knife is always increasing and as a result the power of the reflected echo is also increasing, as shown in Fig. 2.13. Thus, the probability to detect the target should increase as the knife enters the beam. After waiting for the warm-up of the instruments, the knife was placed at a first distance d_k from the IUT. The measurement started, and the linear stage horizontally translated the knife by small steps of x_{step} . At each knife position, the IUT acquire n_{PC} PCs. Once the scanning was completed, the knife was moved to the next d_k distance, and the procedure was repeated.

To correctly evaluate the detection probability, the process must be repeated by moving the knife in a clockwise and counterclockwise direction, thus obtaining the probability function for both sides of the knife. However, if the clockwise translation is large enough, the left edge of the knife samples the same positions it would have sampled during the counterclockwise translation. Therefore, the clockwise translation can also be used for estimating the counterclockwise probability function. The possibility to sample without needing to disassemble and reassemble the knife offers advantages in terms of reducing uncertainty in the repositioning and duration of acquisitions. After the acquisition phase, the ray (θ_t, ϕ_t) was analyzed for each PC. The single ray empirical detection probability was thus calculated by computing the ratio between the number of times the point p related to the beam (θ_t, ϕ_t) detects the knife over the n_{PC} , i.e. the number of acquired PCs for each distance. Let's

define $\Omega_{PC}(\theta_k, n), n \in [1, n_{PC}]$ as the set of all the points belonging to the n -th PC acquired when the knife was at the angular position θ_k respect with the IUT. Thus, the point p was:

$$p(\theta_k, n) = \Omega_{PC}(\theta_k, n) | (\theta = \theta_t, \phi = \phi_t) . \quad (2.16)$$

The radius of point p was checked to indicate whether the IUT had detected the target. Recalling Section 2.3, the axial distance is a discrete random variable that assumes the value of the bins adjacent to the knife. The proposed method defines the target as detected when p falls into the set of n_b bins representative of the target; thus, the number of times the IUT had detected the knife is:

$$p(\theta_k, n) | r \in [r_n - n_b \cdot \Delta r, r_n + n_b \cdot \Delta r] , \quad (2.17)$$

where r_n is the value of the radius that best approximates the knife distance d_k and Δr is the axial quantum of the IUT.

As previously introduced, the procedure involves the calculation of a clockwise probability function Γ_{det}^+ and a counterclockwise probability function Γ_{det}^- . Defining Λ^+ as the set of n_{PC} points acquired during the clockwise translation and when the knife is in the position θ_k , it is possible to calculate the clockwise probability function Γ_{det}^+ as:

$$\Gamma_{det}^+(\theta_k) = \frac{\mathbf{card} \{ \Lambda^+(\theta_k) | r \in [r_n - n_b \cdot \Delta r, r_n + n_b \cdot \Delta r] \}}{\mathbf{card} \{ \Lambda^+(\theta_k) \}} , \quad (2.18)$$

where $\mathbf{card}\{\dots\}$ is the cardinality and $\mathbf{card} \{ \Lambda^+(\theta_k) \}$ is n_{PC} . In the same way it is possible to define, for the counterclockwise translation, Λ^- and Γ_{det}^-

$$\Gamma_{det}^-(\theta_k) = \frac{\mathbf{card} \{ \Lambda^-(\theta_k) | r \in [r_n - n_b \cdot \Delta r, r_n + n_b \cdot \Delta r] \}}{\mathbf{card} \{ \Lambda^-(\theta_k) \}} . \quad (2.19)$$

Fig. 2.15 schematizes the single ray empirical probability extraction. It is possible to observe that $\Gamma_{det}^+(\theta_k)$ is the probability the ray (θ_t, ϕ_t) will detect a target that extends from $(\theta_t - \Delta\theta/2)$ to $(\theta_t - \Delta\theta/2 + \alpha)$. Of course, $\Gamma_{det}^-(\theta_k)$ is the probability the single ray detects a target that extends from $(\theta_t + \Delta\theta/2 - \alpha)$ to $(\theta_t + \Delta\theta/2 +)$. Assuming that the ray detection probability is symmetrical with respect to the optical axis of the (θ_t, ϕ_t) ray, it is possible to define the mean empirical target detection probability:

$$\bar{\Gamma}_{det}(\alpha) = [\Gamma_{det}^+(\alpha) + \Gamma_{det}^-(\alpha)] / 2 , \quad (2.20)$$

where α , the angular extension of the knife within the angular interval of the observe ray, is defined as:

$$\alpha = \begin{cases} \theta_k - (\theta_t - \Delta\theta/2) & \text{clockwise} \\ (\theta_t + \Delta\theta/2) - \theta_k & \text{counterclockwise} \end{cases} \quad (2.21)$$

Note that, in the presence of cross-talk, $\bar{\Gamma}_{det}(\alpha)$ can be greater than zero even for negative α values, since the observed ray has an actual angular extension wider than $\Delta\theta$. As shown in Fig. 2.15, from the empirical probabilities $\Gamma_{det}^+(\theta_k)$ and $\Gamma_{det}^-(\theta_k)$ it is also possible to define the function:

$$\Gamma_{det}(\alpha) = \min \left\{ \Gamma_{det}^+(\theta_k), \Gamma_{det}^-(\theta_k) \right\} , \quad (2.22)$$

As will be described in more detail in the following sections, the $\Gamma_{det}(\theta_k)$ function allows to provide an effective representation of the IUT behaviour in detecting an object. In addition, as will be described in next section, it is possible to define the effective beam waist w_{eff} . If the effective width w_{eff} is greater than the projections of the angular sampling periods $\Delta\theta$, as shown in Fig. 2.13), the (θ_t, ϕ_t) ray will extend beyond the adjacent ray, resulting in cross-talk (error 4).

Knife Width

As previously introduced, the size of the knife is relevant for the measurement results, and its choice must be made accurately. Considering the proposed procedure that regards the analysis of detection probability on the azimuth plan, the height h_k of the knife must be such as to guarantee that it can cover the entire $\Delta\phi$ elevation angular sector (plus any vertical cross-talk). In general, it is convenient to use a knife with an angular height at the distance r of interest greater than $\Delta\phi$, e.g. $3\Delta\phi$. Theoretically, w_k must respect the same rule, thus be enough to cover the angular sector $[0, \Delta\theta]$, that is, referring to Fig. 2.12, $\Delta\theta_k \geq \Delta\theta$. Respecting these condition, during the knife translation there will be a θ_k that entirely intercept the emitted beam. However, to perform the entire measurement without disassembling the knife to obtain both the clockwise and counterclockwise probability, the translation stage requires a significant long run. Thus, it is convenient to evaluate the minimum knife width to reduce the translation stage run. As reported in Section 2.5, the higher the received optical power Φ_R , the higher the target detection probability. Therefore, the higher the target area, the higher the detection probability and reducing the knife size may imply a reduction of the detection probability. Nevertheless, the probability cannot exceed the value of 1, of course. Let's consider a LiDAR beam not entirely intercepted by the knife. In this case, if the detection probability has already reached 1, it cannot increase further, even increasing the area. Thus, it is possible to reduce the knife width w_k , to reduce the translation stage run until the received optical power is such to obtain a detection probability of 1. The minimum value of w_k can be experimentally obtained by checking the minimum angular width at distance r for which the probability Γ_{det} is 1. Recalling the eq. (2.21), α is the angular extension of the knife within the angular interval of the observe ray. Thus

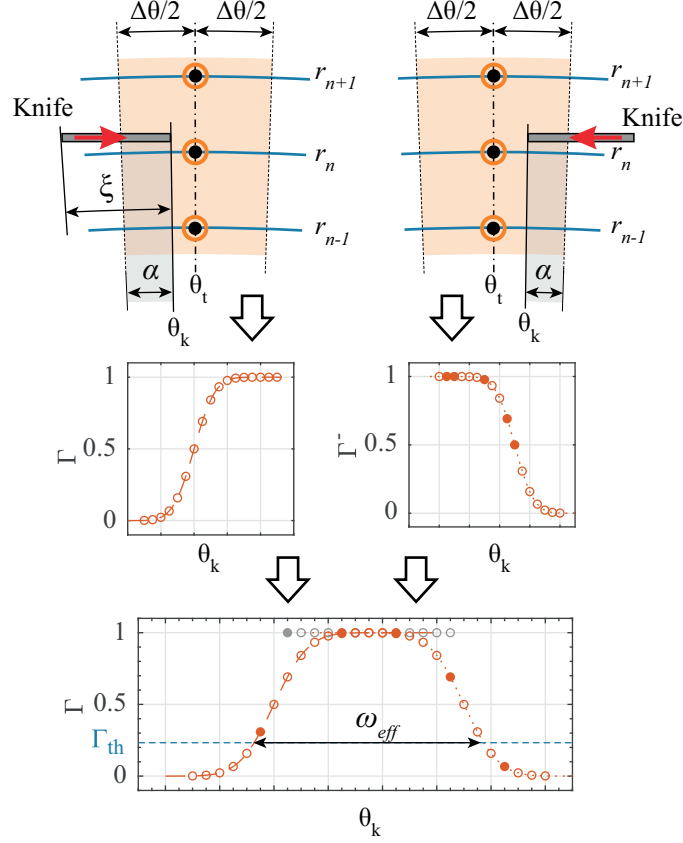


Figure 2.15: Schematic representation of the knife-edge like method for the estimation of empirical detection probability. The top figure shows the knife with a total angular extension ξ and an extension α within the considered beam — the ray (θ_t, ϕ_t) — respect the IUT origin. The knife was translated in one direction and the other (“clockwise” and “counterclockwise”). For each angular position θ_k n_{PC} have been acquired, and the respective single ray empirical probabilities, $\Gamma_{det}^+(\theta_k)$ and $\Gamma_{det}^-(\theta_k)$, have been computed (middle figure). In this representation r_{n-1}, r_n, r_{n+1} are the n_b bins representative of the target. In bottom figure $\Gamma_{det}(\theta_k)$, the union of $\Gamma_{det}^+(\theta_k)$ and $\Gamma_{det}^-(\theta_k)$, from which the effective beam waist w_{eff} can be estimated.

the the minimum angular width of the knife at distance r is:

$$\Delta\theta_{k-MIN} = \alpha_1(r) - \alpha_0(r) , \quad (2.23)$$

where:

$$\begin{aligned} \alpha_0(r) &= \min \left\{ \alpha \in [-\infty, \Delta\theta] \mid \Gamma_{det}^-(\alpha, r) > 0 \right\} \\ \alpha_1(r) &= \min \left\{ \alpha \in [-\infty, \Delta\theta] \mid \Gamma_{det}^-(\alpha, r) = 1 \right\} . \end{aligned} \quad (2.24)$$

α_0 represents the minimum angular extension of the knife within the beam required to obtain a detection probability higher than 0, while the α_1 is the minimum knife extension to obtain a probability 1. Both these parameters can assume negative value due to the cross-talk, as discussed in Section 2.5.2. Note that these quantities are functions of r , thus the minimum angular knife width. For high distance r , the probability never reaches 1; thus, α_1 must be changed as the angular extension for which the probability maximizes.

In conclusion, from the eq. (2.15), the target reflectance ρ_T contributes to the detection probability. Thus, the knife choice must be performed accurately considering this factor.

2.5.3 Error Probability Definition

As reported at the beginning of this section, the goal is to evaluate the magnitude and the probability of transversal error due to quantization. Exploiting the empirical single ray detection probability as in eq. (2.20), it is possible to derive the expression for the probability to observe the errors previously defined.

Let's consider a simple flat target of such an angular extension that involves N_θ . Fig. 2.16 shows the schematic representation of such a scenario. Depending on the distance and optical properties of the target and propagating medium, this target may be represented with a different number of points in the PC. Indeed, the target may be represented with a higher number than N_θ points (**enlargement** and **cross-talk**) or with a lower number (**shrinkage** or **void**).

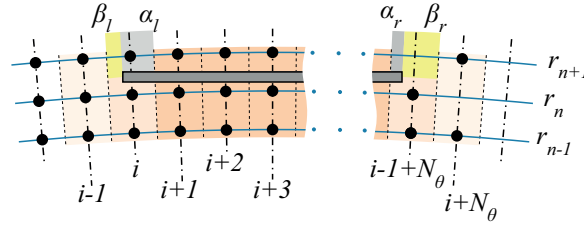


Figure 2.16: Schematic representation, on a single elevation channel ϕ_t , of a target sampled by N_θ rays. Considering the internal rays $\{i+1, i+2, \dots, i-2+N_\theta\}$, the target entirely covers the angular sector illuminated by such beams. The target partially covers the sector of the outer beams $\{i, i-1+N_\theta\}$, thus the most-left and most-right rays hitting the target. The target extends in the outer ray sectors by an angle $\alpha = \alpha_l$ (left edge) and $\alpha = \alpha_r$ (right edge). The uncovered parts of these ray sectors are respectively defined as $\beta_l = \Delta\theta - \alpha_l$ and $\beta_r = \Delta\theta - \alpha_r$.

For simplicity, let's focus on a single elevation channel ϕ_t . To improve the comprehension of the discussion, the parameters presented in this section have been reminded.

- $\Delta\theta$: azimuth resolution of the LiDAR, thus the width of an angular sector illuminated by a single beam.
- θ_t and ϕ_t : the polar coordinates of the single considered emitted ray.
- ξ : the angle under which the target is seen by the IUT, that is, the total angular extension of the target.
- α : angular extension of the target within a single ray — $\alpha \leq \Delta\theta$.

According to the Section 2.5.2, the target has a height such that it completely covers the vertical angular sector $[\phi_t - \Delta\phi/2, \phi_t + \Delta\phi/2]$. Hence, if $\bar{\Gamma}_{det}$ is the empirical probability a ray detects a target after hitting it, the probability P_{det} the LiDAR detects the target with a single ray (θ_n, ϕ_n) is:

$$P_{det}(\theta_t, \phi_t) = \int_0^{\Delta\theta} P_\alpha(\theta_t, \phi_t, \alpha) \cdot \bar{\Gamma}_{det}(\theta_t, \phi_t, \alpha) d\alpha, \quad (2.25)$$

where α is the angular extension of the target within the considered ray as in eq. (2.21) and $P_\alpha(\theta_t, \phi_t, \alpha)$ is the probability the target extends in the angular interval $[\theta_t - \Delta\theta/2, \theta_t + \Delta\theta/2]$ for an azimuth angle in the interval $[\alpha, \alpha + d\alpha]$. By definition, P_α depends on the target position respect with the beam (θ_n, ϕ_n) . In fact, if the beam of interest (θ_t, ϕ_t) is an “internal” point — not a point at the side of the target — the target entirely covers the angular interval illuminated by the beam, and the probability P_α becomes a Dirac delta function. Thus, the detection probability P_{det} reduces to $P_{det}(\theta_t, \phi_t) = \bar{\Gamma}_{det}(\theta_t, \phi_t, \Delta\theta)$. It is possible to define the

number of rays hitting a target with an actual angular extension ξ as:

$$N_\theta = \left\lfloor \frac{\xi}{\Delta\theta} \right\rfloor + 1 . \quad (2.26)$$

Rounding down and then adding one account for instances where the target is an integer multiple of the azimuth resolution $\Delta\theta$ but its edge does not coincide with the beginning of the angular sector of a ray. It is obvious that the outer points must be accurately treated. As shown in Fig. 2.16, and focusing on the outer rays i and $i - 1 + N_\theta$, the target can partially cover the respective angular sectors. It is possible to define the value α_l (angular extension of the target within the leftmost beam i) and α_r (angular extension of the target within the rightmost beam $i - 1 + N_\theta$). Moreover, $\beta_l = \Delta\theta - \alpha_l$ and $\beta_r = \Delta\theta - \alpha_r$ are the respective beam angular sectors that are not covered by the target, and their sum is $\beta = \beta_r + \beta_l$. Observing the Fig. 2.16, it can be inferred that, for the outer rays, the value of α has a minimum value equal to:

$$\alpha_{MIN}(\xi) = \Delta\theta - \beta = \xi - \{[N_\theta(\xi) - 1] \cdot \Delta\theta\} . \quad (2.27)$$

Hence, the probability the probability the target extends in the outer rays is:

$$P_{\alpha-Out}(\alpha) = \begin{cases} 0 & \text{for } \alpha < \alpha_{MIN} \\ 1/(\Delta\theta - \alpha_{MIN}) & \text{for } \alpha \in [\alpha_{MIN}, \Delta\theta] \\ 0 & \text{for } \alpha > \Delta\theta \end{cases} \quad (2.28)$$

Assuming all rays have the same $\bar{\Gamma}_{det}(\alpha)$, and such probabilities are independent random variables, the probability the LiDAR detects the target with all the N_θ rays, thus enlarging the target (error type 1) is:

$$\begin{aligned} P_{det-1-ALL} &= \left[\int_0^{\Delta\theta} P_\alpha(\alpha) \cdot \bar{\Gamma}_{det}(\alpha) d\alpha \right]^{N_\theta} \\ &= [\bar{\Gamma}_{det}(\Delta\theta)]^{N_\theta-2} \cdot \left[\int_0^{\Delta\theta} P_{\alpha-Out}(\alpha) \cdot \bar{\Gamma}_{det}(\alpha) d\alpha \right]^2 . \end{aligned} \quad (2.29)$$

Thanks to the expression eq. (2.29), it is possible to retrieve the magnitude of the type 1 error (**enlargement**) made by the IUT:

$$\epsilon_{1-ALL} = N_\theta \cdot \Delta\theta - \xi . \quad (2.30)$$

As reported at the beginning of the section, if there is an **enlargement**, it also indicates the presence of error type 3 **shift**. In fact, the error ϵ_{1-ALL} corresponds to the error 3 $\epsilon_{3-ALL} = \epsilon_{1-ALL}$ equals to the difference in the position the actual target center and the N_θ rays center. Then, assuming the target can be found within the

N_θ rays with equal probability, the mean value of that error is 0, while the maximum value is:

$$\max\{\epsilon_{3-ALL}\} = (\Delta\theta - \beta)/2, \quad (2.31)$$

Exploiting the same approach, it is possible to derive from eq. (2.29) the probability of the most extreme type 2 error, **shrinkage**, thus the case in which none rays detect the target.

$$P_{det-2-NONE} = [1 - \Gamma_{det}^-(\Delta\theta)]^{N_\theta-2} \cdot \left[1 - \int_0^{\Delta\theta} P_{\alpha-Out}(\alpha) \cdot \Gamma_{det}^-(\alpha) d\alpha\right]^2. \quad (2.32)$$

The flexibility of that method allows to derive the different combinations of error in terms of probability and magnitude. For example, it is possible to compute the probability that only the all internal rays detect the target and the relative error.

$$P_{det-2-NoOut} = [\Gamma_{det}^-(\Delta\theta)]^{N_\theta-2} \cdot \left[1 - \int_0^{\Delta\theta} P_{\alpha-Out}(\alpha) \cdot \Gamma_{det}^-(\alpha) d\alpha\right]^2. \quad (2.33)$$

$$\epsilon_{2-NoOut} = (N_\theta - 2) \cdot \Delta\theta - \xi. \quad (2.34)$$

The same approach can be used to treat the **cross-talk** if it is present, thus deriving the probability of error 4. In this case, at least the rays adjacent to the outer rays must be considered since the LiDAR may detect the target with these beams. Let's assume that cross-talk is present only in the external beams, that is, the rays immediately adjacent to the outer beams, i.e. $\{i-1, i+N_\theta\}$ in the Fig. 2.16. The probability the LiDAR detects the target with each one of these rays is:

$$P_{det-ext} = \int_0^{\Delta\theta} P_{\alpha-Out}(\alpha) \cdot \bar{\Gamma}_{det}(\alpha) d\alpha. \quad (2.35)$$

Hence, the probability to detect the target with all the N_θ plus the two external rays is:

$$P_{det-4-ALL} = P_{det-1-ALL} \cdot \left[\int_0^{\Delta\theta} P_{\alpha-Out}(\alpha) \cdot \bar{\Gamma}_{det}(\alpha) d\alpha\right]^2, \quad (2.36)$$

and the relative maximum type 4 error is:

$$\epsilon_{4-ALL} = (N_\theta + 2) \cdot \Delta\theta - \xi. \quad (2.37)$$

As for the other errors, this approach allows to derive all the other combinations of error, e.g. only one external ray, none external ray etc.

In conclusion, note that the proposed approach has been described considering only the azimuth plane and considering a target that completely cover the vertical angular

sector $\Delta\phi$ plus any eventual vertical cross-talk. Nevertheless, the same consideration can be done for the eventual errors due to vertical quantization, exploiting a linear stage that enable the vertical movement of the target, for example. Moreover, using a two-axis stage the jointly contribution of these errors can be investigated. In Section 3.5, an example of evaluation of single ray empirical probability evaluation is accomplished using an MRS 6000. This example is given to evaluate the results that this method can provide.

Chapter 3

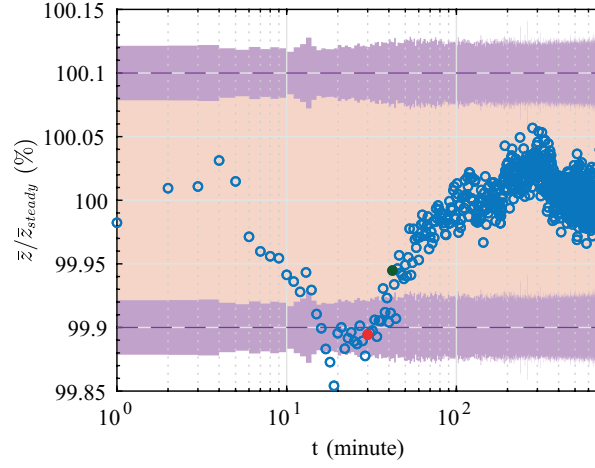
LiDAR Static Characteristics: Results and Discussion

In this chapter I am going to present you the results of the various characterization analysis described in previous chapter. These analysis have been performed to evaluate the measurement method and setup proposed; to do that, by way of example, these approaches have been applied to popular commercial LiDARs. The results obtained have been useful to evaluate the potentiality of the measurement procedures but also reveal some interesting properties of the studied commercial LiDARs.

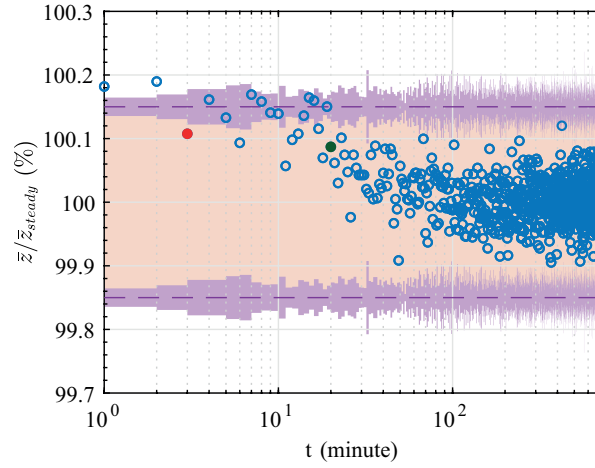
3.1 Warm-up and Stability

In the following the results of the characterization of warm-up and stability. The proposed setup and the characterization procedure were tested by analyzing and comparing the performances of two commercial LiDARs: the VLP 16 and the MRS 1000. The test has been run by placing the target at a distance $d \approx 6.5$ m. Being $P(t)$, the set of point analysed, at this distance, the number of points completely falling on the target, i.e. the cardinality of $P(t)$, is $N_{t-MRS} = 16$ and $N_{t-MRS} = 23$. The test lasted 12 hours, acquiring a PC at a minute, thus resulting in $N_{TOT} = 720$ acquisitions. For the distance z , the tolerance limits, T_L and T_U were set at ± 0.15 % of $\bar{z}_{steady}$. Otherwise, the tolerance limits for the intensity were set at ± 0.10 % of $\bar{I}_{steady}$ because of the greater variability in the signal $\bar{I}(t)$ respect with the estimated distance. The target reflectance for the MRS 1000 (nominal emission 850 nm) is about 67 %, whereas for the VLP 16 (nominal emission 903 nm) is about 72 %. During the test, the ambient temperature ranged from 18 °C to 20 °C, with a mean value of 19 °C. The thermal expansion coefficient of the aluminium rail can be approximated to $2.4 \cdot 10^{-5} \text{ K}^{-1}$. Hence, the changes in the rail length were negligible for the analysis of warm-up and stability. Fig. 3.1 shows the results for the distance

estimation, and Fig. 3.2 shows the results for the intensity. The results refer to the normalized mean distance and intensity. Table 3.1 resumed the results of these analysis. The stability, analyzed through the standard deviation, is expressed with the parameters $\gamma_z = s_{\bar{z}-steady}/\bar{z}_{steady}$ and $\gamma_I = s_{\bar{I}-steady}/\bar{I}_{steady}$.

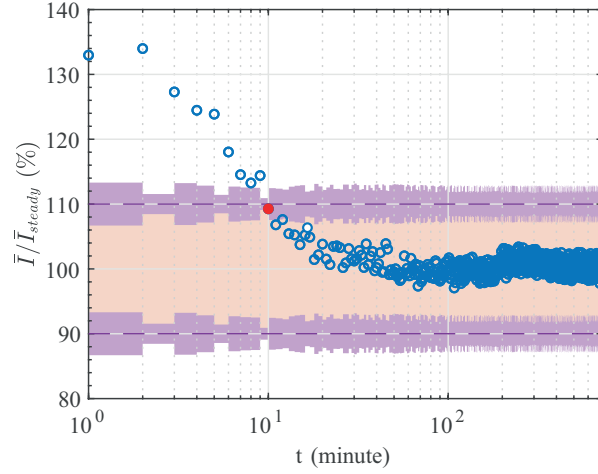


(a) VLP 16

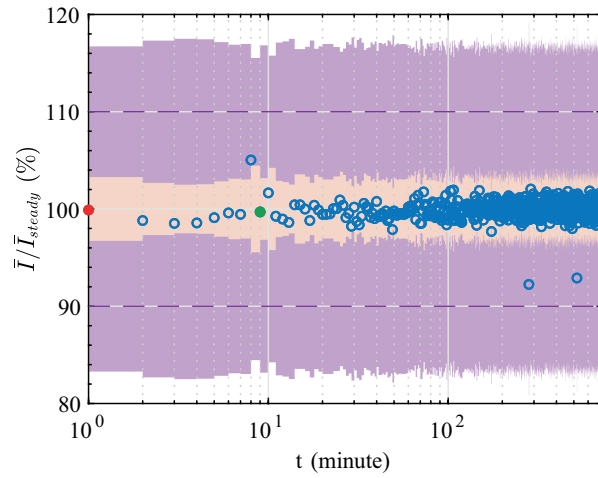


(b) MRS 1000

Figure 3.1: Analysis of the warm-up and stability related to the distance estimate. The tolerance limits (— —), TL and TU are set at ± 0.15 of $\bar{z}_{steady}$. The guard bands are represented by the purple areas. The lower limit of the warm-up time, t_{warm-L} , is highlighted by a red bullet (•), whereas the upper limit of the warm-up time, t_{warm-U} , is represented by a green bullet (•).



(a) VLP 16



(b) MRS 1000

Figure 3.2: Analysis of the warm-up and stability related to the intensity of the detected signal. The tolerance limits ($- - -$), TL and TU are set at ± 0.10 of $\bar{I}_{steady}$. The guard bands are represented by the purple areas. The lower limit of the warm-up time, t_{warm-L} , is highlighted by a red bullet ($\bullet$), whereas the upper limit of the warm-up time, t_{warm-U} , is represented by a green bullet ($\bullet$).

Table 3.1: Estimated Warm-up time and stability.

Parameter	$[t_{warm-L}, t_{warm-U}]$	Stability
MRS 1000 $\bar{z}$	[3, 20] min	$\gamma_z = 3.6 \cdot 10^{-4}$
MRS 1000 $\bar{I}$	[1, 9] min	$\gamma_z = 8.2 \cdot 10^{-3}$
VLP 16 $\bar{z}$	[1, 20] min	$\gamma_z = 2.6 \cdot 10^{-4}$
VLP 16 $\bar{I}$	[10, 11] min	$\gamma_z = 13.6 \cdot 10^{-3}$

The proposed measurement procedure allows us to characterize the warm-up and stability of two commercial LiDARs, being suitable for investigating different instruments. The results reveal a warm-up time lasting a few tens of minutes concerning the distance, and about ten minutes related to the intensity, for both instruments. Regarding stability, the estimated values are very similar for the two sensors. Moreover, the stability parameter γ_z , related to the distance, is an order of magnitude less than γ_I for both the IUTs.

3.2 Estimated Distance Error

In the following, the results of the characterization of the error of commercial LiDARs with respect to an interferometer. The proposed setup and the characterization procedure were tested by analyzing and comparing the performances of two commercial LiDARs: the VLP 16 and the MRS 1000. The test has been run varying the target distance in the range $[1.5, 21]$ m. Assume, $P(d)$ is the set of point analysed at distance d . At the maximum distance, the number of points completely falling on the target, i.e. the maximum cardinality of $P(d)$, is $N_{d-MRS} = 6$ and $N_{d-MRS} = 4$. During the test, the ambient temperature ranged from 18 °C to 21 °C, with a mean value of about 19 °C.

Fig. 3.3 shows the comparison between the distances estimated by the IUTs and measured by the INT. As previously described, the analysis takes into account the offset d_{offset} , estimated as the intercept of the linear interpolation between $\bar{z}(d)$ and the relative d_{INT} . Fig. 3.4 shows the errors calculated according to eq. (2.5). The results are resumed in Table 3.2.

Table 3.2: Mean and Maximum Absolute Errors in the estimate of the axial distance for the MRS 1000 and VLP 16.

Parameter	d_{offset} (m)	Mean Error (mm)	Maximum Absolute Error (mm)
MRS 1000	1.855	3.9	24.2
VLP 16	1.763	-4.9	-12.8

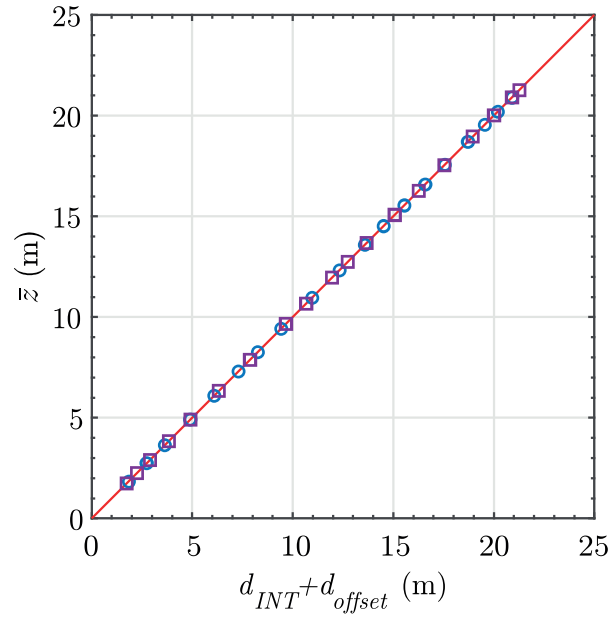


Figure 3.3: Comparison of target distances measured by both the IUTs and the interferometer. The circles ($\circ$) refer to the measurements of the MRS 1000, while the squares ($\square$) refer to the measurements of the VLP 16. The bisector of the first quadrant ($-$) was added to guide the eyes.

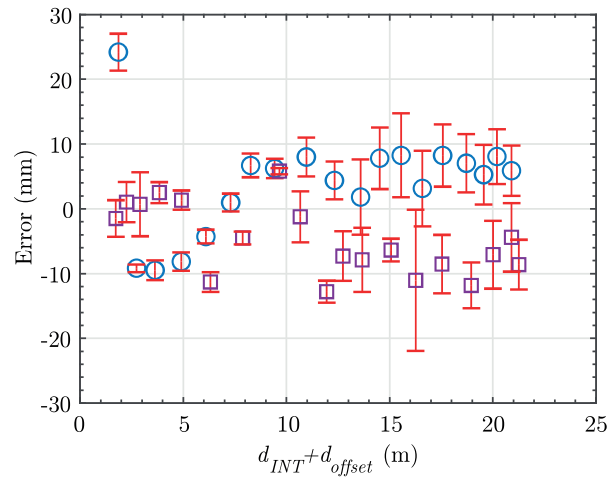
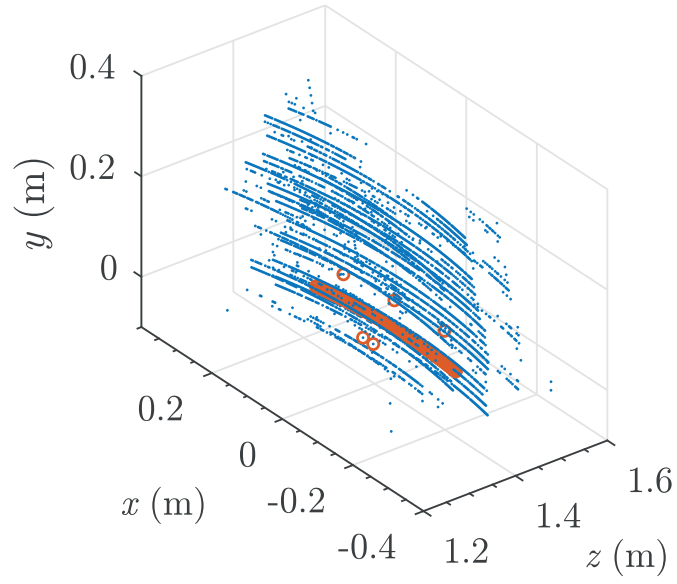


Figure 3.4: Errors estimated according to eq. (2.5). The circles ($\circ$) refer to the measurements of the MRS 1000, while the squares ($\square$) refer to the measurements of the VLP 16. The red vertical bars represent the corresponding experimental standard deviations of the mean $s_{\bar{z}}$.

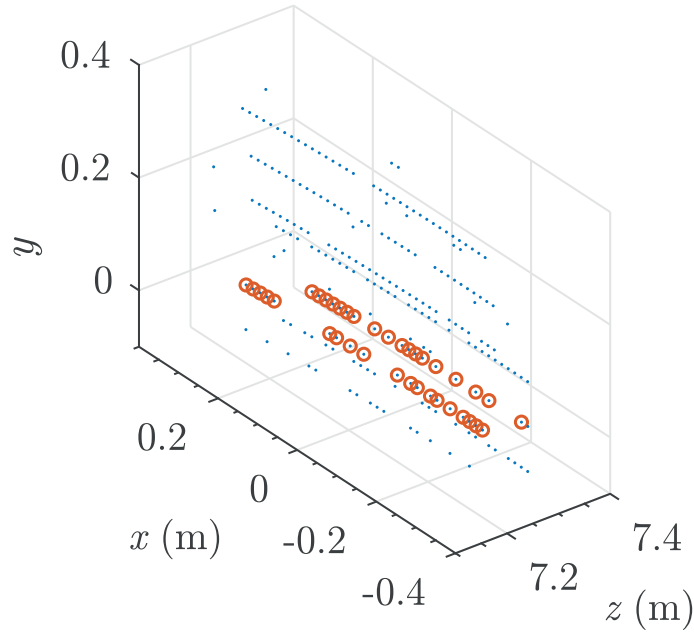
The proposed measurement procedure allows us to investigate the error in measuring the distance of an extended target in a range [1.5,21] m. The interferometer permits to have a very accurate reference for the target distance. The alignment is checked for each distance, ensuring a correct characterization. Both the instruments show good performances in measuring distances, as it is possible to observe in Fig. 3.3. The mean errors are in the order of a few millimetres, while the maximum errors are in the order of tens of millimetres. The MRS 1000 suffers from a higher maximum absolute axial error than the VLP 16, while the mean error is similar.

3.3 Axial Error

In the following, the results of the characterization of axial error and effects due to the approximation intrinsic to 3D pulsed LiDAR. The measurement procedure has been tested by analysing an MRS 6000 by Sick. This 3D ToF Pulsed LiDAR has a fixed scanning frequency of 10 Hz and three echo filter modes named “first”, “last” and “all”. During the tests, the LiDAR was set in the “first” and “last” echo filter mode. Tests were performed in a controlled environment where both temperature and lighting were monitored. Fig. 3.5 shows the example of a PC acquired with the IUT placing the target at $d \approx 1.43$ m and 7.27 m, respectively. These figures highlight the sampling in concentric spheres, mainly observing Fig. 3.5(a), and how the approximation banding flat planes. From these figures, it is also possible to observe that the distance between points along the z-axis is fixed, and it is $\Delta d = 6.25$ cm ($\delta t = 0.4$ ns in time). In the manual of the IUT [51] the value of the quantum is not present, but a systematic error is reported as $R = 12.5$ cm, thus two times the axial distance quantum.



(a)

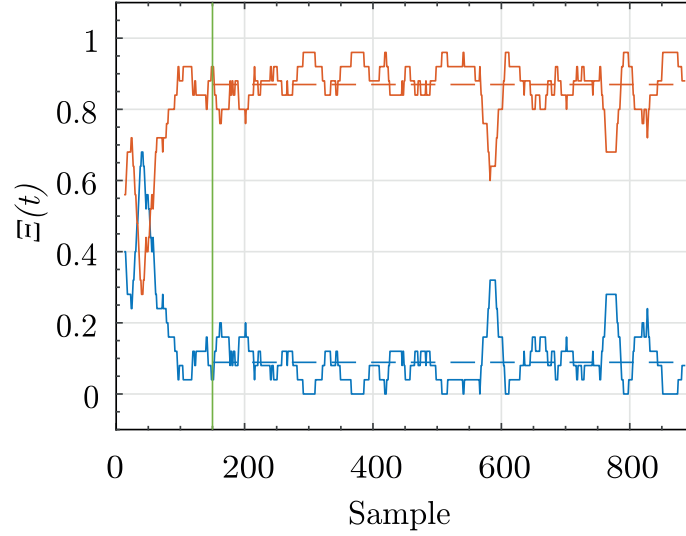


(b)

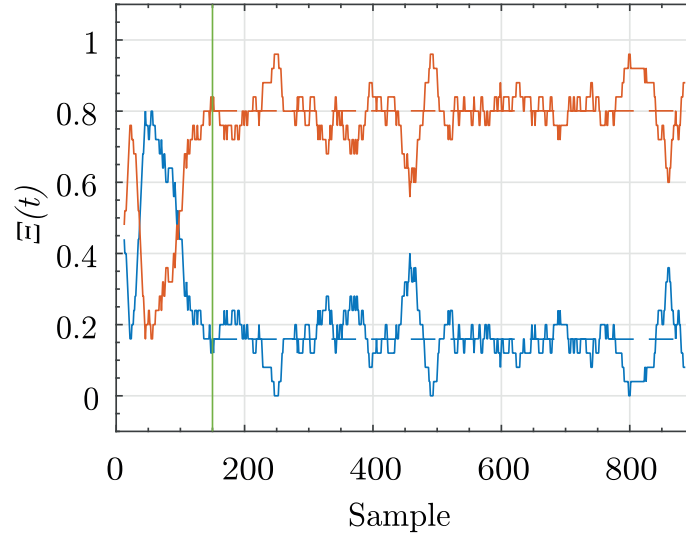
Figure 3.5: Examples of PCs acquired by the IUT. (a) Single PC acquired by the IUT once the target was at a distance $d \approx 1.43$ m (echo filter: “first”). (b) Single PC acquired at a distance $d \approx 7.27$ m (echo filter: “last”). The blue dots ($\bullet$) represent the point falling on the target. The orange circles ($\circ$) represent the central points of the analyzed elevation channel ($\phi = 0^\circ$). Depending on the position of the target respect with to the bins, the points tend to fall only on one bin (a) or to distribute themselves in adjacent bins as in (b).

As described in Section 2.3.2, the warm-up analysis on a single point was performed by analyzing how the P point distributed among the various bins as a function of time. The acquisition frequency was a sample at a minute for 15 hours.

Fig. 3.6 shows $\Xi(t, r_{bin})$ obtained for two different bins r_{bin} at $d \approx 1.43$ m and 7.28 m. As can be seen, after about $n = 150$ samples ($t_n = 150$ min), the trends related to the various bins stabilize. The warm-up time t_w was therefore set equal to 150 min. Moreover, it is possible to see that the fluctuation of the drift of the estimate in time is negligible than the fluctuation of the random variable.



(a)



(b)

Figure 3.6: $\Xi(t, r_{bin})$ for the two bins (—) and (—) between which $P(t)$, the set of point analysed at instant t , distributed. The vertical green lines — represent the warm-up time t_w . The orange and blue dashed horizontal lines (—) represent the mean values of $\Xi(t, r_{bin})$ calculated for $t \geq t_w$. (a) $d \approx 1.43$ m, echo filter “first”. (b) $d \approx 7.28$ m, echo filter “last”.

After checking the Δr of the IUT and warm-up and stability analysis, the axial error was analyzed according to the procedure described in Section 2.3.2. Since

$\Delta r = 6.25$ cm and the “fine step” has to be smaller than the quantum, the “fine” step was set $d_{step} = 10$ mm. The first measurement was, thus, performed by placing the target at $d = 1.3$ m and moving it back from the IUT of 10 mm steps in the range $d \in (1.3, 1.9)$ m. The second measurement was performed by placing the target at $d = 6.8$ m and varying the target distance in the range $d \in (6.8, 7.4)$ m. The analysis of axial error was performed for both the echo filter modes “first” and “last”. Fig. 3.7 shows two example of the statistical analysis and distribution of $\Lambda(d)$ points in different admitted bins. These example refers to the $d \approx 1.43$ m and $d \approx 7.28$ m respectively.

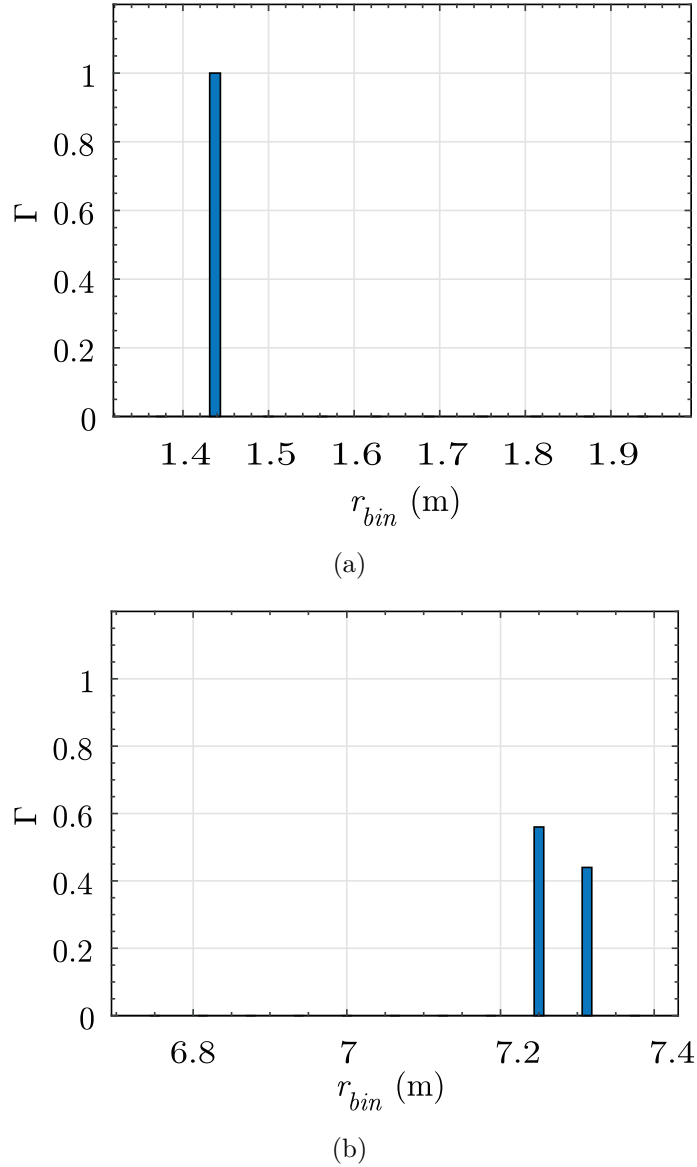


Figure 3.7: Distribution of the $\Lambda(d)$ points between the various bins when the target was at distances $d \approx 1.43$ m (a) and $d \approx 7.28$ m (b). The bars represent the $\Gamma_{det}(d, r_{bin})$ values obtained from the analysis of the $n_{PC} = 25$ PCs.

Fig. 3.7 shows two possible distribution cases. In Fig. 3.7(a) all the points $\Lambda(d)$ distribute in the same bin, differently in Fig. 3.7(b) the points distribute approximately equally on two adjacent bins.

Fig. 3.8 show, for each bin, the trend of Γ_{det} as the target distance vary. By way of example, the results for the echo filter “first” are reported in the figure, since the trend does not change for “last” mode. Each different coloured curve represents the Gaussian fit of $\Gamma_{det}(d, r_{bin})$. As an example, as shown in (a), when the target was at $d = 1.502$ m, almost all the $\Lambda(d)$ points fell on bin $r_{bin} = 1.5$ m (*) and only a few points fell in $r_{bin} = 1.5625$ m (+). In fact, $\Gamma(d, r_{bin} = 1.5 \text{ m}) = 0.88$ and $\Gamma_{det}(d, r_{bin} = 1.5625 \text{ m}) = 0.12$. On the contrary, when the target was at $d = 1.5206$ m, the $\Lambda(d)$ points equally distributed among the bins $r_{bin} = 1.5$ m (*) and $r_{bin} = 1.5625$ m (+). In fact, $\Gamma_{det}(d, r_{bin} = 1.5 \text{ m}) = 0.52$ and $\Gamma_{det}(d, r_{bin} = 1.5625 \text{ m}) = 0.48$.

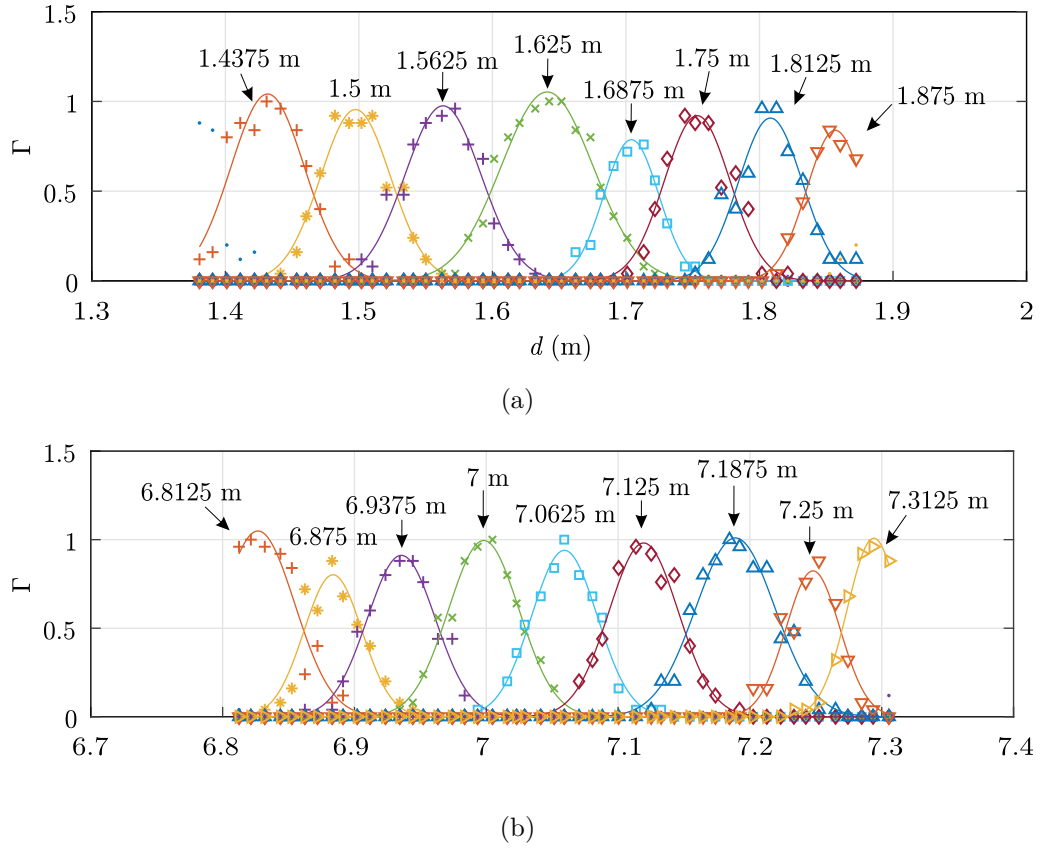


Figure 3.8: Distribution of $\Gamma(d, r_{bin})$ as a function of target position d . Each curve (solid line) represents the Gaussian function obtained by fitting $\Gamma(d, r_{bin})$ values relative to a specific bin; the numbers on the top of the curve represent the r_{bin} values, i.e. the admitted values. (a) $d \in (1.3, 1.9)$ m and echo filter “first”. (b) $d \in (6.8, 7.4)$ m and echo filter “first”.

Fig. 3.9 shows the distribution of the errors e obtained considering all the acquired measurements, that is, $n_{PC} = 25$ measurement for each of the $n_D = 50$ distances.

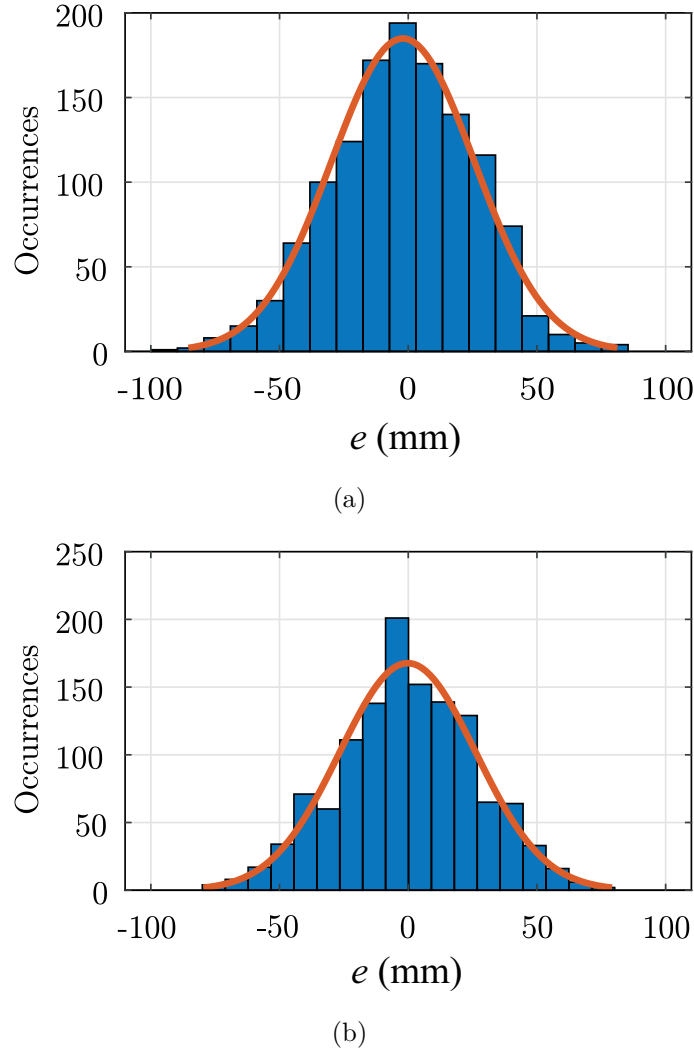


Figure 3.9: Distribution of the errors e . The height of each bar represents the number of errors that fell within the range defined by the base of the bar. The orange curve (—) represents the result of the fitting with a Gaussian function. (a) $d \in (1.3, 1.9)$ m, echo “first” (values obtained from the Gaussian fitting: $\mu_e = -2.08$ mm, $\sigma_e = 27.77$ mm). (b) $d \in (6.8, 7.4)$ m, echo “first” (values obtained from the Gaussian fitting: $\mu_e = -0.21$ mm, $\sigma_e = 26.47$ mm).

The proposed procedure aims to study the axial error, mainly focusing on the error introduced by quantization. As introduced in Section 2.3.1, the axial quantum in 3D pulsed LiDAR is determined by the LSB of the Time to Digital Converter. The time quantization error is one of the main sources of axial error. However, in addition to the time quantization error, the main sources of the axial error in pulsed LiDARs are noise, walk error, and drift [10, 47]. Thus, the presented results must be read by considering these sources. The walk error describes the effect that the

amplitude and shape of the received echo have in defining the trigger instant. The point p considered for the analysis, belonging to the set $\Lambda(d)$, are relative to the same laser source, same CH $\phi = 0^\circ$, and reflected by the same target in the same position ($\theta = 0^\circ$), thus same reflectivity, distance d and viewing angle. It is reasonable to assume that all the $\Lambda(d)$ points suffer from the same walk error. Moreover, considering the “fine” steps of $d_{step} = 10$ mm at a distance of a few meters, it is reasonable to consider the walk error the same also for target adjacent positions. Hence considering a single measurement, the walk error can be assumed negligible with respect other sources.

Considering drift, as it is possible to observe in Fig. 3.6, the drift of Ξ after the warm-up time t_w is negligible compared to its fluctuation. Thus within 750 min, the drift is negligible.

Regarding quantization, according to Rovera *et al.* [52], it is expected to behave like a uniform random variable with type B uncertainty equal to $\delta_t(12)^{1/2}$. Differently, the distributions in Fig. 3.8 and Fig. 2.10 are not uniform but normal. It is thus reasonable to assume that, for the MRS 6000, the effect of quantization is not the only one to consider when defining uncertainty but that noise plays an important role.

Fig. 3.9 reveals for the MRS 6000 an almost normal random variable with σ of about 30 mm. This value confirms and clarifies the generic information “statistical error 30 mm” provided by the manufacturer [51] together with the axial resolution $R = 12.5$ cm. However, through the proposed measurement procedure, it is possible to obtain the nature of such error and observe that the estimated axial distance of the MRS 6000 is a Gaussian random variable with a coverage probability associated with the interval ± 30 mm is about 68%.

Another possible source of error is the reflectance of the target. As described in Section 2.3.2, the procedure involves repeating the measurement at “large” steps to strongly modify the power of the echo reflected and simulate a difference in the reflectance. From this analysis, axial error appears not influenced by the target reflectance, considering these operating distances, since the σ remains constant for both the measurement ranges presented in Fig. 3.9. Hence, the resolution of the IUT is robust against target reflectance variations. Hence, it is possible to affirm that the axial error behaviour is not affected by the reflectance of the target. Differently, as introduced in Section 2.4, and according to the results will be presented in Section 3.4, the target reflectance affects the uncertainty of the estimated distance of a target.

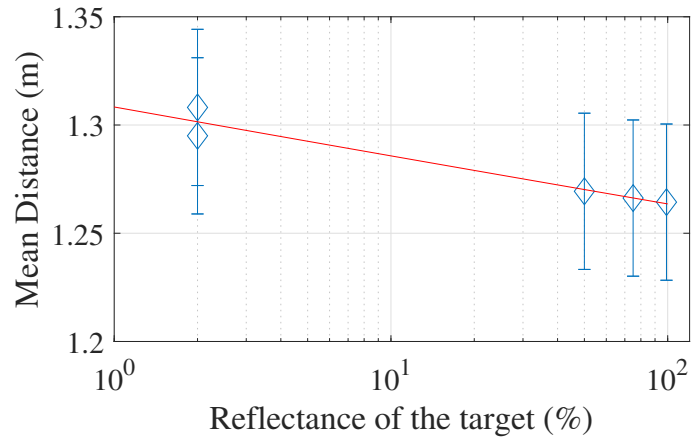
Concluding the discussion of these results, through the proposed approach, it is possible to reveal the approximation introduced in the environmental mapping by 3D LiDAR and study the axial error due to quantization. Since the procedure is

based on the statistical analysis of how the PC points are distributed among the various bins as the target position varies, the proposed method can be applied to any LiDAR affected by axial quantization. Therefore, it is possible to characterize all pulsed LiDARs and also “non-pulsed” LiDARs that exhibit such a quantization in axial measure. Note also that the exploited setup is the same one used for the characterization of error distance for extended targets, showing flexibility being adaptable for various analyses. This is a very important point of the work, as the goal is to provide scalable and simple benchmarking tools.

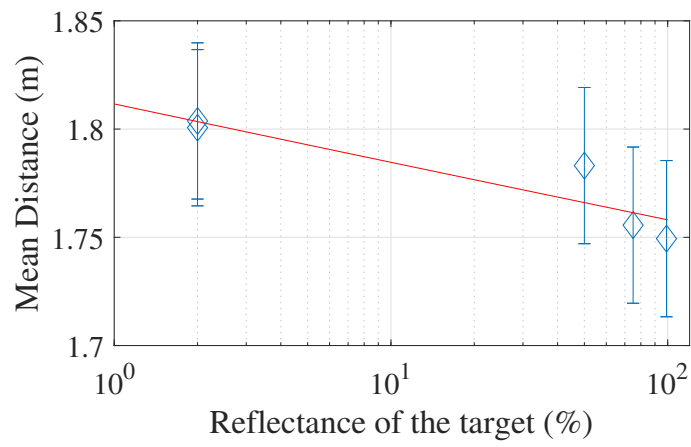
3.4 Reflectance and Multiple Echoes

In Section 2.4, I described the measurement procedure designed for characterizing the effect of reflectance and multiple echoes on the behaviour of a commercial LiDAR. To test and show the potentiality of the proposed method, in this Section, the results obtained characterizing an MRS 6000 will be shown. As for the axial error analysis, the test was run on the MRS 6000 by Sick. The beam emitted by that IUT is at the wavelength $\lambda = 870$ nm, whereas its divergences are 2.1 mrad and 65.4 mrad for the horizontal and vertical directions, respectively. From the manual of the IUT, [51], the systematic error is $R = 12.5$ cm. Hence, the uncertainty is $u_B = 3.6$ cm. This data was confirmed and studied in Section 3.3, in fact it is two times the axial quantum $\Delta r = 6.25$ cm.

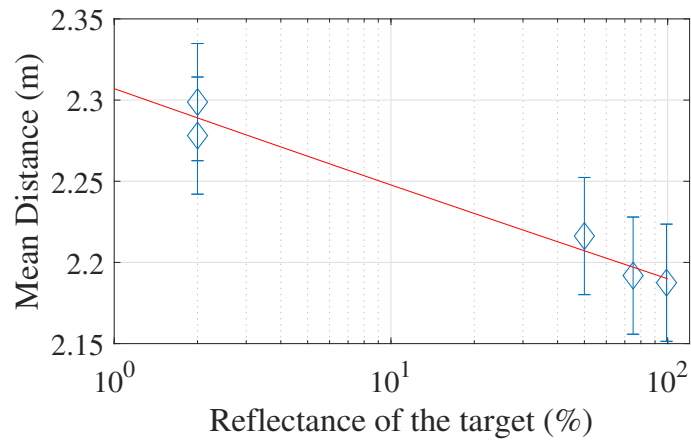
Considering the Single Echo analysis, as introduced in Section 2.4.2, the used targets are 4 circular (1 in radius) Spectralon® Diffuse Reflectance Standards with certified reflectance in the spectral range [250, 2500] nm are: $\rho_1 = 2$ %, $\rho_2 = 50$ %, $\rho_3 = 75$ % and $\rho_4 = 99$ %. The acquisitions were performed, for each of the four targets, at three distances from the IUT: $d_1 = 1.40$ m, $d_2 = 1.90$ m 2.40 m. At d_3 , the maximum measurement distance, the spot size is (5.29 x 27.38) mm thus, the targets were able to intercept the entire IUT beam horizontally. For each target position, $N_{rep} = 100$ PCs were acquired to extract N_{rep} estimated distances for each position. The mean distance was computed according to eq. (2.12) analysing the estimated distance of the single beam at polar coordinate $\theta_t = 0^\circ$ and $\phi_t = 0^\circ$. The results of this test are shown in Fig. 3.10.



(a) 1.4 m



(b) 1.9 m



(c) 2.4 m

Figure 3.10: Results of Single Echo Analysis: Mean Distance vs Target Reflectance. The second acquisition at reflectance $R = 2\%$ refers to the reference acquisition that shows the absence of a temporal drift in the measurement. The bars represent the uncertainty $u_B = 3.6$ cm while the red line is the best linear fit. Fig.(a), Fig.(b) and Fig.(c) refer respectively to the Target fix at $d = 1.40$ m, $d = 1.90$ m and $d = 2.40$ m.

The plots show the mean estimated target distance as a function of the target reflectance, for each target position, with the uncertainty type B bar. It is possible to observe that the mean estimated distance decreases linearly in a log-linear scale at the increase of the reflectance. The decreasing trend is pointed out by the red line — the best linear fit of the mean values. Slopes of the best linear fit about doubled as the distance of the Target increased from 1.90 m to 2.40 m. This increase indicates that the residual absolute measurement error tended to increase as the Target moved away from the IUT. Table 3.3 summarized these slopes as a function of the Target reflectance. By comparing these results with the type B IUT standard uncertainty, it is possible to observe that only in the case of $d_3 = 2.40$ m, which manifests a 1.26-log-variations of Target reflectance, the Target distance measurements were non-compatible.

Table 3.3: Slopes of the best linear fit as a function of target reflectance.

Distance of the target (m)	Slope (mm/log(ρ %))
1.40	-22.4
1.90	-26.8
2.40	-58.4

These results show an actual effect of the target reflectance on the estimated target distance for the considered IUT. However, considering the uncertainty type B, the distance estimation, even affected by the difference in reflectance, are compatible with the measured distance range. Nevertheless, increasing the measurement distance, the residual error increases and the measurements at 2.40 m are not compatible. These results agreed with which ones of Section 3.3 since the error induced by reflectance variations are lower than the axial quantum — $\Delta r = 6.25$ cm — thus they are not visible through the measurement methodology presented in Section 2.3.

The multiple echoes analysis was run using as backgrounds (BG) the Spectralon® Diffuse Reflectance Standards and as Target a 3D printed slab in black Polylactic Acid (PLA) of 15 mm height, 0.80 mm width and 0.2 mm thick. The target was fixed at distance $d_T = 1.3$ m, while the BGs were moved from the target-BG distance $d_{T-B}^{start} = 10$ cm to $d_{T-B}^{stop} = 60$ cm with step of $d_{T-B}^{step} = 1$ cm. As described in Section 2.4.2, multiple echoes for a single beam must be obtained. To ensure this condition, the beam section at d_T must be wider than the target width. According to the IUT manual, the beam size at d_T is about (3x15.5) mm, so only ≈ 27 % of the beam area was intercepted by the target. The size of the spot at $d_T + d_{T-B}^{stop}$ was about (4.5x22) mm, thus the BG was able to intercept the entire IUT beam when translated between d_{T-B}^{start} and d_{T-B}^{stop} . As for the previous analysis, for each position

N_{rep} PCs were acquired to compute the mean estimated distance. The mean value was associated with the uncertainty type B $u_B = 3.6$ cm. Fig. 3.11 shown the results of this characterization for each BG with different reflectance.

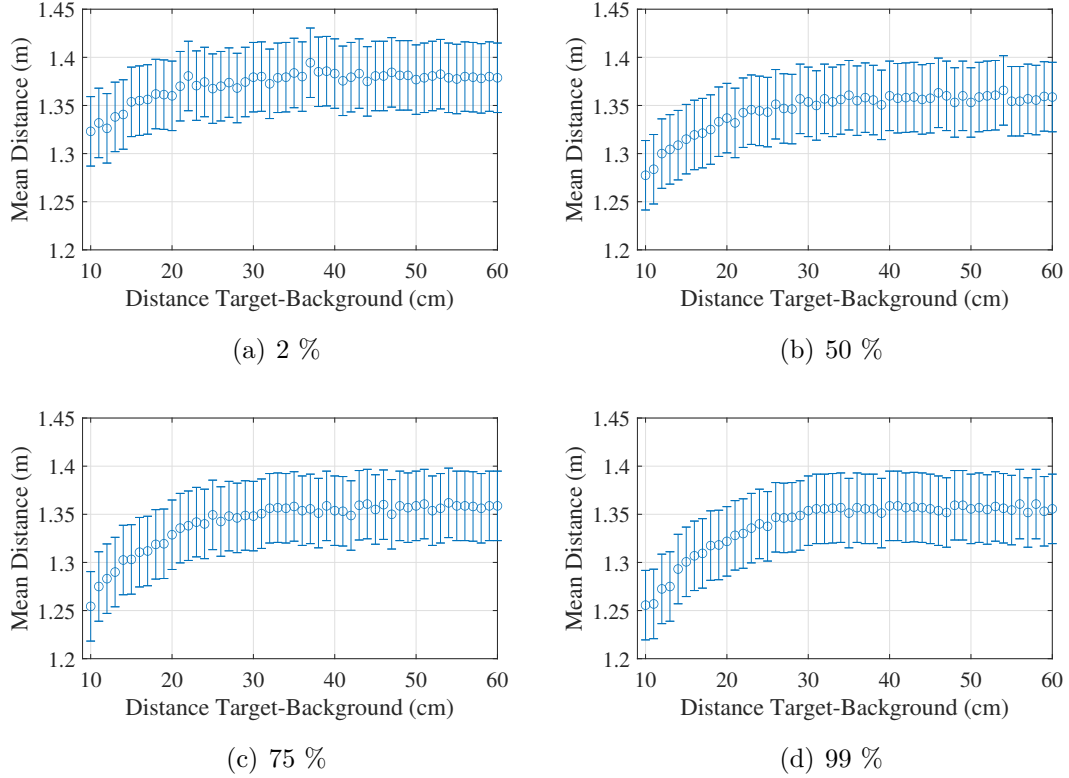


Figure 3.11: Results of Single Echo Analysis: Mean Distance vs Target Reflectance. The error bars represent the measurement uncertainty type B $u_B = 3.6$ cm. Fig.(a), Fig.(b), Fig.(c) and Fig.(d) refer respectively to the background reflectance $\rho_1 = 2$ %, $\rho_2 = 50$ %, $\rho_3 = 75$ % and $\rho_4 = 99$ %.

The results of these test reveal an influence of the background on the target distance estimation. It is possible to observe that when the distance d_{T-B} is higher than 30 cm, the mean estimated distance tends to a stable value, for all the different background. Otherwise, when the BG get closer to the target the mean estimated distance decreases. Let's define the difference D between the “steady-state” value of the mean distance — $d_{T-B} > 30$ cm — and the minimum value of the mean distance — $d_{T-B} = 10$ cm — tends to increase. Observing the results obtained with the different BGs, the difference D increases as the BG increases. Table 3.4 resume the value of D for the four BGs. Focusing on the single measurement, considering the uncertainty type B, it can be deduced that the presence of a background object at less than 13 cm at 99 %, 12 cm at 75 % and 11 cm at 50 % provides non-compatible Target distance measurements respect to the “steady-state” value.

Table 3.4: Difference D as a function of the Background Reflectance

BG Reflectance (%)	D (cm)
2	5.71
50	7.97
75	10.16
99	10.01

Manufacturers adopt various strategies and techniques to make robust the distance estimation to the optical properties of the target and other undesired effects. However, only compensation is possible and not complete removal of that effect. For that reason, it is significant to have a tool for evaluating the actual effect of reflectance or multiple echoes for a single beam. The proposed measurement procedure allows this characterization and adds some important information to the axial error characterization presented in the Sections 2.3 and 3.3. The results of axial error characterization obtained moving the target by “large” steps (1.5 m and 7 m) show that axial error, due to quantization, is not influenced by the reflectance. However, variations in reflectance result in an error in the mean distance estimation, and the addition of a background introduces other sources of errors. Considering the MRS 6000, the error introduced by reflectance variations or multiple echoes may be negligible for applications where long distances must be estimated. Nevertheless, in object recognition applications, the difference in reflectance may deform the object, making it unrecognizable.

3.5 Detection Probability

In this section the results of the single ray empirical probability evaluation are described in Section 2.5. The following results are given to provide an example of commercial LiDAR characterization with the proposed method. The proposed measurement procedure allows retrieving the empirical detection probability Γ_{det} calculated as in eq. (2.22). Γ_{det} can provide immediate information about the IUT, and it can be used to quantify the probabilities and magnitude of the transversal errors due to quantization: i) **enlargement**, ii) **shrinkage**, iii) **shift** and iv) **cross-talk**. In addition, the proposed method can be employed to estimate the effective beam waist w_{eff} as the distance of the target changes.

The presented results have been obtained using as IUT an MRS 6000. The test was run using the following setting.

- Width of the knife $w_k = 10.0$ mm.

- Height of the knife $h_k = 400$ mm.
- Thickness of the knife $t_k = 0.7$ mm.
- Surface Reflectance of the knife $\rho = 75$ %.
- Horizontal run of the linear stage $x = 50$ mm.
- Distance of the knife $d_k = [2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0]$ m.
- Distance of the background $d_{bg} > 100$ m.
- Considered beam with polar coordinates ($\theta_t = 0^\circ, \phi_t = 0^\circ$)

The analysis was performed in an environment with controlled temperature and lighting. Fig. 3.12 shows the behaviour of Γ_{det} varying the knife position θ_k observing the ray θ_t at different knife distances. In the figure, the knife movement is given in linear displacement δx instead of angular displacement to provide a clearer graphical representation. The dashed lines represent the angular sectors of the beam θ_t and of the previous and successive beams, θ_{t-1} and θ_{t+1} .

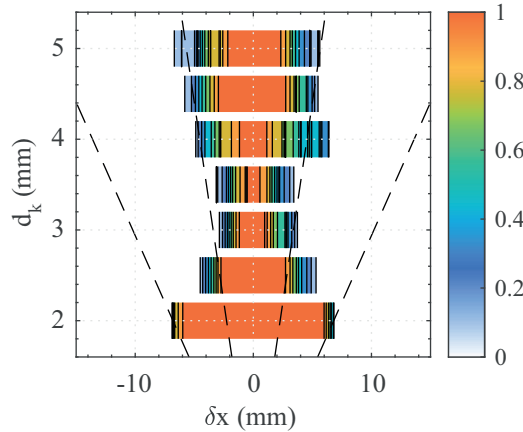


Figure 3.12: Γ_{det} functions obtained analyzing the $\theta_t = 0^\circ$. ray by varying the horizontal position δx of the knife. The measurement has been repeated at different knife distances from the IUT. The dashed lines represent the angular sectors of the θ_t ray and its adjacent beams. It is possible to observe the presence of cross-talk at $d_k = 2$ m and $d_k = 2.5$ m.

From this figure, it is possible to retrieve the effective beam waist w_{eff} setting a probability threshold Γ_{det-th} depending on the application of interest.

Fig. 3.12 shows the presence of cross-talk at knife distance $d_k = 2.0$ m and $d_k = 2.5$ m. Fig. 3.13 reports the Γ_{det} function at $d_k = 2$ m for the beam θ_t and its adjacent beams. In the figure, the grey dot-dashed lines represent the optical axis of the beams, while the black dashed lines represent the relative angular sectors of width $\Delta\theta$. Observing this plot, the relevant presence of cross-talk is evident,

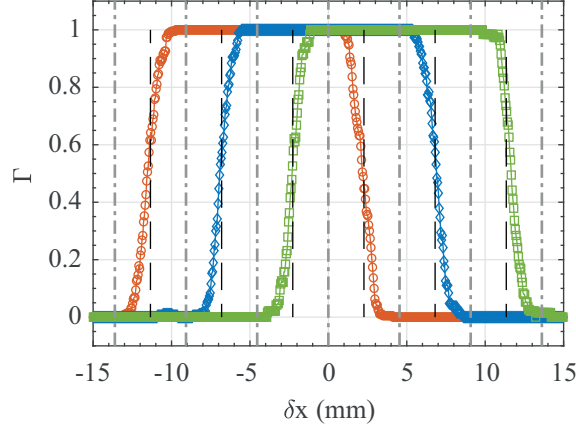


Figure 3.13: Γ_{det} functions obtained analyzing the $\theta_t = 0^\circ$. ray and its adjacent beams at knife distance $d_k = 2$ m. The dashed black lines (---) represent the angular sectors of width $\Delta\theta$, while the dot-dashed grey (— · —) lines represent the optical axis of the relative rays.

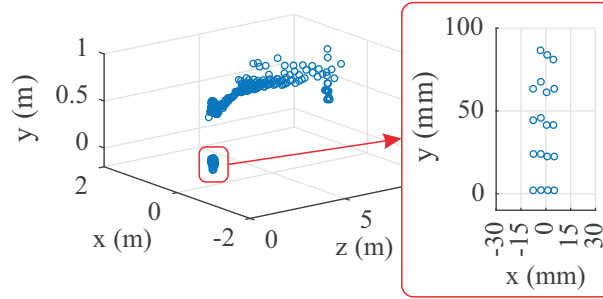


Figure 3.14: PC acquired by position a target of width $w = 3.5$ mm at 2 meter from the IUT. The target has a surface reflectance $\rho_t = 75\%$. The target has an angular extension lower than the azimuth resolution of the width $\Delta\theta$; thus, it should be represented by a single point. However, the target is reconstructed with 4 adjacent points in the PC. This effect is due to the cross-talk.

even in more external beam respect with the beams adjacent to θ_t . To highlight the effect of cross-talk, as an example, Fig. 3.14 shows the PC acquired placing a thin target ($w = 3.5$ mm), with the same surface reflectance of the knife, at $d_k = 2$ m. According to the MRS 6000 manual [51], the horizontal angular resolution $\Delta\theta = 0.13^\circ$, thus at 2 m, the angular sector width is ≈ 4.85 mm. The target is thinner than the angular sector, and in absence of cross-talk, it should be represented by a single point in the PC. However, in Fig. 3.14, the target is represented by four adjacent points, confirming the cross-talk. Due to this phenomenon, the target width is increased by 5 times, from 3.5 mm to 18.5 mm. The results provided in this section show the potentiality of the proposed method in providing useful tools to evaluate the detection capability of a commercial LiDAR. By analyzing the empirical detection probability, it is possible to derive the probability of transversal error presented in Section 2.5, which may strongly affect the recognition capability of such instruments. In particular, the cross-talk between adjacent beams can be

evaluated by defining the distance at which this phenomenon disappears for the target of interest. Furthermore, this approach allows the evaluation of the effective beam waist as the distance varies.

Chapter 4

Real World Adverse Condition

LiDAR operation, as for all the instruments relying on optical measurement technique, strongly depends on the optical properties of the transmission medium. All the characterizations presented in previous chapters, such as many studies and works published in recent years [34, 37, 38, 53], have focused on LiDARs performances in good visibility. Otherwise, real world applications suffers of several conditions that may strongly degrade the performance of LiDARs. Considering agricultural automotive, the phenomena that may influence the transmission medium are mainly two: the dust and, more in general, the debris rising during field operations, and the adverse weather conditions, which are the focus of this chapter.

Adverse weather conditions can significantly alter the optical properties of the environment, affecting the target distance estimation. Therefore, it is important to study how LiDAR estimates are affected by weather conditions such as rain, fog, and snow, and to provide tools to compare the performance of different instruments under these conditions. Fog, in particular, can be a major safety issue in the automotive and agriculture industries, as it can reduce visibility to just a few meters [54], making it difficult for drivers to see their surroundings. However, their performance can be significantly impacted when immersed in a bank of fog. My work is, thus, focused on the study of the performance of LiDARs in a foggy environment.

The best way to experimentally investigate the effect of fog on LiDARs is to immerse both the instruments and the eventual target in fog, and, for example, run the characterizations presented in previous sections. Because typical automotive applications require measuring objects from a few meters to several tens of meters, designing and realizing suitable experimental configurations is very complex and expensive. Examples of a large experimental facilities that allows both LiDAR (Light Detection and Ranging) technology and a target to be placed in a foggy environment is the Adverse Weather Facility at CEREMA (Centre d'Etudes et d'Expertise sur les Risques, l'Environnement, la Mobilité et l'Aménagement) in

Clermont-Ferrand, France, and the weather chamber at the Japan Automobile Research Institute (JARI) in Tsukuba, Japan. These facilities are designed to simulate a range of adverse weather conditions, including fog, for testing and research purposes. Kutila *et al.* published commercial LiDAR characterization results exploiting the setup at CEREMA [35].

The work presented in this Chapter aims to present a measurement method able to provide information about the LiDARs behaviour in fog but at the same time being simple and economic. In continuity with the characterization methods proposed in this work and the idea of the benchmarking tool, I designed a measurement setup and procedure that are extremely simple and inexpensive to implement. The proposed setup does not require to immerse the LiDAR and the target into an environment completely full of fog. To accomplish this achievement, the fog is confined into a compartment or chamber, as will be described in Section 4.1, interposed between the LiDAR and the target. This approach allows testing LiDAR performances at different levels of fog, thus allowing the measurement of targets at considerably greater distances than the size of the fog chamber. By using this method, it is possible to test the capabilities of LiDAR without the need to build a complex and costly physical testing facility.

This approach is based on the theoretical framework that will be described in the following and, allow to relate the performances of a commercial LiDAR to the meteorological visibility. In this section, I will describe the setups and the measurement methods developed for this analysis. To evaluate the potentiality of this approach, two different LiDARs have been tested, and their results will be compared. This work has been published in [55].

4.0.1 Fog and Visibility

The proposed measurement method is based on a simplified model describing what happens to LiDAR beams beam in fog and correlating the amount of fog with the meteorological visibility. As described in Section 2.4, the reflectance of a target may affect the ability of a LiDAR to detect an object because the radiance of the reflected echo needs to be sufficient for the LiDAR to detect the object. In fact, the intensity of the current pulse generated by the LiDAR detector depends on the integral of the radiance within the field of view (FOV) of its aperture. As previously introduced, adverse weather can strongly modify the optical properties of the transmission medium. As a result, the radiance of both the LiDAR beam and the reflected echo is degraded due to these climatic conditions. It is thus crucial to study the impact of conditions such as snow, rain and fog on LiDAR performance.

Exactly calculating the power that reaches the detector requires solving the time-

resolved radiative transfer equation, which can be extremely complex and may not always have an analytical solution. Light propagation in scattering and absorbing media such as fog, rain, and snow results in multi-scattering propagation; photons, undergoing many scattering events, may be absorbed by the transmission medium or the surrounding environment before reaching the aperture of the LiDAR detector. The complexity of this phenomenon is very high, and the complete mathematical treatment of the light beam attenuation is substantially impossible. Therefore, it is convenient to introduce approximations to obtain a more practical model that is more suitable for automotive applications. Considering the fog condition, many models have been developed over the years. The World Meteorological Organization (WMO) proposed a simple and useful parameter to describe the attenuation of light propagating in a fog bank, the Meteorological Optical Range (MOR). This parameter provides an estimate of the fog intensity in a fog bank in terms of meteorological visibility, resulting extremely suitable for automotive applications. According to the definition proposed by WMO [56], the ISO 28902-1:2012 standard [57] defines the MOR (for propagation through fog droplets) as: “*length of path in the atmosphere required to reduce the luminous flux in a collimated beam from an incandescent lamp, at a colour temperature of 2700 K, to 5 % of its original value*”. Then, WMO proposed to model the light beam propagation attenuation in a fog bank through the Lambert-Beer law. Note that the Lambert-Beer law accurately estimates attenuation only when the medium absorbs light without any scattering (purely absorbing medium). Therefore, Lambert-Beer law provides an approximation of attenuation in fog, according to the irradiance of a monochromatic beam radiation that propagates along the z -axis is given by [58]:

$$E(z) = E(0) \cdot \exp \left[- \int_z \sigma(z) dz \right] , \quad (4.1)$$

where $E(z)$ is the irradiance at z , $E(0)$ is the irradiance at $z = 0$, and $\sigma(z)$ is the extinction coefficient per unit length at z . To further simplify the model, assuming fog as an homogeneous medium, eq. (4.1) reduces to its classical form:

$$E(z) = E(0) \cdot \exp(-\sigma \cdot z) , \quad (4.2)$$

where σ is the extinction coefficient of the medium. Based on its definition, the MOR is calculated as [56, 57]:

$$0.05 = \exp(-\sigma \cdot \text{MOR}) \longrightarrow \text{MOR} = \frac{1}{\sigma} \ln \frac{1}{0.05} \approx \frac{3}{\sigma} . \quad (4.3)$$

The proposed method involves using a MOR to measure the amount of fog inside a chamber, so that the performance of a LiDAR device can be studied under various and also severe levels of visibility.

4.0.2 Fog Chamber

The proposed approach provides the confinement of the fog in a compartment interposed between the IUT and the target. This choice aims to greatly simplify the complexity of the test setup and thus reduce the cost of the facility. Note that the scattering centres, i.e. droplets of fog, affect the intensity and angular distribution of the radiation pattern. Therefore, the results obtained with the proposed setup will not be exactly the same as a plant such as the CEREMA facility, where IUT and target are immersed in the fog. However, within the validity of Lambert-Beer — under the approximations previously discussed — it is possible to model the effect of fog on the LiDAR beam. In fact, from eq. (4.1), the attenuation caused by propagating through a medium with a thickness of d and an extinction coefficient of σ is equivalent to the attenuation that would occur if the medium were divided into two layers, each with a thickness of $d/2$ and with extinction coefficients of 0 and 2σ , respectively.

The proposed setup concept is shown in Fig. 4.1, and thus it is based on a chamber interposed between the IUT (Instrument Under Test) and the target along the optical path. The IUT is at a distance d_{FC} from the chamber and a distance d_T from the target. The Fog Chamber (FC) is a box that can be filled with fog generated through an Ultrasonic Mist Maker generating the fog from water, thus allowing a better approximation of actual fog than glycerol. The characterization of the fog used in these tests will be discussed in Section 4.1. As for the analysis of robustness against reflectance of targets in Section 2.4, only a single beam of the IUT is analysed, and thus, it is sufficient that a single ray can pass through the FC. Recalling Section 2.3, 3D Spinning LiDARs emit a beam along predetermined polar directions. Therefore the FC must be designed to let pass a single beam in a specific position. For the intended purpose, the FC must have windows that allow the beams of the IUT to pass through and reach the target. These windows must be optically transparent at the wavelength of the IUT. In the figure, the FC is tilted at an angle α relative to the normal of the optical axis to prevent the IUT from collecting echoes that are specularly reflected by the transparent walls. As a consequence, the geometric path within the chamber z_{FC} — thus the path immersed in fog — is increased by a factor $1/\sin\alpha$ than to the depth of the FC. During the measurement, the FC will be filled with fog, while the attenuation within the chamber will be monitored through a Laser-Photodiode (LD-PD) system.

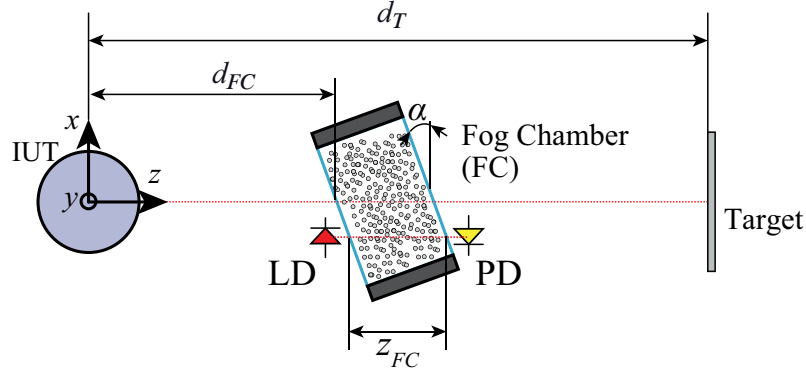


Figure 4.1: Schematic representation of the proposed concept setup. The target is placed at a distance d_T from the IUT, while d_{FC} is the distance between the IUT and the FC. The light attenuation due to the fog is estimated through the LD and PD. The FC is tilted at an angle α relative to the normal of the optical axis (z -axis) of the analyzed ray to prevent it from detecting echoes caused by specular reflections from the transparent walls of the FC (fog chamber). The geometrical path length of the IUT inside the FC is z_{FC} .

This setup has been realized in two different versions to evaluate the proposed approach. The two versions significantly differ in size, i.e. in the length of the path within the chamber. Theoretically, since only the path inside the chamber is changed, according to Lambert-Beer law approximation, the results obtained with the two setups must be the same.

In both setups, the general concept scheme of Fig. 4.1 is maintained. The attenuation monitoring system is also the same for the two versions. The LD is a laser diode model MLS-6X10 by Optical Fiber Systems, INC.), having a wavelength as close as possible to that of the IUT. The results presented in Section 4.1.1 were obtained using an LD with a wavelength of 904 nm, while the IUT wavelength was 870 nm. The beam generated by LD is brought to the FC window through a fiber and then collimated. The optical power of LD is thus measured using a photodiode, PD (model S1223 by Hamamatsu), having an active area wider than the LD laser spot. The PD signal was acquired through a transconductance amplifier.

The first version of the setup is based on a chamber (FC1) whose dimensions are 10 cm in height and width and 5 cm deep. Considering the tilting angle $\alpha = 20^\circ$, the actual path inside the chamber is $z_{FC} = 5.48$ cm. This chamber is a 3D printed box in PLA (polylactic acid), with two transparent windows in 5 mm thick polycarbonate. Because of the limited volume of FC1, the fog is generated in a separate Fog Generation Chamber (FGC) and pumped to FC1 through a pipe. Fig. 4.2 shows the 3D lateral section of FC1. The fog is pumped into the large pipe at the chamber top. Then, the roof of the FC has nozzles that diffuse the fog. The bottom of the FC has small openings on the sides that allow venting of the airflow pumped from

the FGC. The dimension of the chamber allows mounting the setup without the need for a large environment.

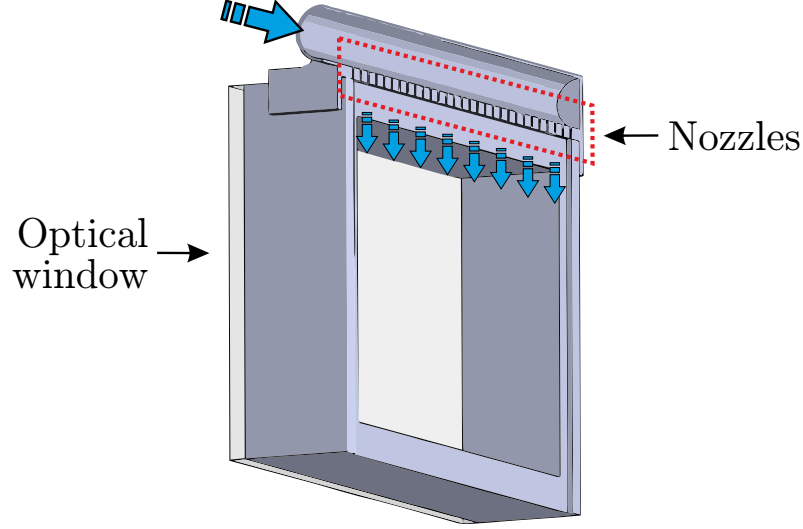


Figure 4.2: Section of FC1. The large blue arrow in the color version represents the flow of fog coming from the FGC. The smaller arrows indicate the flow of fog as it spreads within the chamber. The chamber has an internal width and height of 10 cm and a depth of 5 cm. The Fog Chamber is 3D printed in PLA (polylactic acid). The figure shows the nozzles that diffuse the fog generated in the fog generation chamber (each nozzle has a diameter of 1 mm and the nozzles are spaced 5 mm apart). The optical windows are two 5 mm thick polycarbonate sheets.

According to the proposed approach, the length of the beam travel path immersed in the fog does not influence the characterization results. In fact, the proposed method correlate the attenuation of the fog to the MOR.

To evaluate the validity of the proposed approach, a second version, based on a new Fog Chamber, was realized. The size of the chamber FC2 was significantly increased to obtain an optical path length longer than FC1. The chamber FC2 was thus realized with a $z_{FC} = 100$ cm that is twenty times greater than the depth of FC1. The chamber is a (100x100x100) cm cube with 5 mm thick transparent walls polycarbonate sheets. Because of the notably increased chamber volume (1 m^3), the fog generation system is modified for this setup. The FGC is placed on the top of the FC, as it is possible to see in the 3D render in Fig. 4.3. The fog generated in the FGC is pumped out through a fan. It then diffuses into the FC through two openings in the FGC. A small opening at the bottom of the FC allows for the ventilation of the chamber. The FGC is placed inside the FC to easily manage the huge amount of fog required to fill FC2, avoiding dispersion. According to the general concept of the setup, FC2 is tilted by an angle $\alpha = 20^\circ$ resulting in a $z_{FC} \approx 1.10$ cm.

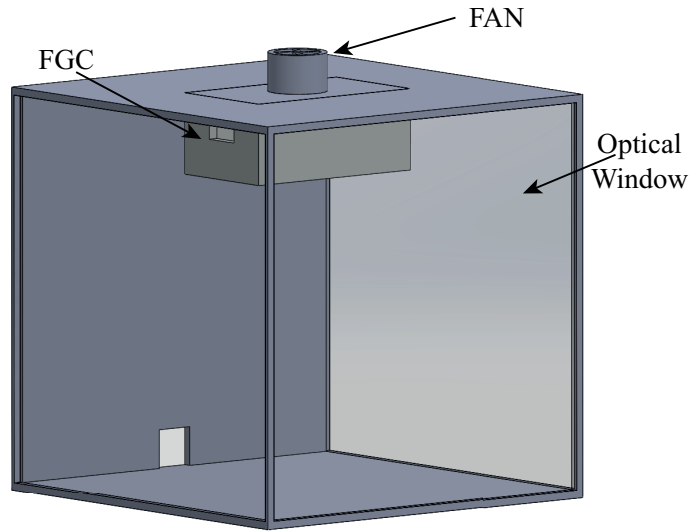


Figure 4.3: 3D view of FC2. The FGC is on top of the FC and has two openings on the sides through which the fog is pumped into the FC by the fan. The FC is a cube with a side length of $l = 1$ m, and its internal optical path is increased by a factor of $1/\sin\alpha$. The FC is made of transparent polycarbonate.

The photos of the two realized setups are shown in Fig. 4.4.

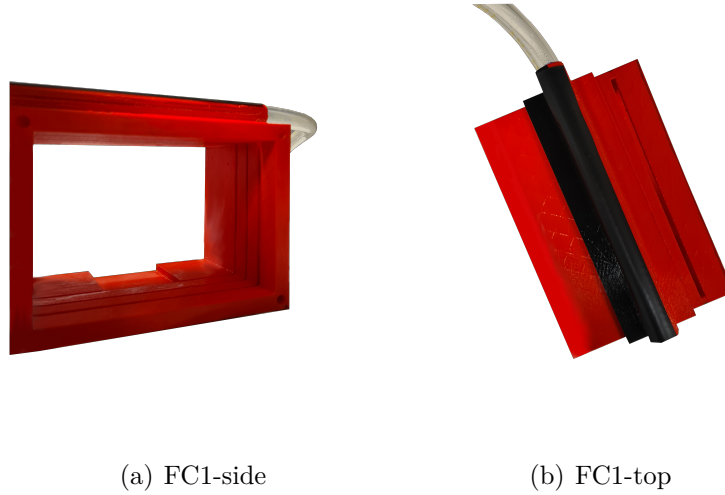


Figure 4.4: Images of the realized setups. Figs. 4.4(a) and 4.4(b) show FC1 with a thickness of 5 cm. Fig. 4.4(c) shows FC2. It is possible to observe the FGC fixed on the top of FC2. The dimension (100 cm) of FC2 is considerably larger than FC1 (5 cm).

4.1 Fog-Induced Error

This characterization aims to observe how the fog degrades the LiDAR performances. The proposed method involves the analysis of the estimated distance of a fixed target and of the error introduced by the fog as the concentration of fog inside the FC varies. The error is, thus, analyzed in terms of light attenuation and meteorological visibility, MOR eq. (4.3). Of course, the fewer the error the stronger the robustness against the fog. The procedure requires the synchronous acquisition of two quantities with a sampling frequency f_c :

1. A point cloud PC, by the IUT.
2. An estimate of the attenuation A , by the LD-PD system.

After waiting for the warm-up time of all the instruments involved, the measurement starts with the acquisition of n_{base} samples before starting to pump the fog. These samples serve as the baseline for both attenuation and target distance estimation. Successively, the fog started to be pumped while PC and attenuation were acquired periodically. After the n_{tot} acquisitions, the measurement ended. This procedure was performed n_{rep} times for each fog chamber. Thus, from each j -th PC, the estimate of target distance $d(j)$ is extracted. As for the procedures presented in Sections 2.3 and 2.4, the analysis of the effect of fog on estimated distance was accomplished by analysing a single beam at fixed polar coordinates θ_t, ϕ_t . For each value of estimated target distance $d(j)$, the respective value of light attenuation is computed by analyzing the photogenerated current i by PD. Assuming i_{base} to be the mean value of the current acquired during the n_{base} acquisitions — absence of fog —, the attenuation relative to the j -th acquisition is computed in term of optical absorbance:

$$A(j) = \log_{10} \left[\frac{i_{base}}{i(j)} \right] , \quad (4.4)$$

where A is the absorbance (quantity of dimension one often indicated using the measurement unit “optical density”, OD), and $i(j)$ is the current relating to the j -th acquisition.

According to the approximation introduced by WMO [56] and discussed in Section 4.0.1, from eq. (4.2) it is possible to extract the extinction coefficient $\sigma(j)$ within the FC:

$$\sigma(j) = \frac{A(j)}{\log_{10}(e)} \cdot \frac{1}{z_{FC}} , \quad (4.5)$$

where e is the Euler’s number. The relative MOR is:

$$\text{MOR}(j) = \frac{1}{\sigma(j)} \cdot \ln \frac{1}{0.05} . \quad (4.6)$$

$MOR(j)$ represents the length of the path in a uniform atmosphere having an extinction coefficient equal to $\sigma(j)$, required to reduce the intensity of a monochromatic collimated beam having the same wavelength as the IUT, to 5 % of its original value.

The analysis of the error on the target estimated distance must be accomplished reminding that for direct time-of-flight (ToF) LiDARs, the axial distance of each point of the PC is a quantized variable, as described in Section 2.3.1. This quantized variable can only assume a finite number of values, the bins, equispaced by the axial quantum Δr . Therefore, also the error induced by the fog on the estimated distance is quantized, because it can assume only a finite number of values. Thus, assuming, x the fog level (x can be both A or the MOR), it is possible to define the empirical probability $P(d(j), x_i, x_{i+1})$ the IUT estimate the target in a specific bin $d(j)$ when the fog level is in the specific interval $[x_i, x_{i+1})$. Defining Ψ as the set of all the d , A , and MOR values recorded during the n_{rep} tests, it is possible to calculate the empirical probability as:

$$P(d(j), x_{i+1}) = \frac{\mathbf{card}\{\Psi | d = d(j) \ \& \ x \in [x_i, x_{i+1})\}}{\mathbf{card}\{\Psi | x \in [x_i, x_{i+1})\}}, \quad (4.7)$$

where $\mathbf{card}\{\dots\}$ is the cardinality, $\mathbf{card}\{\Psi | d = d(j) \ \& \ x \in [x_i, x_{i+1})\}$ is the number of times the distance estimated by the IUT was $d = d(j)$ when the fog level was in the $[x_i, x_i + 1)$ interval and, $\mathbf{card}\{\Psi | x \in [x_i, x_{i+1})\}$ is the number of times the recorded fog level was in the $[x_i, x_i + 1)$ interval. Assuming $d(j)$ is the estimated distance that better approximates the actual target distance d_T , the higher the probability $P(d = d(j))$, the better the LiDAR performance. Note that the ideal LiDAR should have $P = 1$ for $d = d(j)$ and $P = 0$ for $d \neq d(j)$ regardless of the fog level x .

Considering the two setups, the significant difference in thickness could make the comparison between the results obtained with the setups difficult. Therefore, it is convenient to analyse the relative quantized error e_t instead of the estimated distance d :

$$e_t(j) = \frac{d_T - d(j)}{d_T - d_{FC}}, \quad (4.8)$$

where $e_t(j)$ represents the relative quantized error performed by the IUT due to the visibility reduction at the j -th acquisition. Ideally $e_t(j)$ is equal to 0 when $d(j) = d_T$ and it maximizes to 1 when $d(j) = d_{FC}$. Since there is a one-to-one relationship between $d(j)$ and $e_t(j)$, the probability $P(d(j), x_i, x_{i+1})$ calculated for $d(j)$ also corresponds to the probability $P(e_t(j), x_i, x_{i+1})$ of the IUT committing the relative error $e_t(j)$ when the fog level is within the range $[x_i, x_{i+1})$. Because of the quantized nature of the distance and the error, the error $e_t(j)$ may be positive or negative depending on whether the distance estimated by the IUT is below or above the bin that most closely approximates the target. If the IUT estimated distance is

lower than the best bin, the error will be positive. If the IUT estimated distance is higher than the best bin, the error will be negative.

After the computation of P , the results were synthetically represented in a 3D bar graph as the one in Fig. 4.5. On the x-axis is the x parameter representing the fog level (A or MOR). This axis is divided into intervals $[x_i, x_{i+1})$, ranging from the minimum to the maximum recorded fog level. On the y-axis is the quantized relative error e_t or the respective axial distance d ; in the results shown in Section 4.1.1 only the error will be represented. The height and colour of each bar represent the probability P that the error e_t is equal to $e_t(j)$ in a specific fog level, as in eq. (4.7). An ideal LiDAR should be estimated as a target always at the same distance, and, thus, the expected result should be $P = 1$ only for the row $d_T = d(j) \rightarrow e = 0$. As discussed in Section 2.3, due to noise, the distance estimate is a discrete random variable that can assume the value of several bins in the proximity of the target. Therefore, even in absence of fog, $P(d(j) \neq d(j)) > 0$, and as a consequence, $P(e_t(j) \neq 0) > 0$. However, a LiDAR robust against the effect of fog must show a probability P independent of the value of the fog level x . Thus, the value of P should be constant within each row, thus, constant as the fog changes. In Fig. 4.5, the behaviour of a real LiDAR perfectly robust against fog is represented.

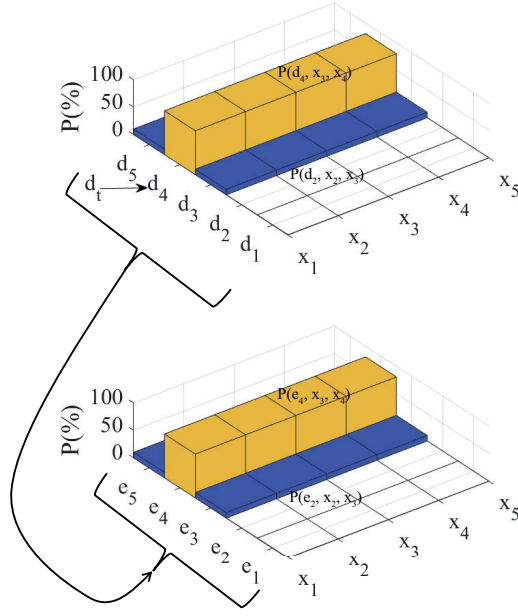


Figure 4.5: Conceptual scheme of the proposed synthetic representation. On the x-axis the fog level represented with A or MOR . The x-axis is divided into intervals based on the minimum and maximum values observed. The y-axis in the top figure shows the distance values recorded by the IUT during the tests, and the y-axis in the bottom figure displays the respective quantized error, which is directly related to the distance. According to eq. (4.7), the height and the colour of the bars represent the probability $P(e_t(j), x_i, x_{i+1})$, that is, the probability that the IUT estimates the target at a distance $d(j)$ ($e = e_t(j)$) when the fog level falls within the $[x_i, x_{i+1})$ range. The warmer the color the higher the probability; the white represents $P = 0$. For example, the probabilities $P(d_2, x_2, x_3)$ and $P(d_4, x_3, x_4)$ are shown in the top figure, and the correspondent probabilities $P(e_2, x_2, x_3)$ and $P(e_4, x_3, x_4)$, in the bottom figure. Assuming that the distance d_4 is the one that best approximates the true target distance d_T , the ideal LiDAR should have a probability equal to 1 for all the $d = d_4$ cells regardless of the value of x (and the probability of all cells for $d \neq d_4$ should be zero).

Note that, as the LiDAR and the target become more distant from each other, the solid angle from which the LiDAR detector can be seen by the target shrinks. Therefore, even in good visibility conditions, increasing the distance the intensity of the collected signal by the LiDAR reduces [10]. Recall the definition of the equivalent distance L_{eq} in [10]:

$$L_{eq}(j) = \frac{d_T}{\sqrt{T_{SP}^2(j)}}, \quad (4.9)$$

where d_T is the actual geometrical distance between the target and the IUT, and T_{SP}^2 is the round trip transmission of the medium, being T_{SP} the single pass transmission of the medium, defined as:

$$T_{SP}(j) = \frac{1}{A(j)} = \frac{i(j)}{i_{base}}. \quad (4.10)$$

L_{eq} represents the optical path length in the absence of fog required to obtain back-reflected echoes with the same power obtained in presence of fog. Considering L_{eq} , it is possible to analyze the results from a geometrical point of view, giving a more complete overview of the effect of fog. Section 4.1.1 will present the results of tests which aimed to highlight the potentiality of this approach, applying it to a commercial LiDAR.

Fog Particle Sizing

The characterization of LiDARs performance in a foggy environment obviously depends on the properties of the fog used in the tests. The fog generation in the proposed setup is provided by an Ultrasonic Mist Maker (UMM) vibrating at a specific frequency (125 kHz). The UMM agitates the water particles, which are present on the surface of the water, going into suspension in the air and thus generating fog. The size of these particles — the scatterers — determines their optical properties. Therefore, to validate the results of the analysis presented in this Section, it is crucial to verify that the size distribution of the fog droplets created by the UMM is consistent with those of the natural fog. This analysis is performed through Dynamic Light Scattering (DLS) [59]. Fig. 4.6 shows the results obtained. The average diameter of particulates is of $12\ \mu\text{m}$, therefore consistent with the size of natural fog [60].

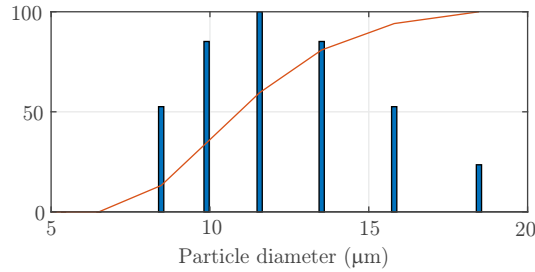


Figure 4.6: Number weighted probability density function (normalized number of particles, blue bars) and cumulative distribution function (—) of the hydrodynamic diameter of the fog particles inside the FC.

4.1.1 Error in Distance Estimation

In the following, the results of the analysis of fog-induced error in a foggy environment. To evaluate the approach described in Section 4.1 the tests were run on both chambers applying the proposed method to the LiDAR model MRS 6000. In Table 4.1.1 the settings of the instrument is recalled.

Table 4.1: Instruments settings for fog induced error test.

LiDAR	Settings
MRS 6000 by sick	Scanning frequency $f_{SCAN} = 10$ Hz Laser Return Modes: Last Wavelength $\lambda = 870$ nm

All the results presented in this section, according to Sections 4.1 and 4.2, regard the estimated distance retrieved from the single LiDAR beam with polar coordinates ($\theta_t = 0^\circ, \phi_t = 0^\circ$). The test for the measurement method for the analysis of fog-induced drift in distance estimation was performed with this measurement setting for both the Chambers FC1 and FC2:

- Distance IUT-target $d_T \approx 2$ m;
- Distance IUT-FC $d_{FC} \approx 1$ m;
- FC tilted by an angle $\alpha = 20^\circ$;
- Acquisition frequency $f_C = 1$ Hz;
- Baseline acquisition $n_{base} = 10$;
- Total acquisition $n_{tot} = 300$;
- Procedure repeated $n_{rep} = 15$;

As a remind for the reader the two chamber differ in size, and their depth are $l_{FC1} = 5$ cm and $l_{FC2} = 100$ cm. considering the tilting angle, the path lengths immersed in the fog are respectively: $z_{FC1} = 5.48$ cm and $z_{FC2} = 110$ cm. The target used in this analysis is a planar black square target 25x25 cm, with reflectance $r = 28\%$.

As an example, Fig. 4.7 shows the trends, obtained with FC1, of: i) the estimate of the target distance, d , obtained from the IUT, ii) the absorbance, A , measured by LD and PD as the fog level increases within the chamber.

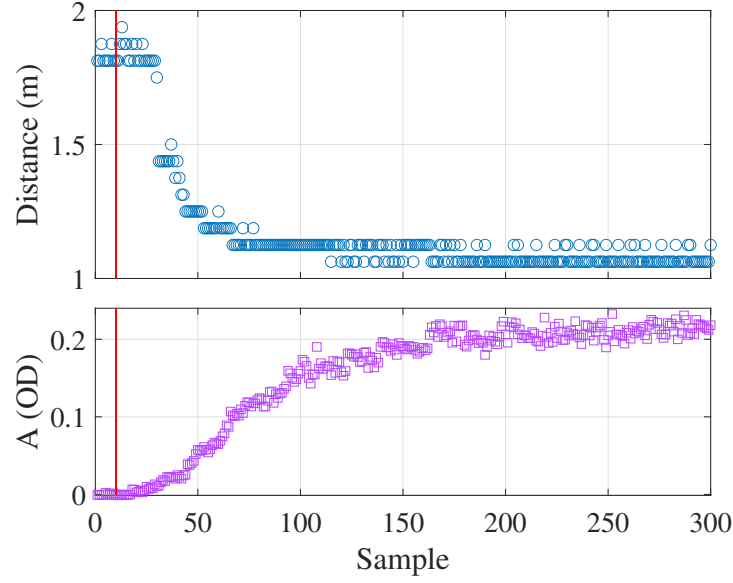


Figure 4.7: Typical acquisition for the LiDAR characterization in foggy environment. The top figure shows the estimated target distance by the IUT d ($\circ$). The bottom figure shows the trend of the absorbance A measure by the LD-PD system ($\square$). The red vertical line ($-$) represent the end of the baseline acquisition and, and the beginning of the fog pumping.

In this figure is possible to observe the quantization of the estimated axial distance, according to Section 3.3. The red line define the start of fog pumping inside the chamber. The initial estimated value is lower than the $d_T = 2$ m, and it oscillates between two different bins. This effect can be explained considering the axial error due to noise described in Section 3.3, to the optical properties of target Section 3.4 and to some contributions of the transparent windows. This phenomenon is not an issue for the test since all the results are referred to the baseline acquisitions. Concerning the fog-induced error, it is trivial that at the increases of the absorbance A within the chamber the distance estimation degrades. Furthermore, when the fog level overcomes a certain threshold the IUT is no more able to correctly reconstruct the target, but only detect the bank of fog. These results justify the study of erroneous fog detection of Section 4.2. As introduced in Section 4.1, to better analyze the fog-induced error, the probability P is calculated according to eq. (4.7). Figs 4.8, 4.9 and 4.10 shows the probability P as a function respectively of absorbance A , MOR and equivalent distance L_{eq} for both the setups. In the figures, on the x-axis is the parameter used to represent the fog level — A , MOR and L_{eq} . As described in Fig. 4.5, the x-axis is divided into fog level intervals, which have to be chosen based on the specific application. On the y-axis is the relative quantized error e_t . The z-axis and the colour of the bars represent the probability P ; the white colour stays for $P = 0$.

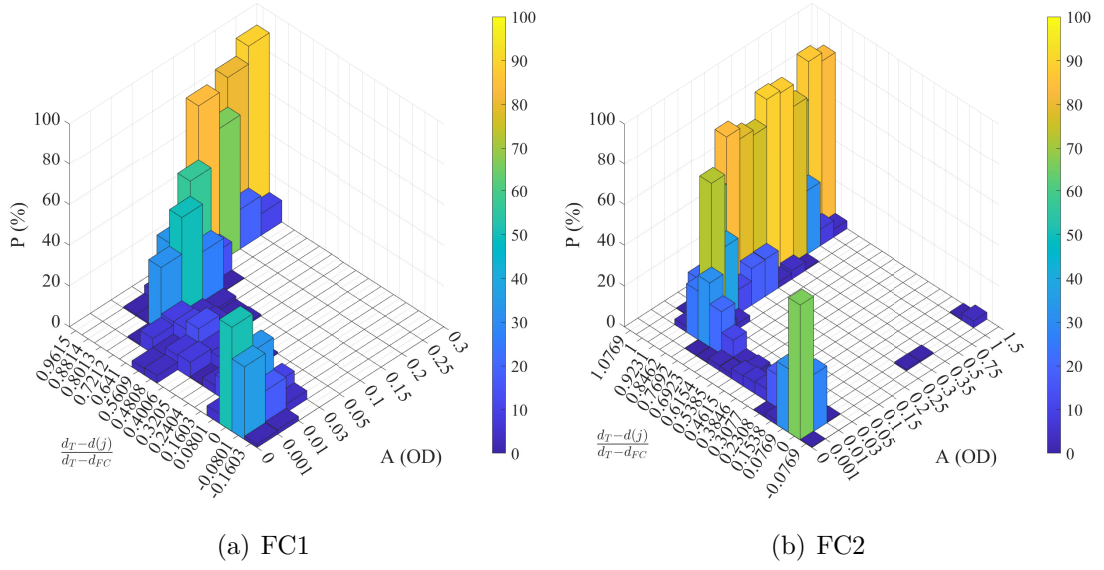


Figure 4.8: $P(\%)$ as a function of A for both the Chambers. In Fig.(a) the results for the chamber FC1 with $z_{FC1} = 5.48$ cm, and in Fig.(b) the results for the chamber FC2 with $z_{FC2} = 110$ cm

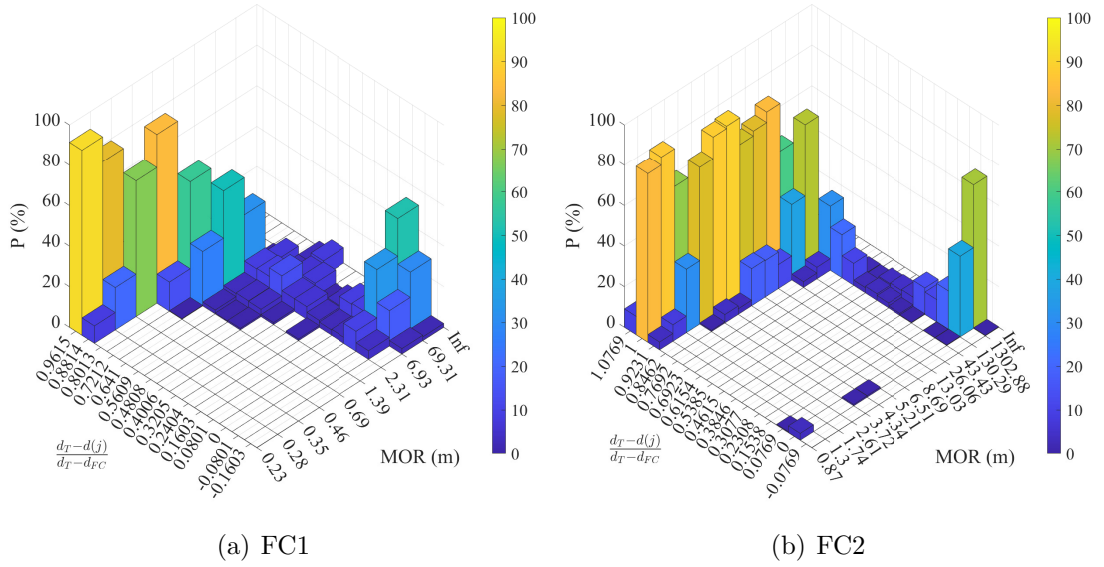


Figure 4.9: $P(\%)$ as a function of MOR for both the Chambers. In Fig.(a) the results for the chamber FC1 with $z_{FC1} = 5.48$ cm, and in Fig.(b) the results for the chamber FC2 with $z_{FC2} = 110$ cm

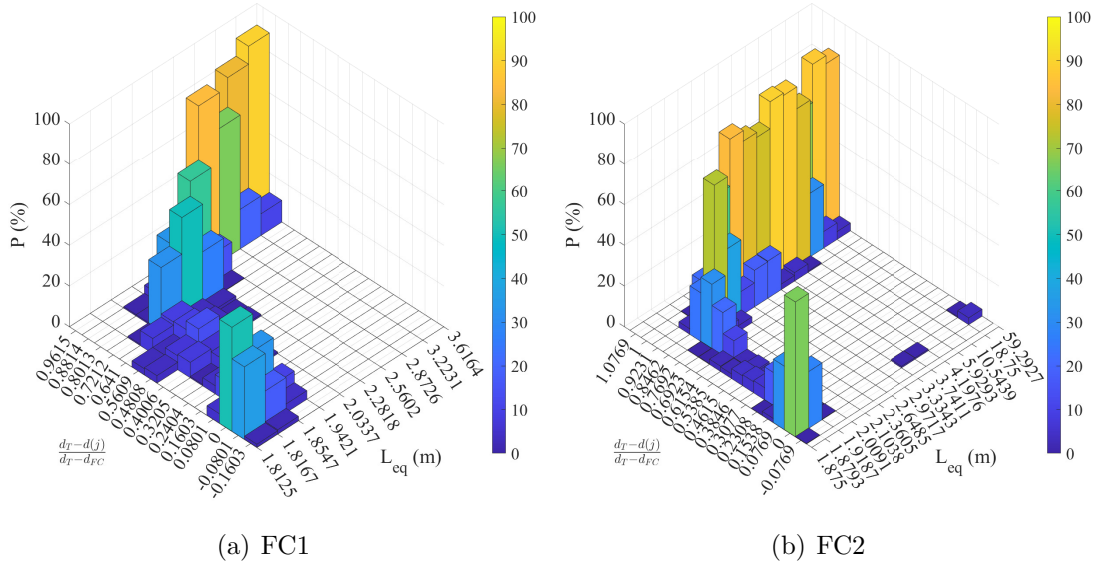


Figure 4.10: $P(\%)$ as a function of L_{eq} for both the Chambers. In Fig.(a) the results for the chamber FC1 with $z_{FC1} = 5.48$ cm, and in Fig.(b) the results for the chamber FC2 with $z_{FC2} = 110$ cm

As deducible from Fig. 4.7, these figures confirm that at the increase of the fog level, the IUT significantly deviates from the idea LiDAR behaviour, for which P is constant respect the fog level (constant P along a row of the plot). The three representations can provide different information. Concerning Fig. 4.8, for both the setups, as long as the absorbance $A < 0.01$, the highest probable error committed by the IUT is $e_t < 0.10$. Hence, the IUT is able to detect the target, correctly estimating its distance. For absorbance $A > 0.1$, the IUT no longer can estimate the target, but it reveals the bank of fog. In fact, error $e_t \approx 1$ means that the IUT is estimating a target at the FC interface, that is, at d_{FC} . Note that such fog levels can actually occur, generating a dangerous situation. This absorbance interval is relevant for the erroneous fog detection analysis. Of course, it is also possible to observe the same behaviour as a function of MOR and L_{eq} in the other representations. However, in Fig. 4.9, the intervals on the x-axis are extremely different. In fact, according to eq. (4.3), the MOR is defined as the length of the path in a uniform atmosphere having an extinction coefficient equal to $\sigma(j)$, required to reduce the intensity of the (monochromatic and collimated) beam to 5 % of its original value. The MOR value depends on the size of FC, and the same absorbance level is obtained for significantly different σ values. Therefore, the MOR is not suitable for comparing the two setups, and it is preferable to use A or L_{eq} for the evaluation of the approach. Indeed, in Fig. 4.10, when $L_{eq} > 2$ m the probability to observe an error $e_t > 0.9$ is higher than 90 %, highlighting the IUT is revealing the bank of fog. Nevertheless, the MOR representation is the best choice for comparing the results

of different LiDARs, since it quantifies the LiDARs performance as a function of the meteorological visibility, that is already used on road to describe the fog level.

4.2 Erroneous Fog Detection

The results of the fog-induced error analysis reveal that high fog density may introduce a dangerous unwanted effect: erroneous fog detection. In fact, if the fog is dense enough, the bank of fog may not only introduce an error due to the light beam attenuation, but the fog itself can produce an echo of sufficient intensity to trigger the LiDAR due to scattering. Thus, it is interesting to investigate the minimum fog density at which a specific commercial LiDAR starts to detect the bank of fog. This test can be accomplished using a modified version of the setup shown in Fig. 4.1. To retrieve this information is required to be able to distinguish the echo back-reflected by the bank of fog from other echoes. Of course, the setup in Fig. 4.1 is not suitable for this analysis. Nevertheless, the proposed method can be adapted to this particular characterization. The target behind the FC produces an echo that can be added to the fog one; this phenomenon causes an incorrect estimate of the minimum fog concentration that can be detected by the IUT. Therefore, in the presence of a target or object inside the FC, it is arbitrary to decide if the collected echo is coming from a real object or is an erroneous fog detection. Hence, this analysis must be performed without a target.

Unfortunately, completely removing the target can be complex. Commercial LiDARs for automotive applications usually have a maximum working distance of hundreds of metres, thus requiring very large spaces to have a no-target setup. To obtain the target absence without requiring big facilities, the proposed method involves the use of a tilted mirror instead of the target in the setup in Fig. 4.1. The mirror prevents the detection of unwanted echoes in good visibility conditions. In Fig. 4.11 is represented the setup used for this specific analysis. If the fog is not dense enough to be detected (top figure) the LiDAR beam travels through the FC, reaches the mirror and will be deflected by the mirror and is lost. Otherwise (bottom figure), if the concentration of fog is sufficient, the bank of fog reflects an echo intense enough to raise a point in the PC. Thanks to this setup, the power reaching the IUT depends only on the scattering echo generated by the bank of fog. The erroneous fog detection analysis based on the setup in Fig. 4.11 follows the acquisition procedure presented in Section 4.1. After the warm-up of all instruments, the synchronous acquisition of PC and attenuation estimates started with the acquisition of the n_{base} samples used as baseline. Successively the fog started to be pumped

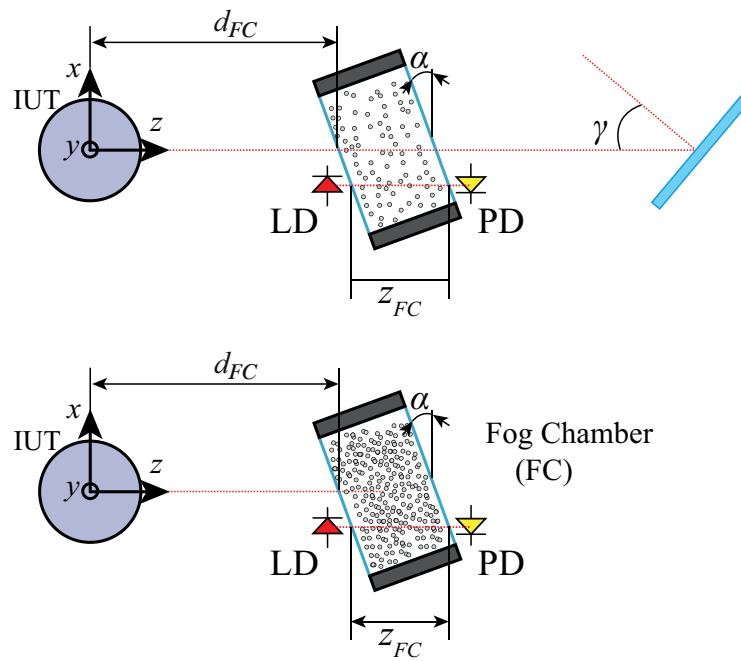


Figure 4.11: Schematic representation of the concept setup used for the erroneous fog detection analysis. The setup is a slightly modified version of the configuration in Fig. 4.1. The target is removed and replaced with a mirror tilted by an angle γ with respect to the IUT axis. The top figure shows the case where the fog is not dense enough to back-reflect an echo with sufficient intensity to detect the fog. The beam travels through the chamber, hits the mirror and is deflected and lost. The bottom figure shows the case in which the fog level is enough to generate a detectable echo by the IUT.

into the chamber, and n_{tot} samples were acquired. The procedure was repeated n_{rep} times. For this analysis, only the FC2 is used.

From each PC, the estimated distance of the target was estimated from a single beam (θ_t, ϕ_t) . Analysing the results, until the fog is not dense enough, the echo corresponding to the these polar coordinates is not picked up by the IUT. As a result, the point $p = (\theta_t, \phi_t)$ is lost and it does not appear in the PC. When the fog concentration overcomes a certain threshold, the IUT starts to collect the echo reflected due to scattering, and the IUT inserts a point at (θ_t, ϕ_t) . It is possible to define MOR_F as the maximum value of visibility for which a point appears in the PC along the half-line (θ_t, ϕ_t) . After repeating the same procedure n_{rep} times, the mean value of MOR_F and its standard deviation of the mean were computed:

$$\begin{aligned}\overline{MOR_F} &= \frac{1}{n_{rep}} \cdot \sum_{k=1}^{n_{rep}} MOR_F(k) , \\ s_{\overline{MOR_F}} &= \sqrt{\frac{1}{n_{rep}(n_{rep} - 1)} \sum_{k=1}^{n_{rep}} [MOR_F(k) - \overline{MOR_F}]^2}\end{aligned}\quad (4.11)$$

The comparison is also obtained defining the relative error in the estimated distance, for the j -th acquisitions, respect the actual distance of the FC:

$$e_F = \frac{d_{FC} - d(j)}{d_{FC}} . \quad (4.12)$$

The error is zero when $d(j) = d_{FC}$ — the IUT detects the front of the fog — and increases with the visibility.

This measurement procedure is evaluated applying on two LiDARs and comparing their behaviour. The results of this test will be shown in Section 4.2.1

4.2.1 Erroneous Fog Detection Results

To evaluate the erroneous fog detection analysis method the were tested the MRS 6000 and the VLP 16 and the FC2. In Table Table 4.2.1 the settings of the two instruments are recalled.

Table 4.2: Instruments settings for erroneous fog detection analysis.

LiDAR	Settings
MRS 6000 by sick	Scanning frequency $f_{SCAN} = 10$ Hz Laser Return Modes: Last Wavelength $\lambda = 870$ nm
VLP 16 by Velodyne	Scanning Frequency $f_{SCAN} = 5$ Hz Laser Return Modes: Last Wavelength $\lambda = 905$ nm

The procedure was performed using the following setting. As for the fog-induced error analysis, the results presented in this Section regard the estimated distance retrieved from the single LiDAR ray with polar coordinates $(\theta_t = 0^\circ, \phi_t = 0^\circ)$.

- Distance IUT-FC $d_{FC} \approx 1$ m;
- FC tilted by an angle $\alpha = 20^\circ$;
- Mirror tilted by an angle $\gamma = -20^\circ$;
- Acquisition frequency $f_C = 1$ Hz;
- Baseline acquisition $n_{base} = 10$;
- Total acquisition $n_{tot} = 300$;
- Procedure repeated $n_{rep} = 15$;

Figs. 4.12 and 4.13 show an example of a typical acquisition for the erroneous fog detection analysis for both the IUTs. The IUTs started to collect the echo when the absorbance overcomes a certain threshold. In fact, in Fig. 4.12 for low fog level, no estimated distance is reported. Fig. 4.13 show the error e_F respect to the FC according to the eq. (4.12). If $e_F \approx 0$, the IUT is detecting the fog bank. It is possible to retrieve the MOR_F value, thus the maximum visibility for which the LiDAR erroneously detects the fog. Observing the figures, it may seem that the axial distance estimate of the VLP is not quantized. However, observing a VLP 16 PC, it is possible to observe that it has an axial distance quantum $\Delta r = 2$ mm. Thus, it is impossible to distinguish the different bins by maintaining a scale that allows a comparison between the two instruments.

The analysis results are resumed in Table 4.2.1. The minimum mean fog level, maximum MOR, for which the IUT detects the fog, is reported with the standard deviation for both the tested instruments.

Table 4.3: Resume of the results of the fog detection maximum MOR

LiDAR	$\overline{MOR_F}$ (m)	$s_{\overline{MOR_F}}$ (m)
MRS6000	13.1	2.0
VLP16	3.3	0.6

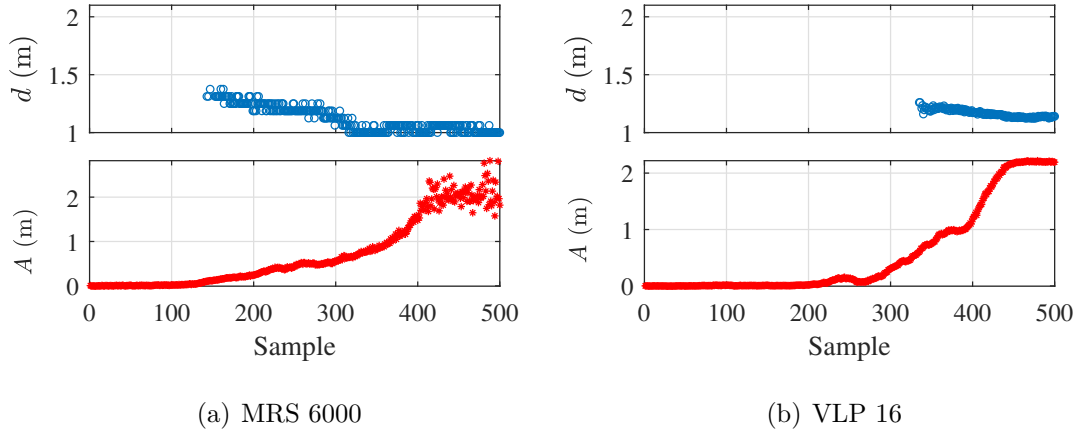


Figure 4.12: Typical acquisition results of erroneous fog detection analysis for both the tested IUTs. The figure on top shows the estimated target distance by the IUT ($\circ$), while the bottom figure shows the absorbance measured through the PD ($*$). Until the visibility is lower than MOR_F the IUT is not able to collect the echo, since the beam is deflected by the mirror.

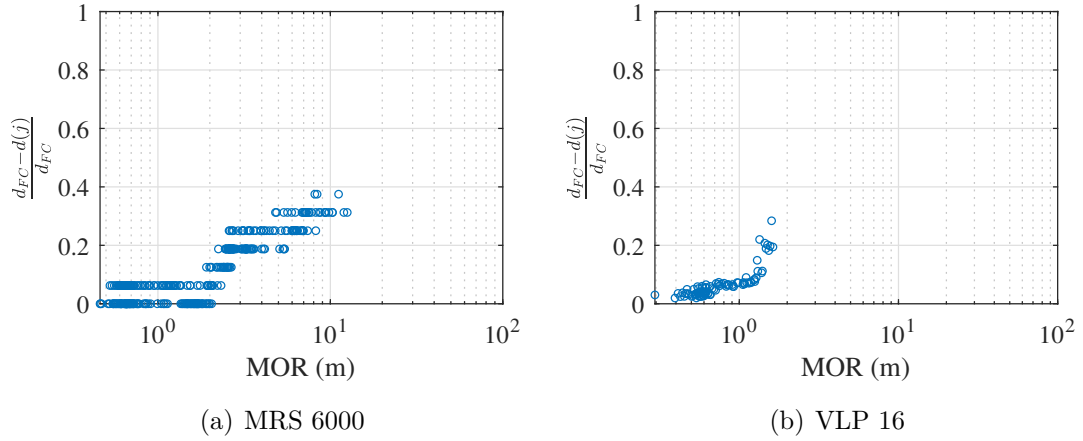


Figure 4.13: Error e_F in the distance estimation of the bank of fog for a single set of acquisitions for both the IUTs.

The VLP 16 shows a fog detection maximum $\overline{\text{MOR}_F} = 3.3$ m with a $s_{\overline{\text{MOR}_F}} = 0.6$ m. Differently the MRS 6000 shows a higher fog detection maximum visibility $\overline{\text{MOR}_F} = 13.1$ m with a $\overline{\text{MOR}_F} = 2.0$ m.

A test was performed using the setup shown in Fig. 4.1, thus replacing the mirror with an actual target at a distance $d_T \approx 2.0$ m, to have a more comprehensive view of the obtained results. This test was used to study the fog-induced drift in both instruments and allow a comparison with the results of the erroneous fog detection analysis. Figs. 4.14 and 4.15 show, as an example, a typical acquisition.

Fig. 4.14 report the estimated target distance d and the absorbance A during the acquisition at the increases of the fog level. Fig. 4.15 show the error e_t calculated as in eq. (4.8) as a function of the MOR. For this comparison, this representation is preferred over the probability plot to better emphasize the difference between these results and the result in Figs. 4.12 and 4.13. The red dashed line shows the value $\overline{\text{MOR}}_F$ retrieved in the previous analysis.

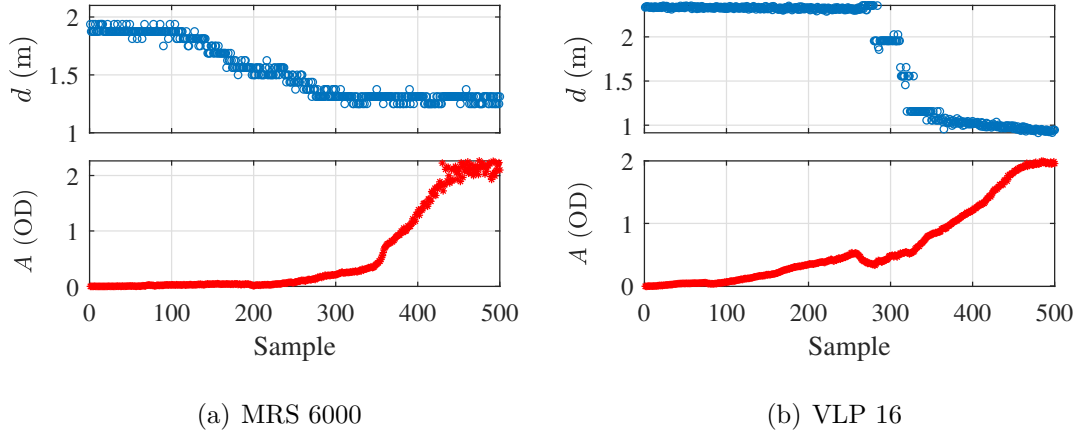


Figure 4.14: Typical acquisition results of a set of acquisitions for both the tested instruments. The figure on top shows the estimated target distance by the IUT ($\circ$), while the bottom figure shows the absorbance measured through the PD ($*$).

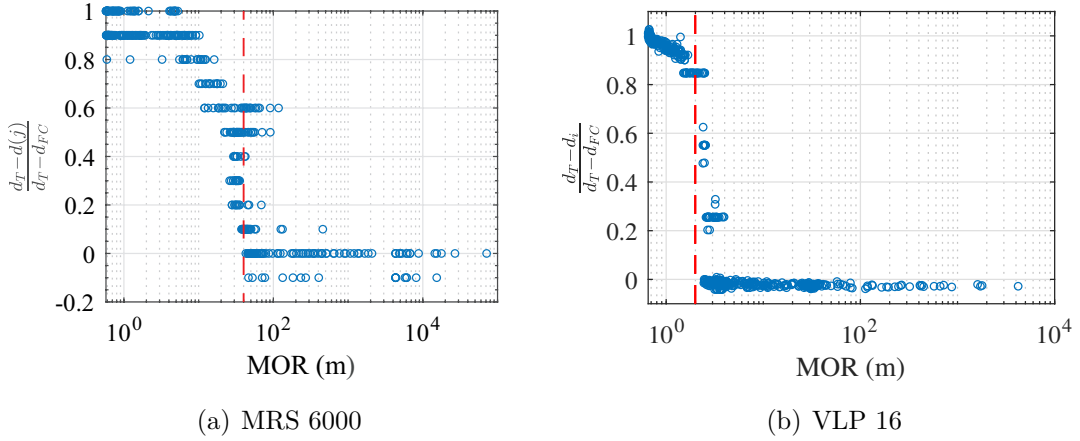


Figure 4.15: Relative error e_t as a function of the MOR for a single set of acquisitions for both the IUTs. The red dashed line points out the MOR_F value retrieved in the erroneous fog detection analysis.

The MRS 6000 shows a relative error e_t in distance estimation that tends to be 1 when $\text{MOR} < 10$ m. As the MOR increases, the error decreases progressively, reaching an error $e_t \approx 0$ when $\text{MOR} \gtrsim 40$ m. Similarly to the MRS 6000, the

VLP 16 shows an error $e_t \approx 0$ when the MOR is considerably lower ($\text{MOR} \lesssim 2$ m). Differently, the error decreases sharper than for the MRS, reaching the actual estimated distance for $\text{MOR} \gtrsim 3$ m. The combined analyses demonstrate that the distance estimation is impacted by fog, even when the fog density is not enough to create an echo that can be collected by the IUTs. Nevertheless, the two LiDARs show completely different behaviour in facing a bank of fog. The VLP 16 shows a “high-low” behaviour. In fact, the instrument detects either the fog bank or the real target, depending on the fog level. Otherwise, the MRS 6000 shows a gradual improvement in the actual target distance estimation, revealing fog level interval where the LiDAR does not detect the fog bank but also fails to correctly detect the target.

Beyond the results obtained for the tested LiDAR, the reported examples of characterization demonstrate the goodness of the proposed approach. The measurement setup and method presented in this work allow an easy-to-implement and not expensive benchmark tool to investigate the performance of a commercial LiDAR in a foggy environment. Studying the fog-induced error as a function of the MOR can be very useful mainly for automotive applications by giving information that is directly linked to environmental conditions. At the moment, one of the major limitations of the proposed method is determining the precise parameters of fog conditions and the target distance within which it can be effectively suitable. Nevertheless, the results in Figs 4.8 and 4.10 show the proposed method as robust against huge variations of the FC dimension and confirm the validity of the proposed method. Moreover, the possibility to change the size of the FC allows for adapting the chamber to specific requirements. A smaller chamber greatly reduces the required space for the testbed, and it is easier to generate and control the fog due to the reduced volume. However, the fog level reachable inside the chamber, thus the minimum MOR, is lower than in the case of large FCs. To conclude, this method is also suitable for different analyses, such as the case of erroneous fog detection, requiring modest variations to the setup.

Chapter 5

Crop

As introduced in Section 1.2, in recent years agriculture industry is giving great relevance to precision farming, thus the possibility to introduce technologies able to automatize and improve production processes. The ability to automatically evaluate the physical and chemical characteristics of harvested products would improve quality of products, waste reduction, and thus a reduction of costs. Of course, the game-changing factor is the possibility of performing such analysis directly on the field, during the harvesting phase, for example. In this way, autonomous machines could also independently assess whether the crop should be harvested since it is ripe or not. In this sense, the Agrobot E-series by Agrobot, described in Chapter 1 [4], is a perfect merging of ADAS technologies and in field product analysis techniques. The difficulty of the on-field analysis requires certain conditions:

- The estimation technology must be fast to avoid slowing down the harvesting phase.
- The analysis technology must be non-destructive to preserve the condition of the products.
- To perform the analysis directly on the field, the technology must not require a pre-preparation of the sample, typical of laboratory analysis.

As introduced in Section 1.2, the moisture content (MC) of the alfalfa is of great relevance for the agriculture industry. This parameter must be accurately controlled to define the correct storage process of the crop. The MC also states the quality of alfalfa, which influences its cost and the quality of the hay. Consider that the crop sample is composed of a mixture of stems, leaves, and air interstices. Thus, the parameter of interest is the total Moisture Content (MC), which is comprehensive of water present in each solid part of the crop and on its surface. As a consequence, the estimation of the MC is a complex procedure. Generally, during storage, the

MC is evaluated by collecting alfalfa samples and analyzing them with laboratory instruments such as humidity testers or more accurate moisture analyzers. This instrument type uses the standard method for estimating the MC according to [15] that will be described in Section 5.2.3. Trivially, the analysis during the harvesting phase is extremely more complicated due to the unfavorable operational conditions. Apart from the requirements already discussed, various factors may affect the estimation, such as mechanical vibrations, electrical and optical disturbances, and dust or dirt can heavily affect the measurements. Note that the measurement technology must be extremely fast since it must be performed while the bale is in motion. Nowadays, there is a presence on the market of commercial devices able to perform such estimation during the harvesting exploiting conductometric measurement method [15]. However, such systems require contact with the sample to provide accurate MC estimation. Therefore, the possibility of performing the MC estimation with a fast, non-destructive, and contactless instrument is highly interesting.

Among the various possible non-destructive approach for estimating the MC and other physical properties, the NIRS is one of the most interesting options [16, 17]. In fact, the analysis of the crop NIR spectra and the analysis of the water absorption peaks present in the NIR wavelength range can provide a very accurate MC estimation. NIRS technology provides all the characteristics for the in field analysis. In fact, that technology is fast, non-destructive and does not require pre-preparation of the sample.

Nevertheless, the NIRS approach suffers from some influences that can affect the MC estimation. The relationship between MC and near-infrared (NIR) spectrum is affected by several conditions requiring an optical system that is compact, robust, capable of operating in extreme environmental conditions and allows a fast self-calibration procedure to compensate for any eventual drifts. In these terms, crop density is a parameter that must be taken into extreme consideration [61]. In fact, this parameter strongly influences the propagation of photons inside the bale since it directly influences the scattering coefficient [62]. Moreover, crop density is a parameter that influences the quality and the cost of the crop. During crop harvesting and processing, the amount of compression applied can affect the ratio of solid to gaseous parts in the sample by altering the volume of air present.

NIRS spectra analysis can be conducted in several ways, for example, by comparing the sample spectra with references or extracting some particular metrics. Statistical analysis can be applied to retrieve the information of interest [22, 63, 64, 65]. To increase the robustness of the MC estimation, the statistical model estimation must be designed starting from a high number of crop samples. In the specific, among the multivariate techniques, Partial Least Square (PLS) is very suitable in the analysis of NIR spectra [66, 67, 68]. PLS is a statistical technique generally adopted as

a regressor model, which finds the best correlation of two matrices, i.e., response variables and predictors. The use of this approach for the NIR spectra analysis is particularly interesting since PLS tries to reduce the number of variables that can accurately predict the response variable while minimizing the loss of information. Thus, PLS provides relevant results for application in which there are numerous predictor variables and a smaller number of observations, as in the case of NIRS analysis. Moreover, the capability to find the best predictor variables make this approach even if the predictors are noisy or collinear [66].

In this chapter the NIRS approach to the alfalfa humidity analysis is investigated by proposing a statistical PLS method for the MC and density estimation jointly to a pre-processing analysis that aims to increase the robustness of the estimate. The method has been developed considering fresh alfalfa (*Medicago sativa L*) and exploiting a NIRS measurement setup realized in laboratory. Successively, a compact, portable and semi-automated NIRS systems has been developed to evaluate the proposed approach directly on the field, thus without any sample preparation or controlled environment.

In the following sections, the proposed approach has been described in terms of model development, measurement procedure, setup and obtained results. Then, the in field instrument is described in its design and some test results have been presented.

5.1 NIRS Approach

As introduced in Section 1.2, NIRS approach for physical and chemical properties estimation is one of the most interesting concerning the organic samples analysis. The great advantages of this technology stays in the wide penetration depth in organic tissue but also in the measurement speed, higher than other spectrometer technologies. This is because two main factors First, the NIR wavelength range is characterized by high absorption coefficients and high photons scattering through many materials. This allows for the measurement of large numbers of chemical species in a single scan, resulting in faster analysis times. NIRS radiation can be easily obtained by a high-intensity broadband lamp, typically a tungsten halogen lamp. A NIR spectrometer acquires the entire transmitted/reflected light by the sample separating each wavelength contribution. Thus, this method allows for rapid data acquisition and reduces the need for multiple scans. The measurement fastness of NIRS approach is very useful also to decrease the uncertainty of the estimation. In fact, since the scan requires few second it is possible to perform consecutive scans to obtain a mean spectrum of the sample.

NIR spectrometer can be used in many configurations, measuring the transmittance or the absorbance. However, Diffused Reflection, thus measuring sample reflected light Fig. 1.11.(b), is a geometry that is very suitable with in field measurements. In the specific, Diffused Reflection exploits the reflected light in the sample due to scattering, observing the amount of light that is absorbed and thus not reflected. In the specific, Total Diffused Reflectance (TR) is a specific approach used in NIRS to increase the sensitivity of the measurement. According to this geometry, the sample is placed close to the optical window of the spectrometer. The light source enlightens the sample with a very shallow angle of incidence. Therefore, the light is totally reflected and then collected by the spectrometer. This configuration allows for increasing the accuracy of estimation [69]. TR is often adopted when the sample under test is irregular or difficult to measure using the traditional configurations. In fact, the TR is the configuration chosen for the crop MC estimation proposed in this chapter. TR allows having good accuracy and high signal-to-noise (SNR), even if the sample is not pre-treated and its surface is not homogeneous or regular, resulting very suitable for crop analysis.

Let's focus on the MC and density of crop estimation — similar reasonings can be performed for others sample properties and components. As previously introduced, NIR spectral absorption and scattering at specific wavelengths are exploited to estimate crop moisture and density. The loss of radiation intensity of the light beam travelling through the sample under test (SUT) is determined by the modified Lambert-Beer law, which considers the absorption and scattering of photons within the SUT. The estimation of MC and density can be performed observing the variation in the absorbed light by the SUT. For example, the MC of a sample can be recovered observing light absorbance at water absorbing peaks as in [18]. Note that, as previously introduced, the SUT NIR spectra depends on several constituents of the crop, which concentrations may vary the absorption and scattering of NIR photons. However, during the harvesting and processing phase, only MC and density vary, assuming all the other quantities constant. Thus, observing the spectrum variation it is possible to recover MC and density variation. After acquiring numerous crop spectra and accurately calibrating the instrument, the parameter of interest can be retrieved.

Photon scattering and absorbance inside the SUT are governed by scattering and absorption. As previously introduced, the modified Lambert-Beer law can be used to quantify light radiation intensity loss. Let I the light intensity read by the spectrometer reflected by the SUT:

$$I = I_0 \cdot e^{-(c_w \cdot \epsilon \cdot L \cdot DPF + G)} , \quad (5.1)$$

where I_0 is the incident beam intensity, c_W the water molar concentration, ϵ the water molar extinction coefficient [21]. L is the geometrical path length of photons within the SUT, and the DPF (Differential Path length Factor) represents the variation of photons' path length due to the scattering presence. Finally, G takes into account the loss due to scattering. The measurement setup, that will be described in Section 5.2, presents a configuration with a high light collection efficiency, allowing neglect loss parameter G . As introduced in Section 1.2, the absorbance can be obtained as:

$$A = -\log_{10} \frac{I}{I_0} = -\frac{1}{2.303} \ln \frac{I}{I_0} = \frac{1}{2.303} \cdot c_W \cdot \epsilon \cdot L \cdot \text{DPF} . \quad (5.2)$$

From this expression, the water content of the SUT, i.e. c_w , can be derived by observing the absorbance in correspondence with the spectral regions where the water extinction coefficient ϵ is maximum. Differently, density can be estimated from the DPF. In fact, this parameter characterizes the scattering within the SUT; supposing that as the density increases, the scattering also increases, resulting in a higher DPF. Unfortunately, the DPF also depends on absorption. Thus it is crucial to estimate density in spectrum regions far from absorption peaks.

As discussed in Section 4.0.1, Lambert-Beer law correctly describes intensity loss only in a purely absorbing medium. The modified Lambert-Beer law is also defined for scattering medium. However, eq. (5.1) introduces significant approximation by greatly simplifying the radiometric process underlying the spectral measurement. Nevertheless, this simplification has been employed with success, allowing the spectral measurement of heterogeneous and highly scattering tissues [70, 71, 72]. Modified Lambert-Beer law associates the variation in light intensity with the variation in the optical properties of the SUT. Thus, it is possible to correlate the variation in scattering and absorption within the sample to the variation of constituent concentrations, i.e. MC and density in our case.

The proposed approach attempts to estimate MC and density from the spectral absorbance measurement by applying a linear regression model. Thus, the logarithmic transformation of the absorbance is derived from the eq. (5.2).

$$\text{LA} = \ln A = \left[\frac{1}{2.303} \cdot c_W \cdot \epsilon \right] + \ln[L \cdot \text{DPF}] \quad (5.3)$$

From the eq. (5.3), the MC and density contributions on the absorbance can be separated. The first add is closely dependent on the water content of the SUT, while the second is on its density. To separately derive the two contributions, it is possible to analyze the absorbance in different spectral bands, where one contribution is maximum and the other negligible. The NIRS band of the NIR spectrometer used can be divided into two separate bands of interest (BOI). B1 is the spectral

region where the molar extinction coefficient ϵ is maximum, thus where the MC contribution is maximum and density contribution neglected. Thus, the LA in B1 is approximated as:

$$LA_{B1} \approx \ln \left[\frac{1}{2.303} \cdot c_w \cdot \epsilon \right] . \quad (5.4)$$

Otherwise, B2 is the spectral region where ϵ is minimum, and thus the second term is maximized. Moreover, the photons' propagation in B2 can be assumed mainly governed by the scattering, and thus the water content effect on the DPF can be assumed as minimal. The density can be derived from the LA approximation in B2:

$$LA_{B2} \approx \ln[L \cdot DPF] \quad (5.5)$$

These approximations allow to separate the different contributions, thus deriving two different models for the MC or density estimation.

The bands choice must be performed accurately to preserve the validity of the approximations in eq. (5.4) and eq. (5.5); thus, varying MC, a huge difference in absorption between B1 and B2 must be observed. In Section 5.2.1, the measurement setup will be described, thus also the spectrometer adopted and the bands choice. By way of example, the Fig. 5.1 shows the example of the NIR spectrum of crop acquired with the spectrometer that will be described in the next section. Specifically, the red line represents a SUT at MC = 43.6 %, and the blue line represents a SUT at MC = 83.9 %. As previously discussed, the bands choice must be accomplished as the SUT shows substantial absorption differences in B1 and B2 as the MC varies. According to Fig. 5.1, B1 can be selected around $\lambda = 1450$ nm, i.e. one of the water absorption peaks. Otherwise, B2 can be selected around $\lambda = 900$ nm. In fact, a variation of ≈ 40 % in the MC, at $\lambda = 1450$ nm means a variation in absorbance of 0.2 units; this means that the attenuation of the light intensity goes from $(I/I_0) = (6.3 \cdot 10^{-5})$ at MC = 43.6% to $(I/I_0) = (2.5 \cdot 10^{-7})$ at MC = 83.9 %. On the other hand, at $\lambda = 900$ nm, the absorbance variation is only about 0.05 units — a variation of intensity ratio from $(I/I_0) = (6.3 \cdot 10^{-4})$ to $(I/I_0) = (2.5 \cdot 10^{-4})$.

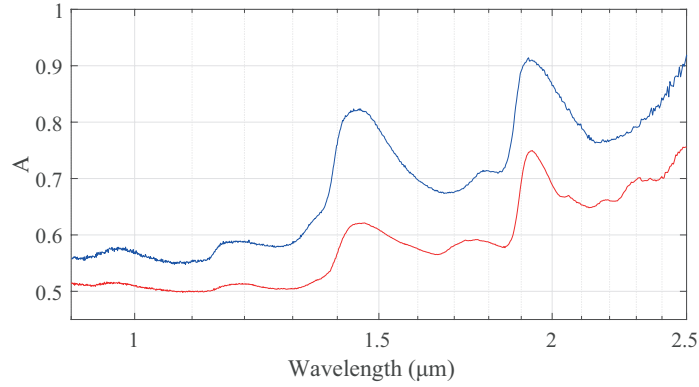


Figure 5.1: Example of Absorption Spectra acquired from the same crop sample at two different MCs. The red line (—) represents the sample at MC = 43.6 %, while the blue line (—) represents the sample at MC = 83.9 %. In the figure, the two main water absorption peaks can be appreciate at $\lambda = 1450$ nm and $\lambda = 1940$ nm.

The different sensitivity of the two bands to MC variation allows to assume that the approximations in eq. (5.4) and eq. (5.5) are reasonable. Note that, the marginal correlation between MC and density will contribute to increasing the uncertainty on their estimations.

The proposed approach involves the use of logarithmic transformation of the absorbance to simplify the MC and density contributions separations [73]. In addition, logarithmic transformation offers another advantage. Linear regression models try to keep constant the absolute fitting error over the considered range. Consider that one of the reasons pushing for the MC and density analysis is their importance in the economic value of the crop. For this reason, a constant absolute error estimation would result in a relevant price error for small quantities of crop. As a consequence, a relative error would be a better choice, and logarithmic transformation also transforms the absolute predictors/outcome difference into a relative difference. Therefore, the regression model tries to keep constant the relative error on the MC/density estimation, guaranteeing a fair economic value even for a small crop quantity.

5.2 Moisture Content and Density Model

In this section, the experimental setup used for the MC and density estimation is described together with the data analysis and model design. This work was presented in [73]. The complete procedure involves:

- The crop sample collection and storage.

- The spectra acquisition.
- The data preprocessing and band selection.
- The Reference MC and density measurement.
- The PLS model design and evaluation.

5.2.1 Experimental Setup

My work aimed to develop an MC and density estimation model. As previously discussed, the statistical model must be designed starting from numerous experimental data. For this reason, a measurement setup was built in our laboratory. Note that this setup was used to collect the spectra of crop samples, and of course, it cannot be used directly on-the-field. However, to evaluate the NIRS approach, a simple laboratory prototype was set up. Fig. 5.2 shows the schematic representation of the setup.

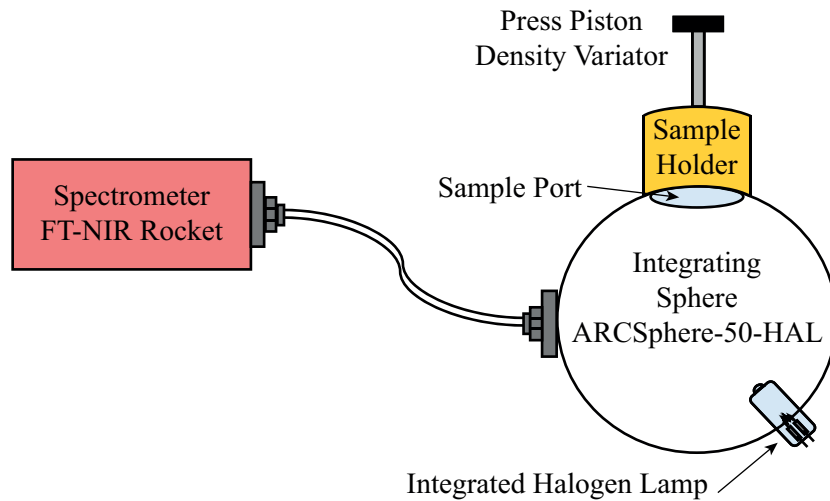


Figure 5.2: Schematic representation of the laboratory setup used for NIR spectrum acquisition. The spectrometer (FT-NIR Rocket by ARCOptix) is connected to the Integrating Sphere (ARCSphere-50-HAL by ARCOptix) through a fiber. The SUT is placed in a custom Sample Holder that allows for changing the sample density. The Sphere has a halogen lamp integrated. The light back-reflected by the sample is entirely collected by the spectrometer, thanks to the Integrating Sphere.

The total diffused reflection geometry was chosen to increase the accuracy and the SNR. This configuration was accomplished by exploiting an integrating sphere (ARCSphere-50-HAL, ARCOptix S.A., Switzerland). The sphere has a halogen lamp inside that enlightens the SUT; thanks to its property, the ARCSphere is able to collect all the back-scattered light from the SUT. The sphere has an internal diameter of 50 mm and a sample port with a 10 mm sapphire window. A Sub Miniature

A (SMA) fiber port allows the spectrometer to acquire the diffused light spectrum. The spectrometer is a Fourier Transform NIRS spectrometer (FT-NIR Rocket, ARCoptix S.A., Switzerland). This type of instrument is able to separate the different wavelength components of the detected light to independently evaluate the intensity of each component; this operation is accomplished through a Transformation of Fourier [69]. The SUT is held on the sample port through a specimen holder realized for this setup, which allows changing the sample density. This sample holder allows obtaining different measurements at different densities with the same MC. Fig. 5.3 is a photo of the actual setup.



Figure 5.3: Photo of the laboratory setup used for the NIR spectra acquisition.

5.2.2 Measurement Procedure and Data Analysis

This setup was used to analyze alfalfa grass samples harvested in June, September and October in farmland in Modena (Italy). The samples were harvested at two different times. First, immediately after the grass is cut (2 cm), and subsequently, waiting a time that depends on farmland conditions. This procedure allowed obtaining naturally different MCs ranging from 9% to 85 %. The MC variability in samples could also be due to the harvesting area. Thus the SUTs were collected from two different areas of the farmland. Samples were stored in plastic sealed bags in the same quantity (4 g) to preserve the MC.

After the sample collection, the measurement procedure started. First, the dark

spectrum (no illumination) was acquired. Successively, after turning on the halogen lamp and waiting for its warm-up, the reference spectrum was acquired by placing a 99 % NIST Standard Diffuser by Labsphere at the sample port. Finally, each SUT was placed into the sample holder, the desired density was set, and the absorbance spectrum was acquired. The absorbance spectrum, and its logarithmic transformation, for each SUT was computed as:

$$A(\lambda_i) = -\log_{10} \frac{I_{SUT}(\lambda_i) - I_D(\lambda_i)}{I_{Ref}(\lambda_i)/0.99 - I_D(\lambda_i)} \quad (5.6)$$

$$LA(\lambda_i) = \ln A(\lambda_i) ,$$

where $I_{SUT}(\lambda_i)$, $I_D(\lambda_i)$, and $I_{Ref}(\lambda_i)$ refer, respectively, to the back-scattered spectrum by the SUT, dark spectrum acquired with the halogen lamp turned off and the reference spectrum acquired from 99 % NIST Standard Diffuser. The used spectrometer allows to analyze wavelength λ_i ranges from $0.9 \mu\text{m}$ to $2.5 \mu\text{m}$, with $i \in [1, \dots, 1024]$. The spectral resolution is 8 cm^{-1} in term of wavenumber; thus the resolution varies from 1 nm at $\lambda_i 1 \mu\text{m}$ to 5 nm at $\lambda_i = 2.5 \mu\text{m}$. By way of example, Fig. 5.4 shows the sample and reference spectra acquired by the instrument and the absorbance and LA spectra.

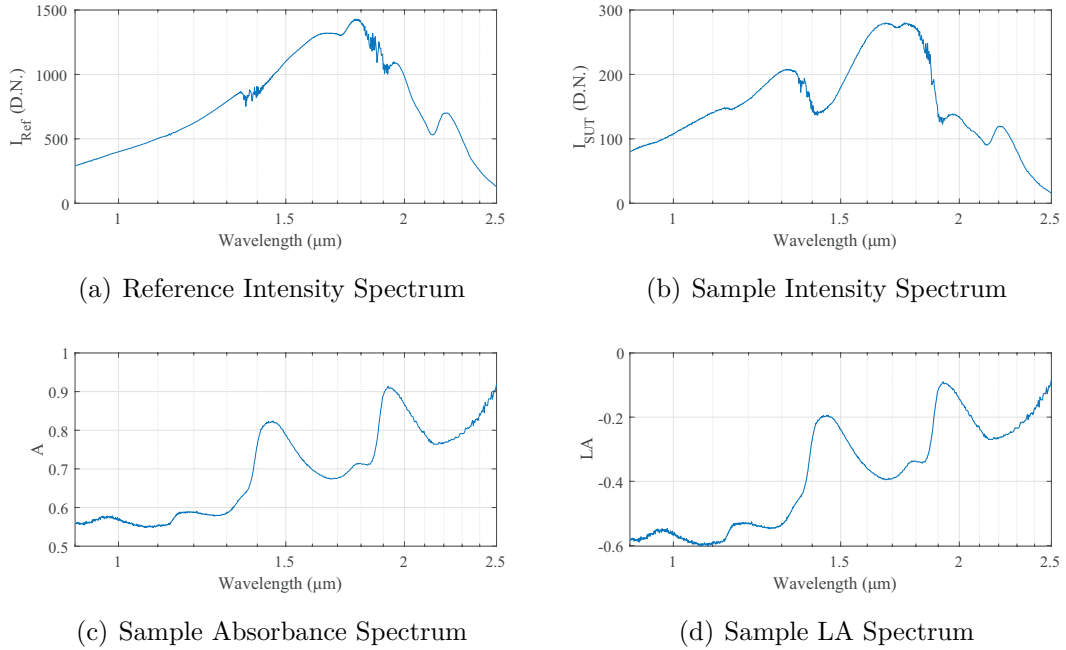


Figure 5.4: Example of acquired spectra. Fig.(a) shows the reference spectrum acquired without the sample turning on the lamp. Fig.(b) shows the acquired SUT spectrum expressed as light detected light intensity. Fig.(c) shows the SUT spectrum in terms of light Absorbance, while Fig.(d) shows the logarithmic transformation LA of the SUT spectrum.

After the acquisition phase, the spectra were used to calibrate the PLS model.

Acquired spectra were first preprocessed to improve the accuracy of the model. This phase has a relevant impact on the prediction capability of the regression model since it is possible to remove noise and unwanted effects that are not correlated with the MC and density of the SUT. The data handling was performed differently for MC and density model. Considering the MC predictor, the first derivative of the LA spectrum was computed as:

$$\text{FDLA}(\lambda) = \frac{dLA(\lambda)}{d\lambda} = \frac{d\ln A(\lambda)}{d\lambda} \quad (5.7)$$

This operation aims to remove the baseline effects and highlight the absorbance peaks [74, 75]. However, the first derivative increases the high-frequency noise; thus, a filter was applied to maintain the SNR to a reasonable value before the first derivative. The chosen filter was a Savitzky–Golay (SG) spectral smoothing filter of the second degree [75]. Then the resulting spectrum was normalized to its maximum value. Otherwise, for the density predictor, I experimentally observed that the First Derivative does not improve the model accuracy. Therefore, for the density estimation, only the SG filter and the normalization were applied.

Fig. 5.5 shows an example of data processing of an LA spectrum. Fig. 5.5(a) shows an example of LA spectrum, Fig. 5.5(b) shows the SG filtered spectrum. Fig. 5.5(c) shows the first derivative directly applied to the LA spectrum, in which the spectrum is noisier than in Fig. 5.5(a). Finally, Fig. 5.5(d) shows the spectrum used for the MC prediction, thus the normalized and filtered FDLA. Note that for density, the normalization is directly applied to Fig. 5.5(b) spectrum.

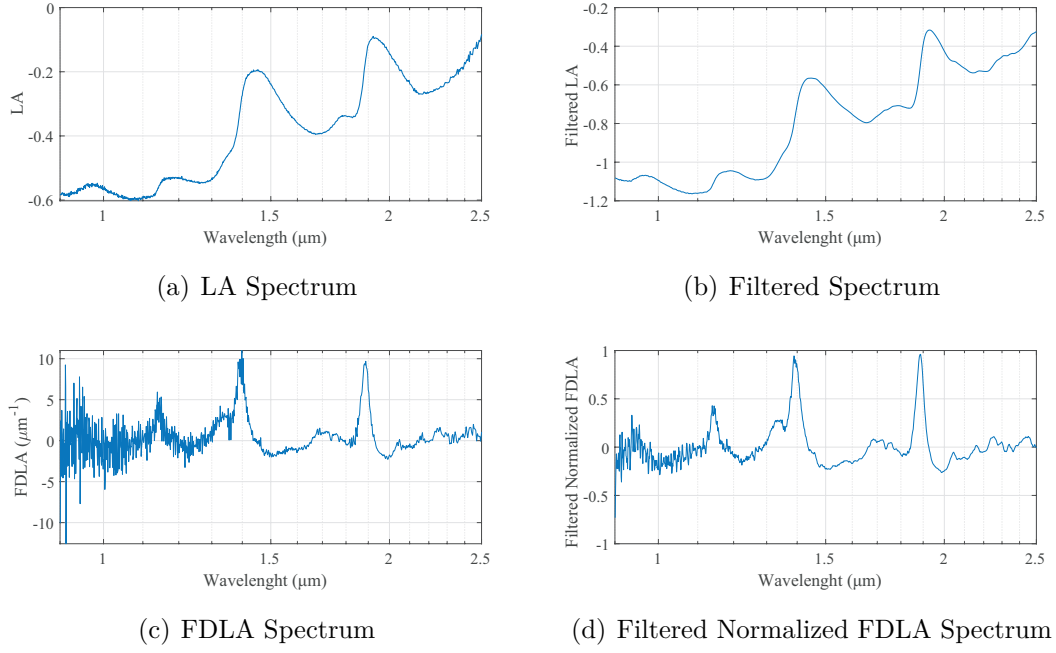


Figure 5.5: Example of spectrum pre-processing. The spectra were pre-treated to improve the prediction capability of the PLS model. Fig.(a) shows the logarithmic transformation LA of the SUT spectrum. Fig.(b) shows the SG filtered spectrum. Fig.(c) shows the FDLA, thus the first derivative of the logarithmic transformation of the spectrum. Fig.(d) shows the normalized FDLA, i.e. the spectrum used for the MC estimation. For the density estimation, the first derivative was not applied.

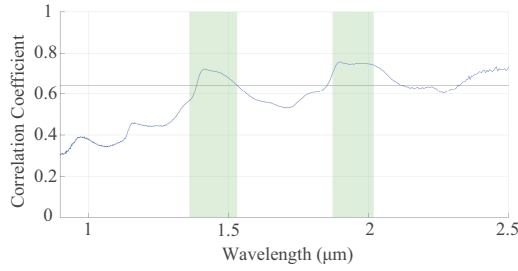
As described in Section 5.1, the MC and density estimations were performed on specific bands, B1 and B2, of the NIR spectrum. The selection of these bands has been accomplished taking into account the water molar extinction coefficient [21]. The band B1, for the moisture estimation, considers the two main water absorbance peaks in the NIR spectrum, thus $\lambda_{w1} = 1.38 \mu\text{m}$ and $\lambda_{w2} = 1.88 \mu\text{m}$, while B2, for the density estimation, refers to a region with minimum absorption $(0.9 - 1.1) \mu\text{m}$. The wavelengths of interest in the spectral bands B1 and B2 were chosen by analyzing the correlation coefficients between the reference and predictor variables. These coefficients were calculated as follows:

$$C(\lambda_i) = \frac{1}{N-1} \sum_{j=1}^N \left(\frac{Y_j - \mu_Y}{\sigma_Y} \right) \left(\frac{X_j(\lambda_i) - \mu_{X(\lambda_i)}}{\sigma_{X(\lambda_i)}} \right), \quad (5.8)$$

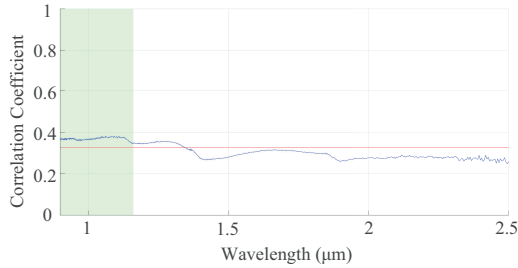
where X and Y are the predictor and response variables and N is the number of collected samples. Specifically, Y_j is the reference value of MC or density, computed as will be described in Section 5.2.3, of the j -th SUT, and $X_j(\lambda_i)$ is the spectrum component of the wavelength λ_i of the j -th SUT. μ_Y and $\mu_{X(\lambda_i)}$ are their mean computed over the k response variables considered (the k SUT spectra) and σ_Y and $\sigma_{X(\lambda_i)}$ are their relative standard deviations. The choice of B1 and B2 was performed

considering correlation coefficients higher than 85% of its maximum value, which means 0.65 for MC and 0.4 for density. As anticipated, the correlation with MC is significantly higher in absolute terms due to the relevant absorption contribution of water. However, it is known that density estimation is more challenging in a highly heterogeneous medium as it is related to the mean scattering coefficient. The low value of the correlation coefficient highlights this challenging aspect. Afterwards, a final wavelength range refinement was performed by adding or removing some wavelengths to reduce the prediction errors. As shown in Fig. 5.6, some wavelengths outside B1 and B2 respect the selection criterion of $C(\lambda_i) > 85\%$. Nevertheless, this behaviour is not supported by physical reasons; the repeatability of these behaviours is usually poor and closely tied to the specific set of samples chosen. The final selected wavelengths for the PLS analysis were:

$$\begin{aligned} \text{B1} : \lambda_i &\in (1.37 - 1.53) \cup (1.87 - 2.02) \mu\text{m} \\ \text{B2} : \lambda_i &\in (0.90 - 1.16) \mu\text{m} . \end{aligned} \tag{5.9}$$



(a) BOI for MC estimation



(b) BOI for density estimation

Figure 5.6: Correlation Coefficients between reference and predictor values. The top figure shows the correlation coefficient for the MC, while the bottom figure shows the coefficient for the density estimation. The blue line (—) shows the trend of $C(\lambda_i)$ as a function of the wavelength. The red line (—) represents the 85% threshold applied for the BOI choice. Finally, the green areas highlight the BOIs were chosen for the MC and density estimation.

5.2.3 Reference Measurements

The design of the regression model requires the reference value of MC and density, of course. Reference gravimetric water content MC was computed according to the American Society of Agricultural and Biological Engineers standard [15]. First, the SUT weight m_{SUT} was measured with an electronic weighing balance (PCB 3500-2 Kern, Balingen, Germany) with resolution $r = 0.01$ g. Successively, the sample was dried to remove all the water content and weight again to obtain the dried weight m_d . This procedure was accomplished in a humidity and temperature controlled environment. The second weighing was performed immediately after the drying operation to avoid any possible rehydration of the SUT, thus preventing errors in the MC measurement. Thus, the gravimetric water content MC was computed as:

$$MC = \frac{m_w}{m_{SUT}} , \quad (5.10)$$

where $m_w = m_{SUT} - m_d$ is the mass of water in the SUT. The relative uncertainty on the reference MC value was $\dot{u} = 0.4$ % was given by the weight scale accuracy. The sample is heterogeneous because it is composed of several elements, such as stems, leaves and air interstices. Thus, it is not feasible to determine the density of the sample based on the single densities of each component of the SUT. As previously reported, the sample holder of the measurement setup allows changing the volume of the SUT through a press. The press piston, driven by a screw spindle and equipped with a measuring gauge, allows lowering the height of the sample chamber to a specific value of h . The procedure was performed considering the total volume of the holder including air and solid part of the SUT. According to [76], the SUT density ρ is calculated as:

$$\rho = \frac{m_{SUT}}{A_{base} \cdot h} , \quad (5.11)$$

where A_{base} is the base area of the sample holder.

5.2.4 PLS Model

After the data handling and BOI selections, the PLS model is applied to the SUT spectra. The model is designed starting from N_{cut} alfalfa cuttings at different MCs. From these N_{cut} alfalfa cuttings, we extracted N different SUTs, as will be better described in Section 5.2.5. Each SUT was compressed differently during the measurement to obtain 160 nonidentical and practically independent samples due to their poor uniformity. Note that since the logarithmic transformation of the absorbance spectrum was considered a predictor variable, the reference value used for

the calibration and validation of the model was the logarithmic transformation of the reference MC and density values. Moreover, the PLS response variables are expressed as logarithms of MC and density; thus, to retrieve the value of interest, it is required to anti-transform the responses.

The Linear Regression Model is described by the following matrix expression:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ \cdot \\ Y_N \end{bmatrix} = \begin{bmatrix} X_1(\lambda_1) & X_1(\lambda_2) & \cdot & X_1(\lambda_n) \\ X_2(\lambda_1) & X_2(\lambda_2) & \cdot & X_2(\lambda_n) \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ \cdot & \cdot & & \cdot \\ X_N(\lambda_1) & X_N(\lambda_2) & \cdot & X_N(\lambda_n) \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \cdot \\ \beta_N \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_N \end{bmatrix}, \quad (5.12)$$

where Y_j is the response variable, thus the logarithmic transformation of reference value (MC or ρ). Predictor variable $X_j(\lambda_i)$ is the pretreated FDLA component relative to λ_i of the j -th SUTs in the case of MC estimation, or simply the pretreated LA component in the case of ρ estimation. β_j represents the calculated coefficient of the weighted regression, while the ε_j stands for the residuals, which are the difference between the reference and predicted response. To avoid model over-fitting, PLS performs the regression of eq. (5.12) on a set of uncorrelated latent variables obtained finding combinations of original variables that have a large covariance with the response values. The number n of latent variables was chosen trying to optimize the RMSE and the R^2 . Initially, n was set to 10, and after several simulation the choice fell to $n = 12$. This operation allows to improve the model prediction capability, avoiding the over-fitting. After the model was computed, the fittings are evaluated through the following statistics: i) The calibration and validation Root Mean Square Error (C-RMSE and V-RMSE), and ii) the coefficient of determination R^2 (C- R^2 and V- R^2). RMSE is calculated as follows:

$$\text{RMSE} = \frac{1}{N} \sum_{j=1}^N \sqrt{\sum_{i=1}^Q \frac{\varepsilon_j^2 |_i}{q}}, \quad (5.13)$$

where Q is the number of predictors associated to the j -th reference value, and $\varepsilon_j^2 |_i$. R^2 is computed as:

$$R^2 = 1 - \frac{\sum_{j=1}^N \sum_{i=1}^Q (Y_j |_i - Yref_j)^2}{\sum_{j=1}^N (\bar{Y} - Yref_j)^2}, \quad (5.14)$$

where $Yref_j$ is the reference value associated to the response $Y_j |_i$ and $\bar{Y}$ is the average of the $Q \times N$ reference values.

After the application of the models, the logarithmic estimations were converted into

linear MC and density. The root mean square relative error between estimated and reference values was calculated for each reference value:

$$\begin{aligned}\varepsilon_r(\text{MC}) \% &= \frac{1}{Q} \sqrt{\sum_{i=1}^Q \left(\frac{\text{MC}_{est} | i - \text{MC}_{ref}}{\text{MC}_{ref}} \right)^2} \cdot 100 , \\ \varepsilon_r(\rho) \% &= \frac{1}{Q} \sqrt{\sum_{i=1}^Q \left(\frac{\rho_{est} | i - \rho_{ref}}{\rho_{ref}} \right)^2} \cdot 100 ,\end{aligned}\tag{5.15}$$

where *est* and *ref* indicate the estimated and reference values, respectively

5.2.5 PLS Model Results and Evaluation

In this section, the results of the calibration of the PLS model and its evaluation were presented for both the MC and density estimation. The cuttings were harvested in a farmland in Modena, Italy.

Moisture Content Estimation

The samples considered for the MC model have reference moisture ranges from 9.4 % to 83.9 %. For each of the N_{cut} cuttings a sample is produced — number of SUTs $N = 40$. For each sample, $Q = 4$ spectra were acquired by setting the SUT density at different values. Thus, $Q \times N = 160$ independent predictor variables were considered and randomly divided in the calibration and validation dataset. The calibration dataset consisted of 128 predictors, while the validation dataset was composed of the remaining 32 predictors. Fig. 5.7 and Fig. 5.8 show the response of the PLS model as a function of the MC reference values obtained respectively from the calibration and validation dataset. In addition, Fig. 5.9 shows the relative error in MC estimation as defined in eq. (5.15) as a function of the reference value for both calibration and validation.

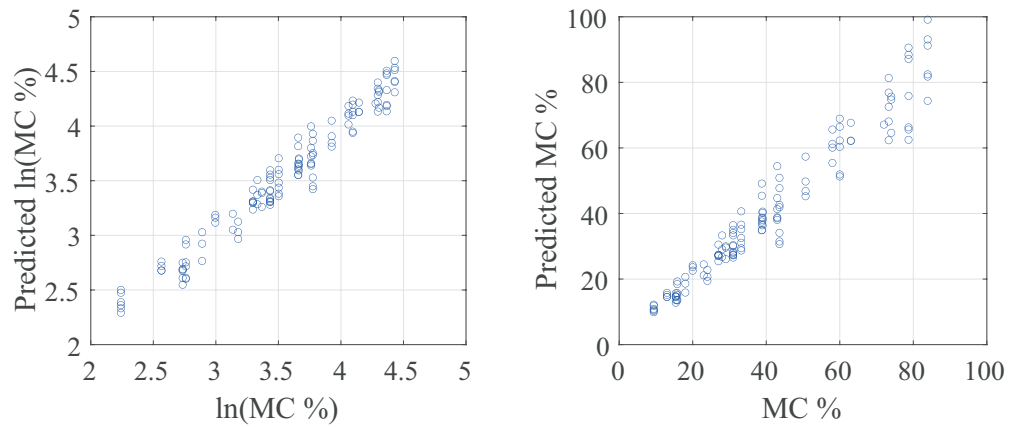


Figure 5.7: PLS calibration response for MC estimation. Fig.(a) shows the response values vs the reference values, thus the logarithmic transformation of the estimated and reference MC values. Fig.(b) shows the estimated MC as a function of the reference MC values.

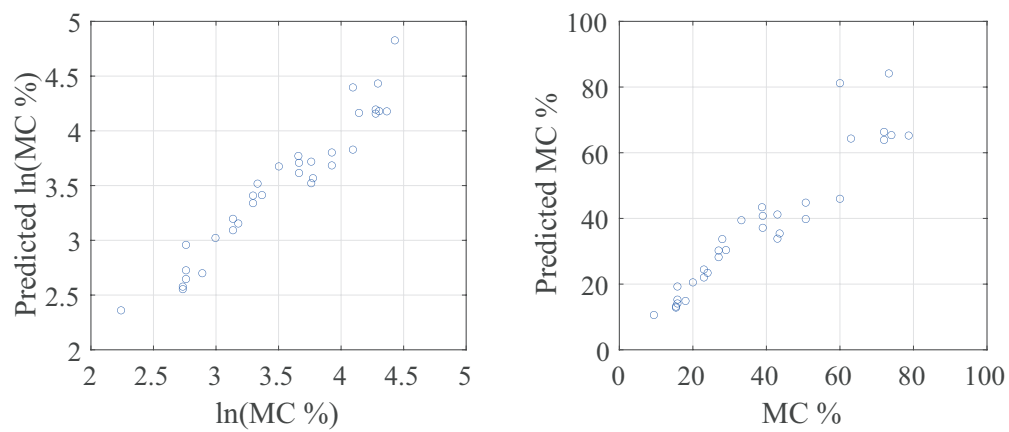


Figure 5.8: PLS validation response for MC estimation. Fig.(a) shows the response values vs the reference values, thus the logarithmic transformation of the estimated and reference MC values. Fig.(b) shows the estimated MC as a function of the reference MC values.

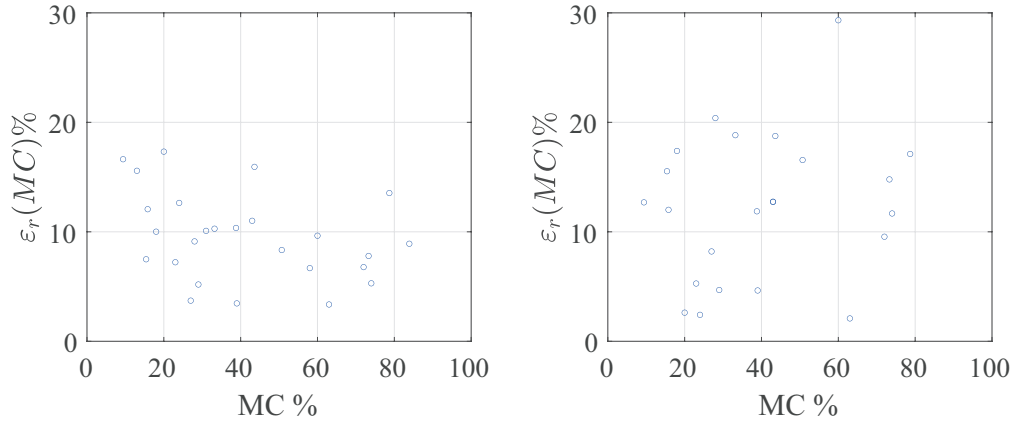


Figure 5.9: Relative RMSE between the estimated and reference MC values. Fig.(a) refers to calibration, while Fig.(b) refers to validation.

Table 5.1 summarize the evaluation statistics described in Section 5.2.4 for the MC estimation model.

Parameter	FDLA
C-RMSE	0.1230
$C-R^2$	0.9581
V-RMSE	0.1599
$V-R^2$	0.9249
V-MEAN-ERROR	13.82 %

Table 5.1: Statistics related to the moisture estimation model performed using the FDLA signals. C-RMSE and $C-R^2$ refer to the calibration model, while V-RMSE and $V-R^2$ refer to the validation model.

Density Estimation

The same $N_{cut} = 40$ cuttings used for the MC estimation were used for generating another set of SUTs. The density estimation set was composed of samples with $N = 15$ different densities with Q different MCs. In this case, Q is a variable number depending on the density value. The MC values cannot be controlled, thus the variability of MC with respect to the density value varies depending on the collecting month and field. The resulting number of predictors was 160. The SUT density ranges from 46 to 236 kg/m³. These values simulate the range of density values obtained by the forage harvesting machines (personal communication from CNH Industrial Italia S.p.A, Modena, Italy). As for the previous model, the calibration set was composed of 128 predictors, while the validation model by the remaining 28. Fig. 5.10 and Fig. 5.11 show the response of the PLS model as a

function of the density reference values obtained respectively from the calibration and validation dataset. Fig. 5.12 shows the relative error in D estimation as defined in eq. (5.15) as a function of the reference value for both calibration and validation.

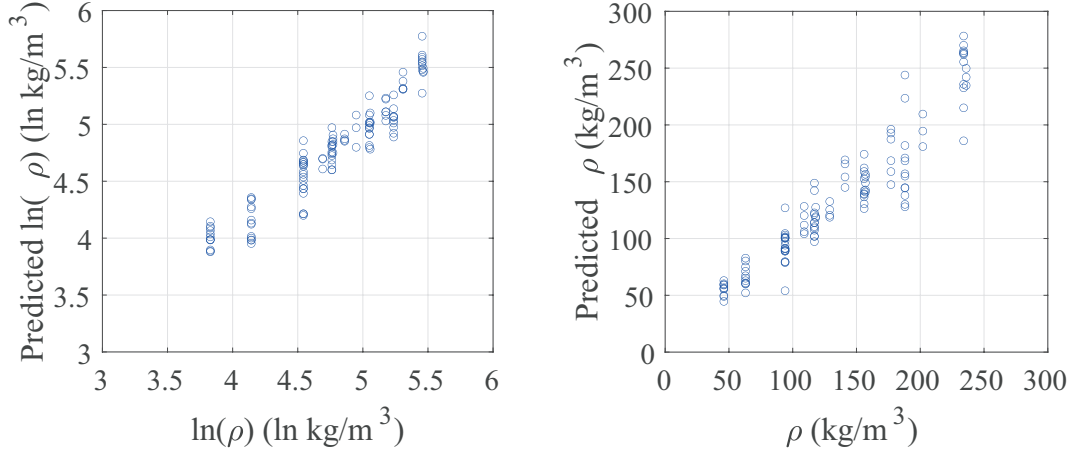


Figure 5.10: PLS calibration response for density ρ estimation. Fig.(a) shows the response values vs the reference values, thus the logarithmic transformation of the estimated and reference density values. Fig.(b) shows the estimated MC as a function of the reference density values.

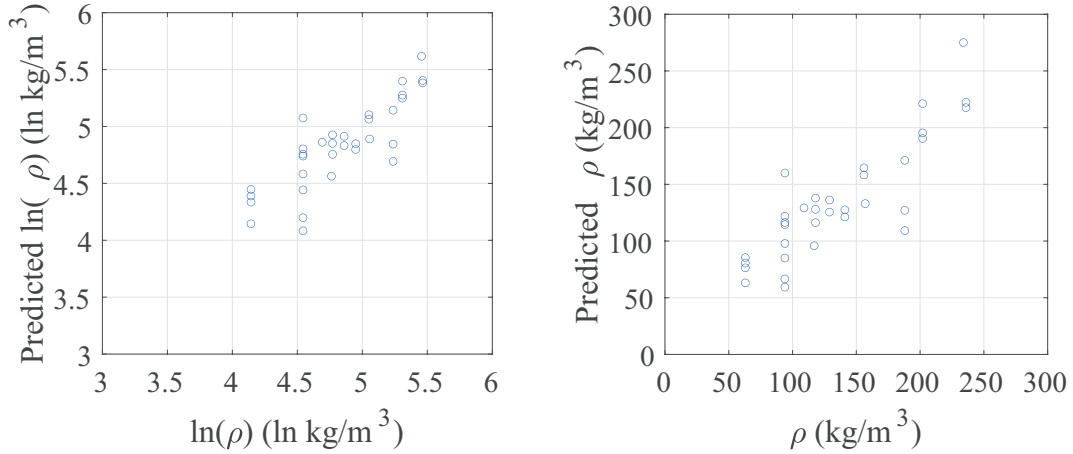


Figure 5.11: PLS validation response for density ρ estimation. Fig.(a) shows the response values vs the reference values, thus the logarithmic transformation of the estimated and reference density values. Fig.(b) shows the estimated MC as a function of the reference density values.

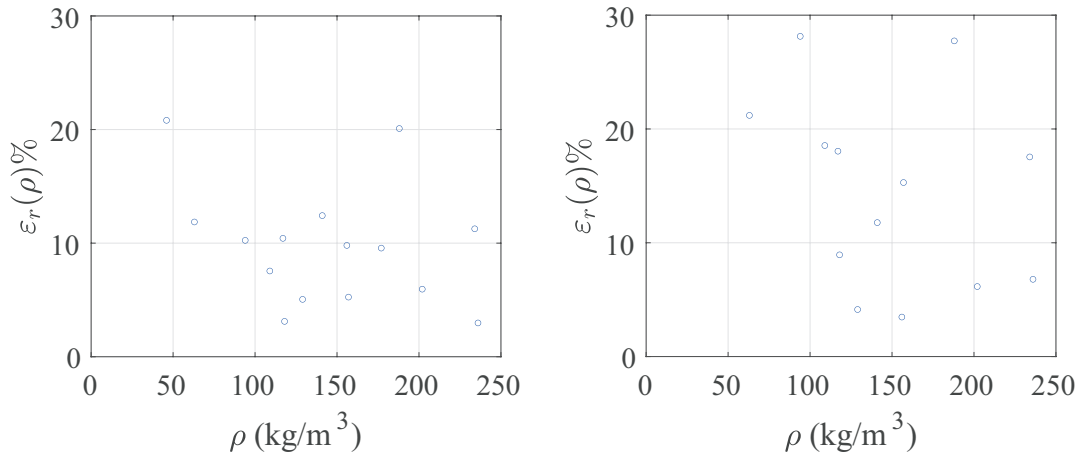


Figure 5.12: Relative RMSE between the estimated and reference ρ values. Fig.(a) refers to calibration, while Fig.(b) refers to validation.

Table 5.2 summarize the evaluation statistics described in Section 5.2.4 for the MC estimation model.

Parameter	LA
C-RMSE	0.1240
C-R ²	0.9008
V-RMSE	0.1791
V-R ²	0.6806
V-MEAN-ERROR	14.44 %

Table 5.2: Statistics related to the density estimation model performed using the LA signals. C-RMSE and C-R² refer to the calibration model, while V-RMSE and V-R² refers to validation.

The presented results demonstrate the goodness of the NIRS approach and PLS analysis for the estimation of MC and density. As it is possible to observe, this approach offers better performance for MC estimation instead for density estimation. In fact, the RMSE, both in calibration and density, is higher for density than MC. This effect may be due to several aspects. First, the lack of homogeneity of the samples leads to a scattering phenomenon very dependent on the measurement position. On the other hand, the absorption in band B2 may depend on other constituents and factors of the SUT. Nevertheless, the results from fresh alfalfa grass samples, as shown in Table 5.1 and Table 5.2, show a strong correlation between the estimated and reference values for moisture content and density. Finally, the uncertainty of the reference density measurement method should certainly be taken into account. Moreover, exploiting the logarithmic transformation of the spectra as predictor variables allows for avoiding a constant absolute error. In fact, from

Fig. 5.9 and Fig. 5.12, the relative RMSE is practically independent of the reference value and has average values of 13.82 % and 14.44 % for the estimated MC and density, respectively.

5.3 In Field Prototype

The PLS model presented in the previous section reveals the potential of the NIRS approach in density and mostly MC estimation. However, the instrument used to calibrate and validate the model is a laboratory prototype, thus totally unusable in the field. The next step towards complete automation of that process is the realization of an instrument that allows performing the NIR spectrum acquisition directly in the field and implements the PLS model for the live MC evaluation. In this section, a semi-automatic instrument for the NIR spectrometry is presented. The prototype is characterized by performing warm-up, repeatability and reflectance sensitivity tests. Then, the instrument is tested by acquiring in-field spectra of alfalfa. This work was presented in [77].

5.3.1 Prototype Design

The design of the in-field prototype was chosen to respect as much as possible the laboratory prototype. The prototype must be portable and easy to use, so it must be composed of a single and relatively small element. In addition a Data Acquisition and Control Units must be present, to elaborate the spectra and provide a quasi-real-time estimation.

The core of the instrument is obviously the spectrometer. For this instrument version, the microspectrometer (MSN) NIR1.7 OEM (INSION GmbH[®], Obersulm, Germany) has been chosen. This spectrometer is smaller than the one used for the laboratory prototype, thus more suitable for a portable and integrated instrument. The NIR1.7 has a measuring range from 900 to 1700 nm with 8 nm spectral resolution and pre-integrated readout electronics based on an ADC with 16-bit resolution, which offers high performances in terms of accuracy, sensitivity, and SNR. This instrument is not able to directly perform the Fourier Transform, however this operation is provided by the Data Acquisition Unit. As for the ARCOptix, the NIR1.7 entrance is coupled with an optical fiber, a 300/330 nm low OH-silica optical fiber. Fig. 5.13 provides a schematic representation of the realized instrument and Fig. 5.14 shows a photo of the actual prototype.

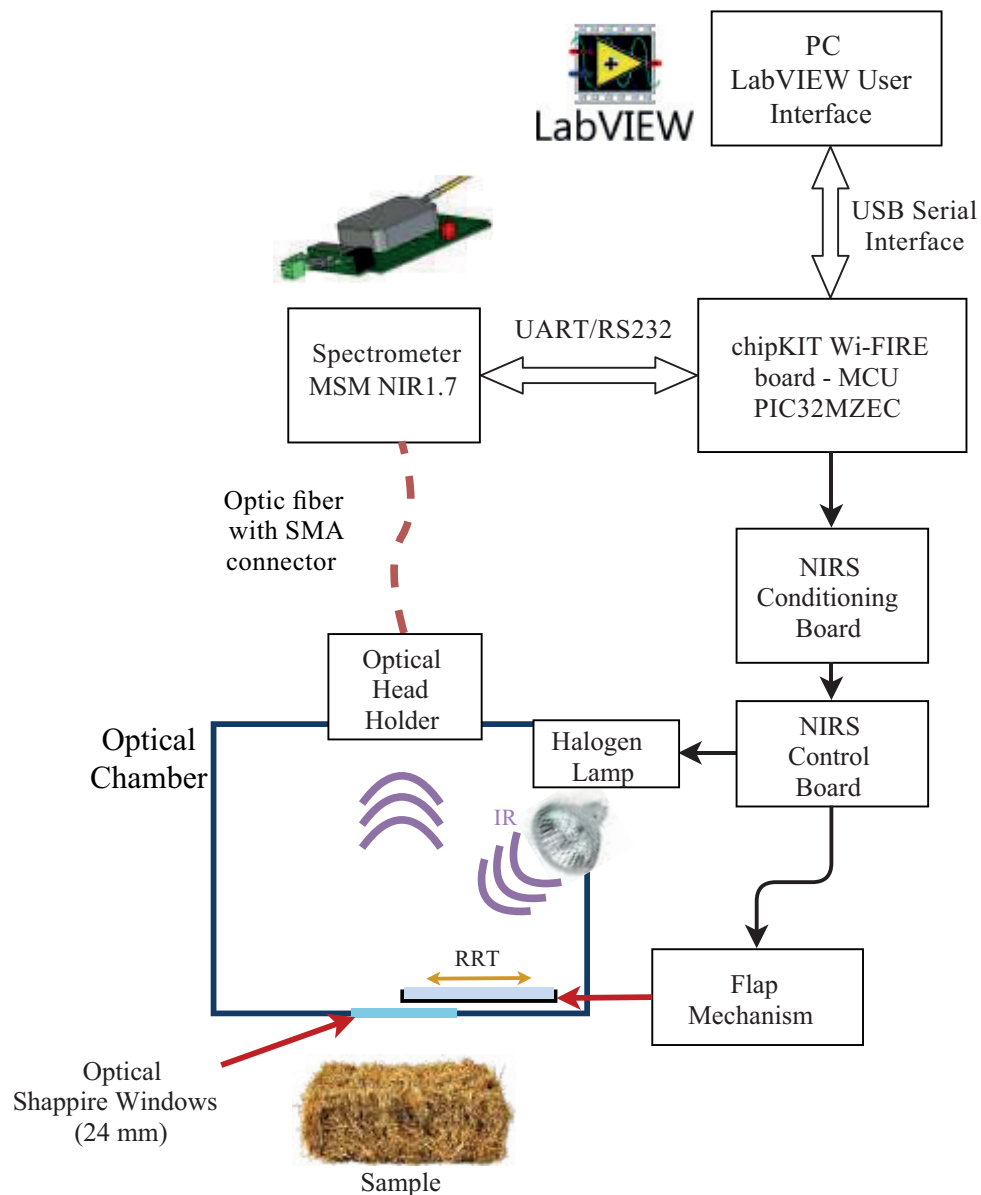


Figure 5.13: Schematic representation of the realized prototype. The optical chamber acting as an integrating sphere is realized to reduce light loss. The lighting is provided by a halogen lamp integrated into the optical chamber. The optical window is provided with a mechanical flap that allows obscuring the chamber, and so is the calibration procedure. The spectrometer is connected to the optical chamber through a fiber. The chipKIT Wi-FIRE board controls all the components and communicates with the host PC. The user can control the system through a LabVIEW GUI running on the host PC.

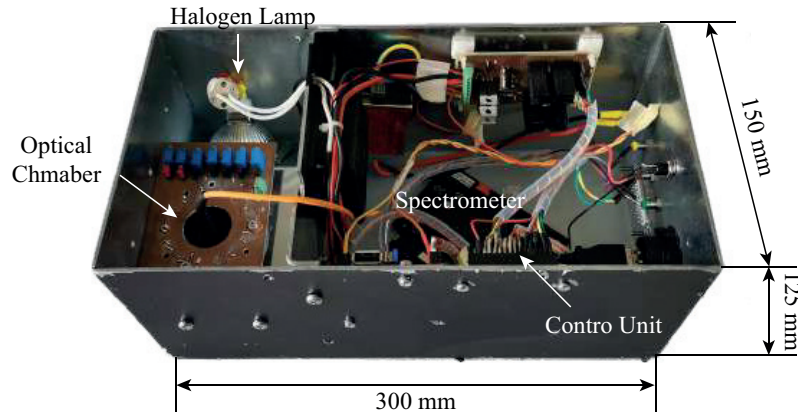


Figure 5.14: Photo of the realized in-field prototype. In the photo the main elements of the instrument are recognizable: i) the spectrometer is connected with a fiber to the optical chamber, ii) the halogen lamp is integrated into the chamber, and iii) The Control Unit is connected to the other element. The instrument is 300 mm (W) $\times$ 150 mm (D) $\times$ 125 mm (H).

The 24 mm-diameter sapphire optical window, the interface between the instrument and the SUT, must be placed as much as possible closer to the sample to guarantee the total reflectance. Furthermore, the optical window ensures that the optical components are permanently shielded from dust and other forms of external contamination present during in-field operation. To obtain a configuration similar to the laboratory one, an Optical Chamber with reflective walls has been realized to emulate the behaviour of an integrating sphere. This chamber allow to reduce the back-scattered light loss, even if its efficiency is not higher than for a commercial integrating sphere. The objective of that chamber is to keep the factor G in eq. (5.1) negligible. The illumination is provided by a 20 W halogen lamp, the DECOSTAR 51 ALU (OSRAM GmbH®, Munich, Germany). The lamp is inserted in the Optical Chamber, and its distance respect with the optical window was chosen to ensure the highest level of irradiance on the sample surface, while also maintaining a sufficient level of uniformity in the illumination. Fig. 5.15 shows the normalized spectrum of the DECOSTAR 51.

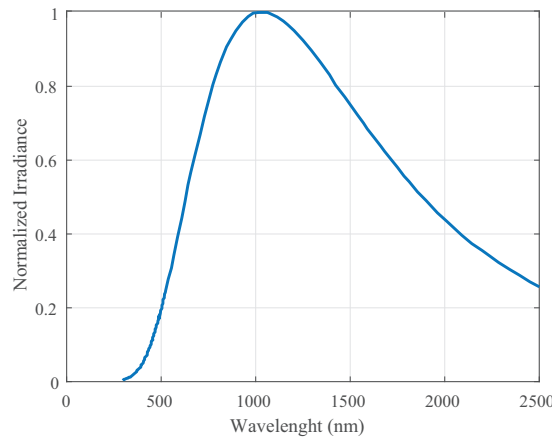


Figure 5.15: Halogen lamp DECOSTAR 51 normalized spectrum.

As discussed at beginning of this section, the NIRS approach requires an accurate and fast calibration procedure that can be periodically performed during a measurement campaign. Moreover, differently from the previous laboratory prototype, this instrument must work in a not controlled environment, with varying enlightenment conditions, possible dust and grit partially obscuring the optical window and with relevant vibration of the entire system. To fulfil these requirements, an optical window can be opened and closed using a flap mechanism. This element allows automatically acquiring the reference and dark spectrum. When the flap mechanism is closed and the lamp is turned off, the dark spectrum is acquired. Successively, by turning on the lamp, the reference spectrum is acquired. In fact, the flap actually contains a sheet of white paper — the reflectance reference target (RRT). The reflectance of this RRT has been determined by comparing it to a NIST certified reflectance standard Spectralon[®] by LABSPHERE. Finally, when the flap is opened, the lamp enlightens the SUT, and the back-scattered light can enter the window and be detected by the spectrometer.

Control and Acquisition are performed by the micro-controller unit (MCU) based on a ChipKIT Wi-FIRE (Digilent©, Pullman, WA, USA) board. This board was chosen because it is tiny, thus integrable in a portable instrument, and powerful (32-bit MCU running at 200 MHz). The board simultaneously acquires data through a serial connection with the NIR1.7 and performs the hard-coded fast Fourier transformation on the acquired absorption spectrum. The board is also connected to a host PC that sends the control commands and receives the acquired spectra. In addition, the board controls the cooling system (a fan), the mechanical flap and the halogen lamp. Finally, a LabVIEW GUI running on the host PC allows the user to control the instrument.

5.3.2 Measurement Procedure

As previously discussed, the measurement procedure is automatically controlled by the Control Unit. Thus, after waiting for the warm up time — successively described — the SUT is place closer to the optical window, and the procedure can start. The measurement is divided in 4 steps:

1. Halogen Lamp off and Flap close. The instrument acquires the instrument offset intensity spectrum I_{DarkI} .
2. Halogen Lamp off and Flap open. The instrument acquires the ambient offset intensity spectrum I_{DarkA} .
3. Halogen Lamp on and Flap close. The instrument acquires the reflectance reference intensity spectrum I_{RRT} .
4. Halogen Lamp on and Flap open. The instrument acquires the sample intensity spectrum I_{SUT} .

Note that, through the GUI, it is possible to enable subsequent measurements. Since the measurements are repeated at short intervals, the ambient conditions (temperature, distance, and lighting) can be assumed to be constant. Thus, in the case of subsequent measurements, only step 4 is executed. Otherwise, the entire procedure is repeated.

Successively, the Control Unit memorized all the acquired spectra and process the data to obtain the sample reflectance spectrum from:

$$R_{SUT}(\lambda_i) = \frac{I_{SUT}(\lambda_i) - I_{DarkA}(\lambda_i)}{I_{RRT}(\lambda_i) - I_{DarkI}(\lambda_i)} \cdot R_{RRT}(\lambda_i) , \quad (5.16)$$

where $R_{RRT}(\lambda_i)$ is the reflectance spectrum of the RRT, determined during the calibration phase that will be described in Section 5.3.3. From the reflectance spectrum, the absorbance spectrum of the sample is derived as in:

$$A(\lambda_i) = 1 - R(\lambda_i) . \quad (5.17)$$

5.3.3 System Calibration

After the realization of the prototype, and the choice of the measurement procedure, the instrument must be calibrated. The calibration phase is crucial to obtain accurate sample spectra and thus physical properties estimation. Basically, the calibration is required to make the measurement independent from the instrument characteristics (avoid instrument induced errors), and make the reference target traceable. This topic is crucial to allow the comparison between the measurements

acquired with the realized prototype with other devices. For this purpose, the acquired spectra must be referable to certified standard.

In the proposed prototype, the RRT is a simple paper sheet, allowing the reduction of costs and to be easy integrated in the prototype. However, this type of target is not referred to any standard. Thus, the RRT reflectance R_{RRT} must be evaluated comparing the RRT spectra to a certified target, over the spectral range of interest. The standard targets Spectralon[®] Diffuse Reflectance Standards by LAB-SPHERE were employed. Specifically, for the calibration the standard target $S_{0.99}$ with reflectance $r = 0.99 \%$ was used. The target $S_{0.99}$ was placed in front of the optical window of the instrument, and the measurement procedure presented in Section 5.3.2 was run. Thus, the instrument acquired the intensity spectrum $I_{S_{0.99}}$ of the standard, and then, according to eq. (5.16), the RRT reflectance was derived as:

$$R_{RRT}(\lambda_i) = \frac{I_{RRT}(\lambda_i) - I_{DarkI}(\lambda_i)}{\frac{I_{S099}(\lambda_i) - I_{DarkA}(\lambda_i)}{0.99}}, \quad (5.18)$$

The standard spectrum acquisition was repeated 60 times — in different measurement session, no subsequent — and the mean $\bar{R}_{RRT}(\lambda_i)$ was calculated.

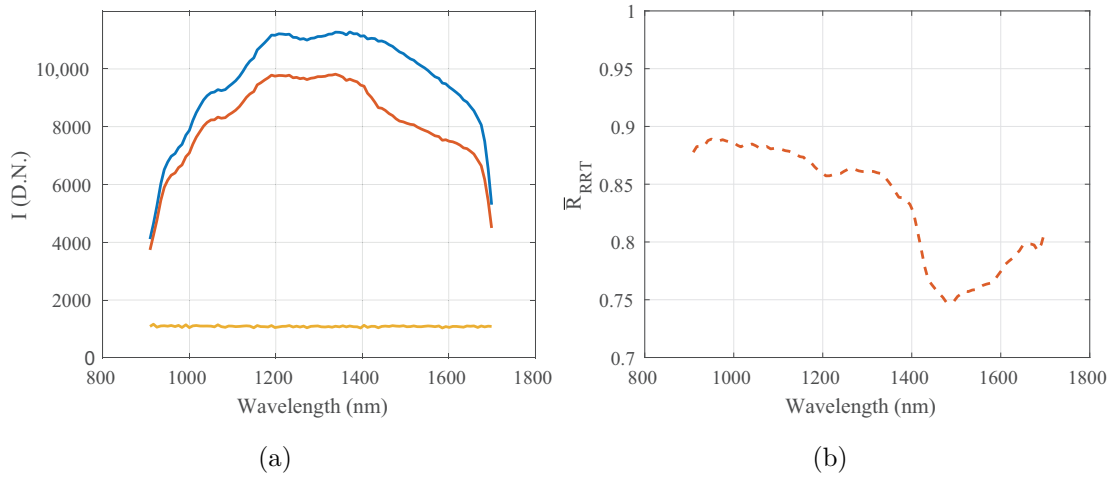


Figure 5.16: Results of Reference Reflectance Target Analysis. Fig.(a) shows an example of acquired spectra during the instrument calibration. The red line (—) represents the standard reflectance spectrum I_{S099} , the blue line (—) represents the reference reflectance target I_{RRT} . The yellow line (—) represents both dark intensities I_{DarkA} and I_{DarkI} , since these spectra were almost equal over the measured spectral range. Fig.(b) shows the mean reflectivity $\bar{R}_{RRT}$.

5.3.4 Instrument Characterization

After the calibration phase, it is crucial to characterize the instrument in terms of warm-up, linearity and repeatability.

First, the warm-up is investigated. Thus, the behaviour of the instrument was

evaluated until the system thermal regime was reached, thus waiting for the time the system requires for reaching a stable measurement. Then, the instrument was kept off waiting for all parts to reach room temperature. Successively, the instrument was power-on, and the standard target $S_{0.50}$ with reflectance = 0.50 % was placed at the optical window. The measurement procedure involves an acquisition each 30 s for 120 min, for a total of $N = 240$ acquired spectra. After the acquisition, the reflectance spectrum R_{S050} of the standard target was calculated according to eq. (5.16), together with its mean $\bar{R}_{S050}$ over the N measurements. Fig. 5.17 shows the results of the warm-up analysis. The figure, shown a constant decrease of the reflectance in the first hour. Then the reflectance stabilized. The decrease trend can be approximated through an exponential decay (R^2). The average reflectance reduction was about 1.4 % with a decay constant of 13.6 s. At the end of the transient, the measurement error was 0.6 %.

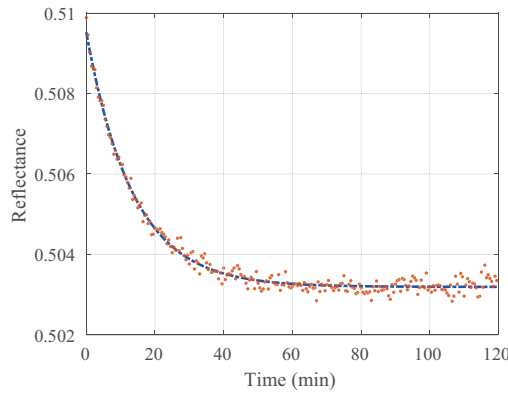


Figure 5.17: Results of the warm-up analysis on the instrument. The figure shows the trend of the reflectance as a function of the time elapsed from the system power-on. The orange dots (●) represent the experimental point, while the blue line (—) represents the exponential decay fit.

Successively the linearity of the system was evaluated. In this case, after warm-up and calibration of the system, ten intensity spectra for each of the standard targets $S_{0.99}$, $S_{0.75}$, $S_{0.50}$ and $S_{0.02}$ were acquired, and their mean was computed. Then, the mean reflectance spectrum for each targets was computed. Fig. 5.18(a) shows the mean reflectance standard spectrum. Then, the mean reflectance over the entire spectral range was computed. The graph demonstrates a relatively flat trend with a slight positive slope at higher wavelengths. Fig. 5.18(b) shows the mean measured reflectance vs the nominal reflectance of the standard target. It is possible to observe that the instrument presents a good linearity in the measurement, and the linearity error was found to be 0.93 %.

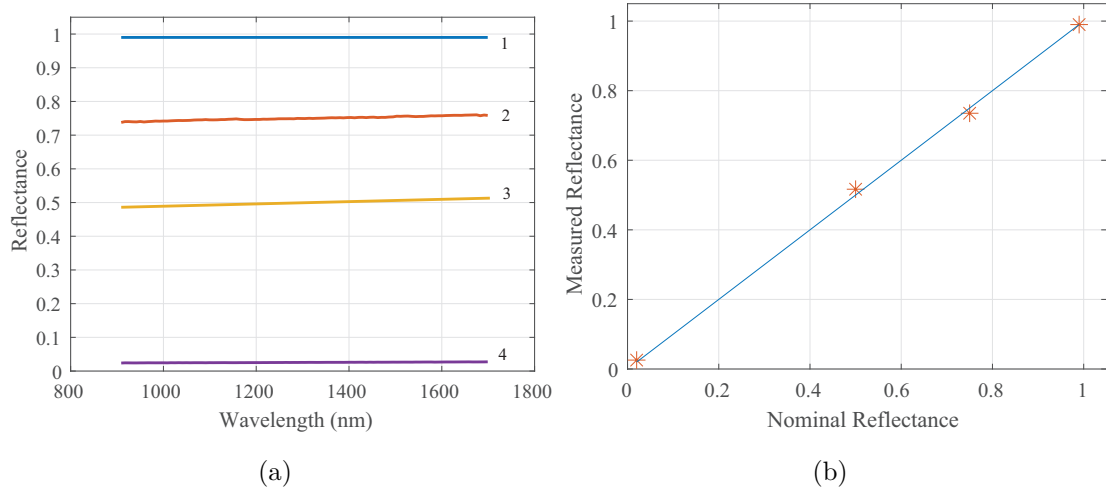


Figure 5.18: Results of the linearity analysis on the instrument. Fig.(a) shows the mean reflectance spectra of the standard target. The blue line (—) represents the standard reflectance spectrum R_{S099} . The orange line (—) represents the standard reflectance spectrum R_{S075} . The yellow line (—) represents the standard reflectance spectrum R_{S050} . The purple line (—) represents the standard reflectance spectrum R_{S002} . Fig.(b) shows the measured reflectance vs the nominal reflectance of the standard targets. The (*) represents the experimental points, while the blue line (—) represents the linear best fit.

Finally, the repeatability analysis was run to investigate the measurement consistency. The test was performed on a single standard target, the S_{050} . After waiting for the warm-up and calibration, the analysis started. A spectrum of the standard target was acquired each 30 min for 13 h, for a total of 26 measurements. For this analysis, a single measurement corresponds to the mean $\bar{R}_{S050}(\lambda_i)$ of 8 subsequent spectrum acquisitions. Successively, the mean $\bar{R}_{S050}$ of the mean reflectance spectrum over the entire spectral range was computed. After each measurement, the S_{050} standard was moved randomly to simulate a different positioning of the SUT. Fig. 5.19 shows the results of this analysis. The measurements showed an average value of 49.76 % and a sample standard deviation equal to 0.71 %. The error in repeatability is contained, demonstrating good accuracy.

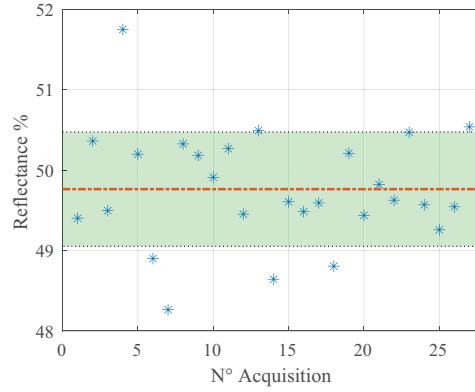


Figure 5.19: Results of the repeatability analysis on the instrument. The (*) represent the mean reflectance $\bar{R}_{S050}$. the red dashed line (—) is the averaged reflectance over the 13 h, and the green area corresponds to the standard deviation of the entire set of data.

5.3.5 In Field Measurements

Once the instrument was calibrated and characterized, it was possible to proceed with the crop measurements. In this phase, it was not possible yet to set up direct in-field measurement. However, the in-field conditions were partially reproduced in the laboratory. Successively, a PLS model based on the spectra of the new instrument was used to estimate the MC. In this case, 12 cuttings (2 g) were harvested from three different cultivation to increase the variability of the sample. The sample was stored in sealed plastic bags to preserve MC. For the test, the cuttings were placed in 12 Petri dishes. Note that the Petri dishes were only used to contain the SUT; no pre-treatment of the sample was performed, and the SUT was not pressed inside the Petri. Each sample is a heterogeneous mix of stems, leaves, and air interstices with variable moisture content related to the specific conditions of the cultivation field. The reference MC of each sample was evaluated after the spectra acquisition employing the reference method described in Section 5.2.3. The analysed samples have naturally different MCs ranging from 8 % to 76 %.

Since it was preferred not to apply pressure to the sample, the sample density was given by the dish volume and sample mass. As a result, three different densities were obtained, each for 4 Petri dishes: 83 kg/m³, 125 kg/m³, and 250 kg/m³. Of course, this type of density measurement is not accurate enough to be taken as a reference. Thus, in this first evaluation phase, only the MC is considered, and the density is provided only as sample information.

After the SUT preparation, the NIR spectra were acquired. Spectrum acquisition was performed in eight different positions of the Petri dish to have a more comprehensive view of the heterogeneous SUT. Hence, 96 spectra were acquired and used for the MC estimation PLS model design. The model was developed following

the procedure explained in Sections 5.2.2 and 5.2.4. Thus, the same data handling was performed, obtaining the filtered normalized first derivative of the logarithmic transformation of the absorbance spectra of the sample. Also, the BOI selection was performed in the same way, observing the correlation coefficient of the MC. The BOI was chosen by finding the wavelength range in which the correlation coefficient is higher than 85 % and taking into account the water absorption peak at $\lambda = 1450$ nm. Thus, the chosen BOI was:

$$\text{BOI} : \lambda_i \in (1.37 - 1.55) \mu\text{m} . \quad (5.19)$$

Finally, the number of latent variables was set to 10. The dataset was divided into 67 predictor variables for calibration and 29 predictor variables for validation. Fig. 5.20 and Fig. 5.21 shows the results for the calibration and validation of the PLS model, respectively. In addition, Fig. 5.22 shows the relative RMSE of the MC estimation for calibration and validation. Table 5.3 reports the statistics of the developed model.

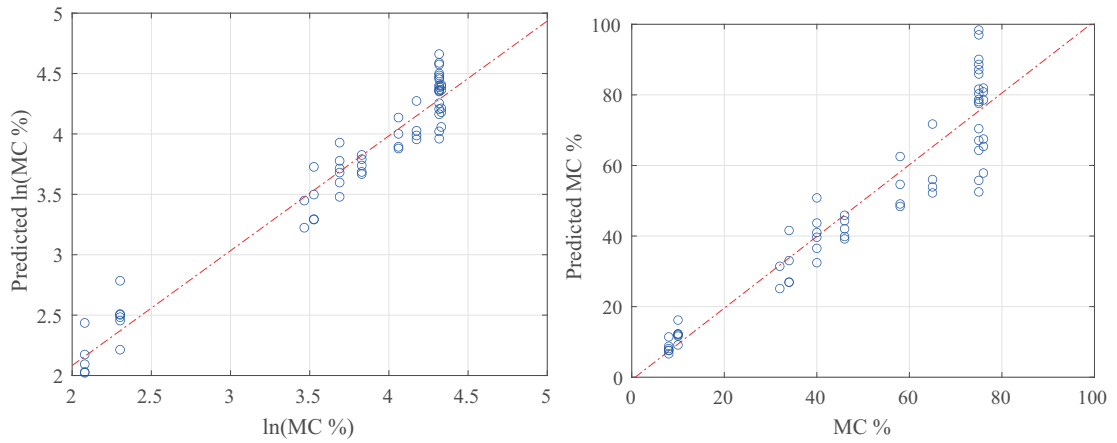


Figure 5.20: PLS calibration response for MC estimation of the in-field prototype. Fig.(a) shows the response values vs the reference values, thus the logarithmic transformation of the estimated and reference MC values. Fig.(b) shows the estimated MC as a function of the reference MC values.

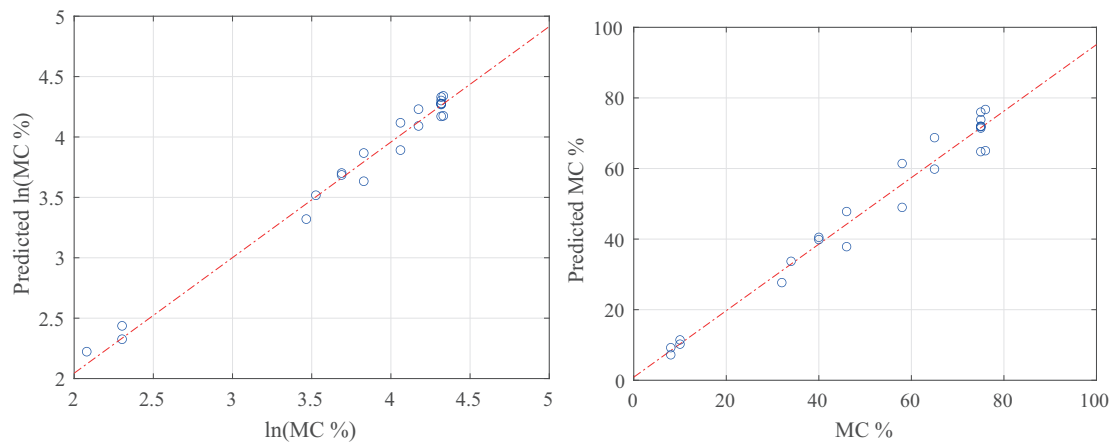


Figure 5.21: PLS validation response for MC estimation of the in-field prototype. Fig.(a) shows the response values vs the reference values, thus the logarithmic transformation of the estimated and reference MC values. Fig.(b) shows the estimated MC as a function of the reference MC values.

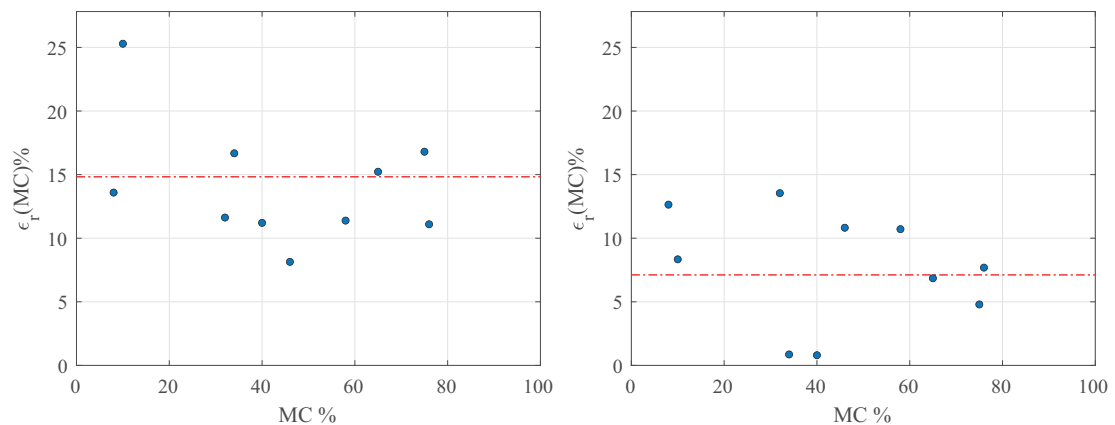


Figure 5.22: Relative RMSE between the estimated and reference MC values of the in-field prototype. Fig.(a) refers to calibration, while Fig.(b) refers to validation.

Parameter	FDLA
C-RMSE	0.1671
$C-R^2$	0.9507
V-RMSE	0.0867
$V-R^2$	0.9846
V-MEAN-ERROR	7.11 %

Table 5.3: Statistics related to the moisture estimation model performed using the FDLA signals. C-RMSE and $C-R^2$ refer to the calibration model, while V-RMSE and $V-R^2$ refer to the validation model.

This work aims to evaluate the NIRS approach in crop MC and density estima-

tion. NIRS was investigated because it has all the characteristics that would allow the measurement directly on the field. The presented results show the feasibility of the NIRS approach jointly with a multivariate PLS statistical model for the MC and density estimation. This technique suffers from various influence quantities that affect the measurement, among which the density variability introduces errors in the estimation. Nevertheless, the presented results show good estimation capability regarding the MC, while density estimation offers worse performance in comparison. Then, the introduction of the logarithmic transformation allows keeping the relative error constant, improving the goodness of the estimation from an economic point of view.

The proposed approach was brought to the next level by realizing an in-field prototype. The instrument performance, in terms of linearity and sensitivity, is satisfactory. The calibration procedure design for the instrument allows for overcoming some issues typical of that approach, such as the sensitivity to environmental conditions. In fact, the results obtained by applying the acquired spectra to a PLS model are better than for the laboratory prototype. In conclusion, combining that analysis approach with ADAS systems has the potential to enable fully autonomous crop moisture estimation.

Conclusion and Future Improvements

Total automation of complex industrial processes will be the future of many industries, including agriculture, which is one of the most active sectors in this regard. Fully automation can be reached only by merging different technologies. This doctorate work aims to investigate agriculture vehicle automation by focusing on two main aspects. The harvest process requires an autonomous vehicle that can assess the status of the products to be harvested.

The first topic regards autonomous driving and ADAS systems, particularly LiDAR, focusing on the analysis and characterization of such instruments. In this dissertation, several LiDAR characterization procedures have been presented to provide tools for the LiDAR comparison. The described analyses regard the main characteristics of ToF Spinning 3D LiDARs, ranging from the warm-up to detection probability. Moreover, the performance of LiDARs in facing a bank of fog has been evaluated. The setups proposed are all easy to implement and inexpensive, providing fast benchmarking tools that may help manufacturers to find the best instrument for specific applications. All the presented methods have been proposed with a specific measurement setup. However, the basis of the proposed setups is very similar, highlighting the scalability and versatility of the proposed approach, which allows performing different analyses with slight modification of the stage. The characterizations procedures proposed have been evaluated with commercial LiDAR (MRS 1000 and MRS 6000 by Sick and VLP 16 by Velodyne) to investigate their limits of applicability and potentiality. In the specific, the static analysis proposed regards: i) the warm-up time and the stability in the distance estimation, ii) the error in the distance estimation respect with to a reference interferometer, iii) the axial error due to the quantized nature of the 3D LiDARs, iv) the effects of target reflectance on the axial distance and vi) the transversal errors due to quantization with a focus on target detection probability. Regarding this last topic, the procedure aims to evaluate the empirical detection probability of a target, and this metric is employed to investigate the transversal error due to the Point Cloud quantization

that may deform a target. In addition, an analysis of the effect of fog on the LiDARs performances is presented, proposing a new approach and setup that distinguishes for the reduced size and costs. The measurement method is evaluated by testing a commercial LiDAR and using natural fog. The obtained results reveal that the proposed approach is promising, thus allowing an inexpensive benchmarking tool for a crucial analysis.

Further improvements concerning the characterization of ADAS systems regard three main topics. First, the developed measurement procedures have been designed concerning the possibility of characterizing various types of 3D LiDARs. However, only ToF Spinning 3D LiDARs have been used for testing such procedures and plants. Even if it was chosen to keep the procedure as generic as possible, a step forward would be to verify the applicability of such methods by testing LiDARs of different natures, such as MEMS or Flash. Another point refers to the staticity of the tests. All the measurement methods described in this work concern the static analysis of LiDAR performance. However, the realization of setups in which the LiDARs can be evaluated in motion will allow obtaining a more comprehensive view of LiDAR properties and mainly provide more accurate benchmarking tools for autonomous driving applications. Static analyses can furnish relevant information about such systems. Nevertheless, the LiDAR movement, especially at high speed, may introduce deformations and distance estimation errors that must be taken into consideration. For example, target recognition will be strongly affected during movement. Finally, a relevant improvement regards the adverse condition analysis. This thesis focuses on how the presence of fog affects LiDAR performance. However, investigating LiDAR performance in other adverse conditions can give a complete perspective of its capabilities in real-world scenarios. In particular, considering agriculture vehicles, an important aspect regards the performance of such systems in facing dust, stems, leaves and generic organic particulate in air suspension. This condition is frequent during in-field operations. Thus investigating the behaviour of LiDARs in such conditions is crucial to reach total automation. Following the same approach of fog analysis, it would be possible to evaluate how dust affects these systems estimation. However, the setup must be accurately realized to avoid explosion due to the static charge produced by dust friction on the eventual chamber walls. Of course, another very interesting improvement will be the possibility of performing adverse weather condition analysis with the LiDAR in movement. Nevertheless, considering the fog, controlling such a quantity of mist to fill a room in which the LiDAR may move will be dramatically complex.

The second topic treated in this dissertation regards the other side of automation in agriculture. Autonomous driving is something more and more present, even in agricultural vehicles. However, reaching complete automation is not enough. Pre-

cision agriculture requires technologies that can evaluate the quality of products to be harvested and the correct field point for seeding, for example. According to this concept, this work presents a measurement approach for the Moisture Content evaluation in the crop directly on the field. The NIRS approach for the crop Moisture Content and Density estimation is evaluated. These parameters have great importance in the quality and cost of the crop. NIRS technology reveals very promising since it provides all the characteristics required for an on the field analysis. In fact, i) it is fast, ii) particularly adapted to the analysis of organic samples, and iii) it does not require sample preparation. Specifically, total diffused reflectance configuration is employed to increase the accuracy and the Signal to Noise Ratio. The proposed approach involves the NIR spectra analysis exploiting a Partial Least Square model that is particularly suitable for spectra analysis. In addition, I propose to analyze the logarithmic transformation of the crop absorbance spectrum. In such a way, it will be possible to separate the Moisture and Density contributions. Moreover, the relative error in the PLS estimation is kept slightly constant, instead of the absolute error, with a reduction of price errors on small crop quantities. The proposed measurement approach is evaluated, designing a laboratory prototype of NIR spectrometer and testing it on alfalfa grass samples. Since the results were encouraging, a prototype for in-field analysis has been developed. The realized instrument is characterized by a calibration procedure that makes it more robust against environmental changes. The prototype was characterized, and then it was tested with alfalfa grass samples. The obtained results respect the expectation, revealing the potentiality of this approach.

Further improvements in this work regard the improvement of the instrument and the testing directly on a harvesting machine. First, the prototype reveals good accuracy in spectra acquisition. Nevertheless, with respect to the laboratory prototype, using the optical chamber instead of the integrating sphere increases the reflected light loss and decreases the Signal to Noise Ratio. Thus, the introduction of an actual integrating sphere or an improvement in the optical chamber would lead to an improvement in performance. Moreover, the estimation accuracy will be increased by acquiring more samples for model calibration, especially for density estimation. Finally, since the crop is a heterogeneous material, the possibility of performing the simultaneous spectrum acquisition in different areas will give a more accurate MC and density estimation.

Then, the possibility to perform measurements directly on the field will provide useful information about the limits of the prototype that can be used to modify the design and obtain more accurate estimation. For example, the effect on the measurement of vibration and dust could be evaluated. Moreover, the integration of the instrument with an actual vehicle machine should be evaluated.

Another improvement refers to the possibility of merging the NIRS approach with other estimation technologies, such as microwave and imaging. Sensor fusion will provide different information about the crop or other samples and a more robust estimation.

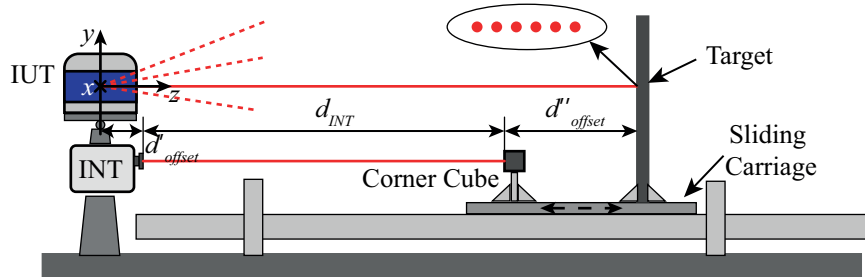
Concluding, this work explores two main aspects of the automation of industrial processes focusing on agriculture applications. Automation will be more and more present in industries, and the fusion of different technologies will be the key to reaching a new level in agriculture processes.

Appendix A

Setup Alignment Procedure

For the LiDAR distance error analysis, the setup involves the presence of an interferometer (INT). The Instrument Under Test (IUT) and the INT are separate and independent instruments, characterized by their radius r , zenith angle ω ($\phi = \pi/2 - \omega$, ϕ elevation angle) and azimuth angle θ . Thus, recalling the scheme already present in Section 2.4, the setup used has 6 degrees of freedom. As a consequence, any potential misalignment between IN and IUT would result in a cosine error. To avoid misalignment errors, an alignment procedure is presented:

- Step 1: **Orient the INT.** The INT laser source is oriented to a reference direction ($\theta_{INT} \approx 0^\circ, \phi_{INT} \approx 0^\circ$). The laser beam must travel parallel to the floor.
- Step 2: **Align and Orient the Rail System.** The rail system must be aligned with the INT laser beam. This procedure can be accomplished through the H-shape adjustable supports.
- Step 3: **Roughly Align the IUT With the Rail and the Target.** The IUT must be roughly aligned with the centre of the target, i.e. the IUT origin of the axis must be aligned with the centre of the target.



Schematic representation of the side and top view of the setup used for the characterization of the error of the IUT respect to an interferometer.

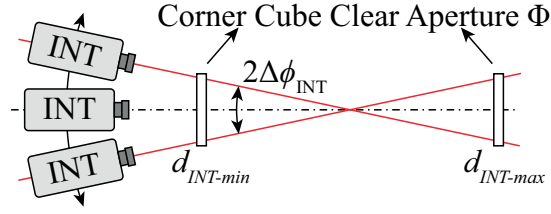


Figure A.1: Schematic representation of the alignment between INT and the Rail. $\Delta\phi_{INT}$ is the maximum misalignment between INT and the rail, $d_{INT-max}$ and $d_{INT-min}$ are the maximum and minimum distance between the INT and target and Φ the aperture of the corner cube diameter.

Step 4: Control the alignment. The target must be placed at a short distance from the IUT to maximize the Point Cloud (PC) points. A PC is acquired and analyzed, interpolating the target points in the PC to obtain a plane. After that, the IUT is rotated and moved until i) the resulting plane is orthogonal with the xy plane of the IUT reference system (target orthogonal to the IUT geometrical axis) and ii) the centre of the target is approximately at the coordinate $x = 0$ and $y = 0$.

step 5: Finley align the IUT with the rail. The target must be positioned at the maximum distance from the IUT. Then, the IUT must be finely moved by exploiting the multiaxis stage as long as the $(x = 0, y = 0, z)$ point and at least other three adjacent points of the PC fall on the target.

According to the procedure, it is possible to obtain an accurate alignment. Nevertheless, it can be relevant to evaluate the angular error that can afflict the measurement. Consider the INT and the corner cube mounted on the sliding carriage employed to reflect the INT laser beam. The diameter of the clear aperture of the corner cube used in the setup is $\Phi = 5$ cm, and the maximum and minimum corner cube distance, due to the rail system, are $d_{INT-min} \approx 1$ m and $d_{INT-max} \approx 20$ m, respectively. According to Fig. A.1, the maximum misalignment between the elevation angle of the INT and the rail can be expressed as:

$$\Delta\phi_{INT} = \arctan \left(\frac{\Phi}{d_{INT-max} - d_{INT-min}} \right) \approx 0.15^\circ . \quad (\text{A.1})$$

Of course, the same reasoning also applies to the azimuth angle, and due to the symmetry of the problem $\Delta\phi_{INT} = \Delta\theta_{INT}$.

The misalignment of the IUT with respect to the rail can be evaluated in a similar way. Considering Fig. A.2, Δh is the offset between the y origin of the axis and the center of the target, and $h_T = 24''$ is the height of the target used in the setup. Thus, the maximum misalignment between the elevation angle of the IUT and the

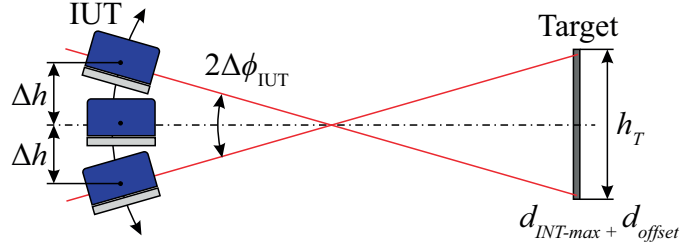


Figure A.2: Schematic representation of the alignment between IUT and the Rail. $\Delta\phi_{IUT}$ is the maximum misalignment between INT and the rail. $d_{IUT-max}$ is the maximum IUT-Target distance, d_{offset} is the offset between the IUT-Target distance and the INT-Target distance, Δh is the difference between the origin of the axis of the IUT and the center of the target, and h_T is the height of the target.

rail can be expressed as:

$$\Delta\phi_{IUT} = \arctan \left(\frac{\Delta h + h_T/2}{d_{INT-max} - d_{off}} \right) \approx 0.15^\circ . \quad (\text{A.2})$$

where d_{offset} is the offset between the distance d_{INT} , INT to corner cube, and d , IUT to target. The misalignment should be significantly low if the alignment procedure is performed accurately. However, by way of example, in the case of $\Delta h = 5$ cm, the resulting misalignment would be $\Delta\phi_{IUT} = 0.97^\circ$. In the alignment procedure, the condition of obtaining at least four adjacent points falling on the target is required. Thus, the maximum misalignment between the azimuth angle of IUT and the rail $\Delta\theta_{IUT}$ is less than $\Delta\theta_{INT}$, thus, it is possible to approximate $\Delta\theta_{IUT} = \Delta\phi_{INT}$. Finally the maximum elevation and azimuth angular error, due to this misalignment, between the IUT and the INT can be calculated as:

$$\epsilon_\phi \approx \epsilon_\theta = \Delta\phi_{IUT} + \Delta\phi_{INT} \approx 1.12^\circ . \quad (\text{A.3})$$

Thus the overall maximum error in alignment between IUT and INT is expected as:

$$\epsilon_{TOT} = \arctan \left[\sqrt{(\tan \epsilon_\phi)^2 + (\tan \epsilon_\theta)^2} \right] \approx 1.58^\circ . \quad (\text{A.4})$$

Appendix B

Publication List

Journal Articles

1. S. Cattini, D. Cassanelli, L. D. Cecilia, L. Ferrari, and L. Rovati, “A procedure for the characterization and comparison of 3-d lidar systems,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.
2. D. Cassanelli, N. Lenzini, L. Ferrari, and L. Rovati, “Partial least squares estimation of crop moisture and density by near-infrared spectroscopy,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–10, 2021.
3. S. Cattini, D. Cassanelli, G. D. Loro, L. D. Cecilia, L. Ferrari, and L. Rovati, “Analysis, quantification, and discussion of the approximations introduced by pulsed 3-d lidars,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–11, 2021.

Conference Proceedings

1. D. Cassanelli, S. Cattini, G. Di Loro, L. Di Cecilia, L. Ferrari, and L. Rovati, “Comparison of vlp-16 and mrs-1000 lidar systems with absolute interferometer,” in *2021 IEEE International Workshop on Metrology for Automotive (MetroAutomotive)*, 2021, pp. 54–59.
2. D. Cassanelli, S. Cattini, G. Di Loro, L. Di Cecilia, L. Ferrari, D. Goldoni, and L. Rovati, “A simple method for the preliminary analysis and benchmarking of automotive lidars in fog,” in *2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2022, pp. 1–6.
3. D. Cassanelli, S. Cattini, G. D. Loro, L. D. Cecilia, L. Ferrari, and L. Rovati, “Lidars detected signal and target distance estimation: measurement errors from target reflectance and multiple echos,” in *2022 IEEE International Workshop on Metrology for Automotive (MetroAutomotive)*, 2022, pp. 59–64.

4. D. Cassanelli, S. Cattini, L. Ferrari, L. Rovati, “A method for the estimate erroneous fog detection in automotive LiDAR”, in 2023 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) [ACCEPTED].

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