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PhD Thesis:

"Monitoring Of Daily Living Activities In A Perspective Of Telerehabilitation"

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"To my family and to the memory of Luigi.."

SUMMARY

Foreword

The increase of population age, hospitalization costs and limited availability of qualified medical professionals suggest the development of new health care services delivered directly in the home of patients. The deployment of home care services still represents an exception and not the rule in the clinical practice.

Among the care services those related to the assessment and monitoring of motor functions greatly impact on the quality of life and can reduce the instances of pain, anxiety and depression in elderly and/or motor impaired people. Tele-monitoring could help in reducing fall risk, in assessing metabolic expenditure, in classifying daily activities, while tele-rehabilitation could improve the life of impaired people by reducing the transfers toward clinical facilities and by allowing therapeutic treatments in a more comfortable environment.

The design of such services implies the development of integrated systems for collecting, processing and transferring motion data. These systems should integrate processing techniques to extract information by kinematic, kinetic and electrophysiological signals, indexes of functional scales, to be calculated and transferred to clinical centers, for the assessment and follow up of the motor functions, hardware devices for data collection and transfer, communication protocols.

This PhD thesis aims at the analysis of Activities of Daily Living (ADLs) for monitoring and eventually improve patient's quality of life. In particular, motor functions of both upper and lower limbs have been considered using several sensors to collect data and different processing techniques to extract motion information. While for the upper limbs finalistic movements have been studied, for lower limbs several activities, such as walking, climbing/descending stairs, standing up and sitting on a chair, have been analyzed by pattern recognition techniques in order to obtain automatic classification.

Lower limbs activities have been classified after recording motion data by accelerometers. Such sensors have a low cost, are minimally invasive and the provided information has been proved to be highly significant. In literature, accelerometers have been used for activity monitoring and classification (Mathie et al., 2004) and they can also be applied to fall risk evaluation and metabolic expenditure estimation. Moreover, the possibilities offered by accelerometer monitoring appear worth to be explored further.

In this thesis, several algorithms for extracting useful information from data recorded by accelerometers are proposed, and a novel integrated wireless system for home monitoring is designed. Body posture was also taken into account. The algorithms developed and tested aim at the recognition and the classification of motor activities and try to take into account the speed variability during movement execution. In order to facilitate the data transfer, special attention has been devoted to keep as low as possible the processing workload.

The algorithms have been integrated in the system that has been developed in this work to collect, elaborate, wirelessly transfer and visualize accelerometer signals using a cost effective and novel design, which can be integrated with other commercial wireless instrument. Different configurations were tested to better fit the needs of a tele-monitoring context.

For the assessment of upper limbs ADLs, a different approach has been used, that is based on video analysis technique. Recording a video sequence during movement analysis is rather common in clinical practice, nevertheless this information is often used only for extracting qualitative or semi-quantitative data.

'Markerless' video elaboration algorithms have been used to study the movements. This choice has been driven by the unsuitability of marker based techniques for the home environment. The video sequences were captured during the execution of physical exercises on a digitizing tablet, which was used as reference. Movement reconstruction performance was tested varying the number of cameras and image resolution.

The chosen physical exercises, defined together with the medical staff of the Department of Neuroscience of "La Sapienza" University of Rome, were further analyzed by finding a set of kinematic parameters, which proved to be useful for the functional analysis of upper limbs.

The present study is connected to the FIRB research project SIR-LOOK (Sistema Integrato e seRvizi teLematici per il mOnitOraggio multimodale dell'attività motoria nell'anziano) funded by Italian MIUR and carried on by the University of Roma TRE in collaboration with the University of Genova and the Polytechnic of Torino during the years 2004 – 2006.

More details about this work can be found in the web site of the Biolab[3] laboratory of the Roma TRE University (*www.dea.uniroma3.it/biolab*).

2 Project introduction

The objective of this work is the definition of a set of instruments and methods for the assessment of human movement in a telemonitoring context. In particular the focus was set on the determination of qualitative and quantitative parameters for the extraction of significant information regarding movement kinematics. Activities of Daily Living (ADLs) were the principal objects of this study, because more relevant for the quality of life.

The choice of the ADL set to analyze was done considering the impact to quality of life, according to the principal disability grading scales (FIM and Barthel scales).

The ensemble of ADLs is very heterogeneous as it can be demonstrated by considering that each ADL involves each limb with different extents, and its execution implies different amounts of workload and of cognitive or coordination skills.

In this work, ADLs involving mostly upper limbs will be distinguished from those that involve mostly lower limb, and two different methodological approaches will be used for the related analysis.

For **lower limbs** ADLs, such as gait and climbing/descending stairs, the study was concentrated on the possibility of extracting relevant information by monitoring physical activity with accelerometers. Both hardware design and data elaboration were carried on in a context of continuous monitoring with wearable sensors. In particular, a pattern recognition algorithm was developed with the aim of shedding light on two different relevant aspects that were not treated extensively in literature:

- the determination of execution speed for the recognition of motor activity;
- the need of avoiding an initial calibration.

For **upper limbs** ADLs, a periodically-subministred monitoring is proposed. A novel combined technique for movement assessment, based on video markerless techniques and a graphics tablet is presented.

Video data was collected in order to reconstruct global human movement kinematics exploiting a markerless point tracking elaboration technique, while the graphics tablet was used as reference to estimate movement reconstruction error and to assess global motor performance using guided motor exercises.

Together with the development of the proposed combined technique, a collection of software tools was also implemented, to assist professionals and patients in conducting movement analysis in a telemonitoring context.

2.1 Lower limbs activity monitoring

2.1.1 Algorithms for activity monitoring classification

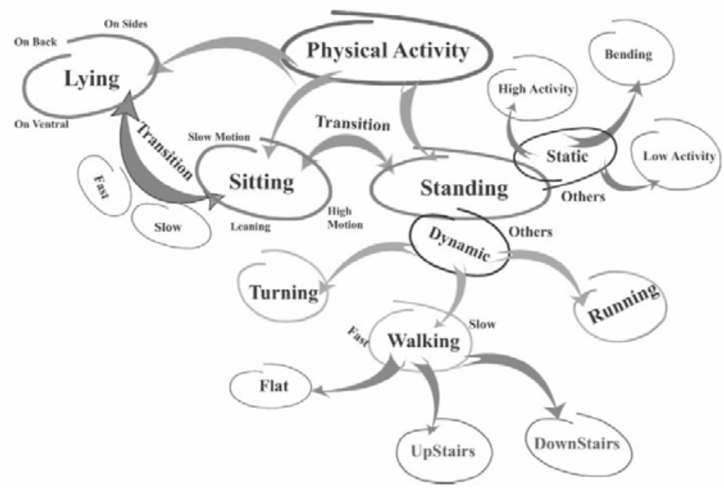
A set of algorithms for activity monitoring, aimed at the recognition and the classification of motor activity, was built up. Motor activity was reconstructed starting from accelerometer signals using a time based on a pattern matching technique which extracts signal templates associated to each motor activity and exploits cross-correlation coefficients to compare signal with templates.

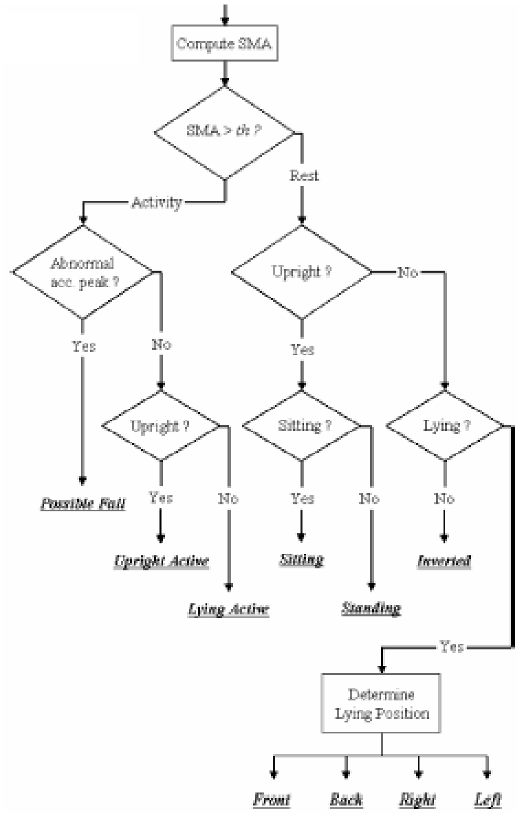
The recognition algorithm implemented, respect to a classical cross-correlation algorithm, introduces a time-warping technique which takes in account the variability of execution speed in the motor activity analyzed. Reviewing literature, it was in fact evident that using cross-correlation coefficients, it was not possible to correctly classify motor activities when they are executed at different speeds (Veltink et al. 1996, Sekine et al. 2000). Activity versus inactivity was detected implementing an algorithm already present in literature (Veltink et al. 1996).

Algorithm performance was tested displaying a consistent number of sensor channels and setting up several measurement campaigns. The first analysis aimed also at finding the best sensor locations and orientation of accelerometer sensors.

The recognition method exploits a hierarchical classification algorithm, often proposed in literature (Aminian & Najafi 2004, Karantionis et al. 2006), but never implemented fully (see **Figure 1**).

Examples of hierarchical algorithms proposed in literature:





The proposed algorithm:

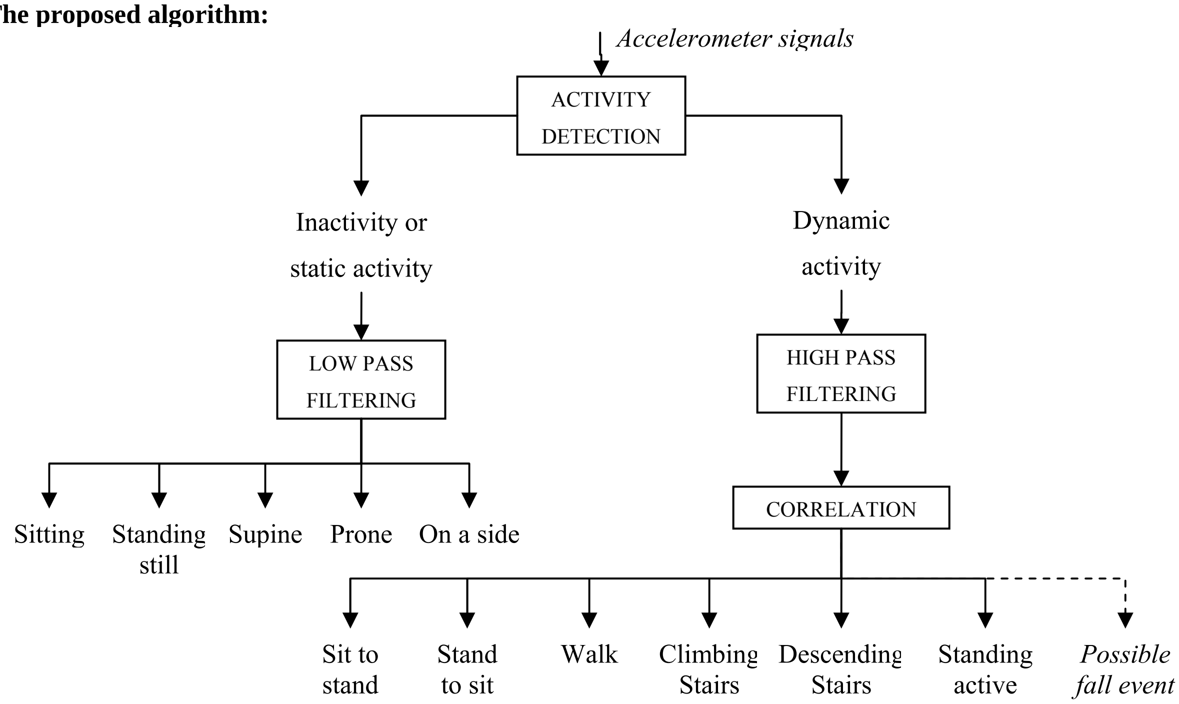


***Figure 1**: <u>UPPER PANEL</u>: hierarchical algorithm presented in literature:, Aminiam & Najafi, 2004 (left) and Karantonis et al., 2006 (right). <u>LOWER PANEL</u>: the proposed algorithm.*

2.1.2 Collected data

Data were collected with a 3-stages process, described below:

Template extraction: for the extraction of a complete set of template 5 sensor channels were displayed in the position and orientations reported in **Figure 1**. In order to calibrate the system, gait phases were extracted using foot switches and knee angles were recoded with two electrogoniometers.

Protocol for template extraction			
Execution order	**Session**	**Total cycles**	**Cycles per recording**
I	Gait	25	12
II	Sit-to-stand e Stand-to-sit	25 per activity	1
III	Climbing, decending stairs	25 per activity	9

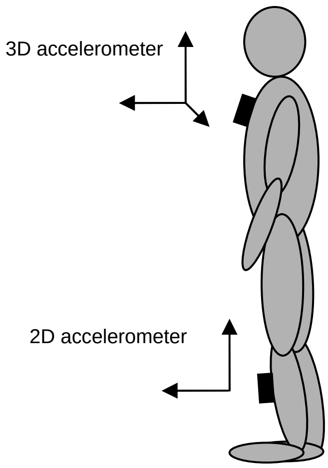
***Figure 2**: UPPER PANEL: Sensor layout, picture during tests. LOWER PANEL: Experimental protocol..*

All signals were recorded with a tradition system of movement analysis. Tests were performed on 6 adult subjects and were divided in three session as reported in **Figure 2**.

For template extraction of gait, climbing and descending stairs, foot switches were used as triggers. For the sit-to-stand e stand-to-sit activities, an algorithm of activity versus inactivity detection was exploited.

Setting up algorithms and system layout: The aim of this test was to preliminarily assess and optimize the performance obtained with the implemented recognition algorithms and point out the best sensor locations and orientations. The layout of these tests was similar to the one used during the Template Extraction stage.

Testing algorithms with different execution speeds and in a home-like environment: Algorithms implemented where thus tested using different systems and reducing the sensor layout to the minimally invasive configuration. The aim was to assess the movement using remote monitoring exploitable system. The algorithm performance was tested recording activities executed at different speeds. In such tests, subject could wear comfortably their own clothes. Both wireless and wired system were also exploited. The sensors layout, constituted only by accelerometer sensors, is the one described below:



Protocol for activity recognition at different speeds

Execution order	**Session**	**Mode**	**Recordings**
I	Gait	70 cycles	a) Low speed b) High speed
II	Sit-to-stand e Stand-to-sit	70 cycles	a) Low speed b) High speed
III	Climbing, decending stairs	70 cycles	a) Low speed b) High speed
IV	Other activities	1 minute recording	a) Normal Speed

***Figure 3**: UPPER PANEL: Sensor layout. LOWER PANEL: Experimental protocol.*

Trials were divided in 4 sessions (described in **Figure 3**). Each session, except the last one, was divided in 2 repetitions of the same task executed at different movement speed. A commercial video camera was also used for troubleshooting analysis. In the last session other ADLs were recorded as controls.

2.1.3 The proposed algorithms

Recognition algorithm: The proposed algorithm takes inspiration from the algorithm designed by Veltink et al. in 1996 and aims at increasing the recognition performance taking into account the variability of execution speed. Therefore, the template associated to each activity was warped through time n times. All the n copies obtained were thus matched with the corresponding accelerometer signal (see **Figure 4**).

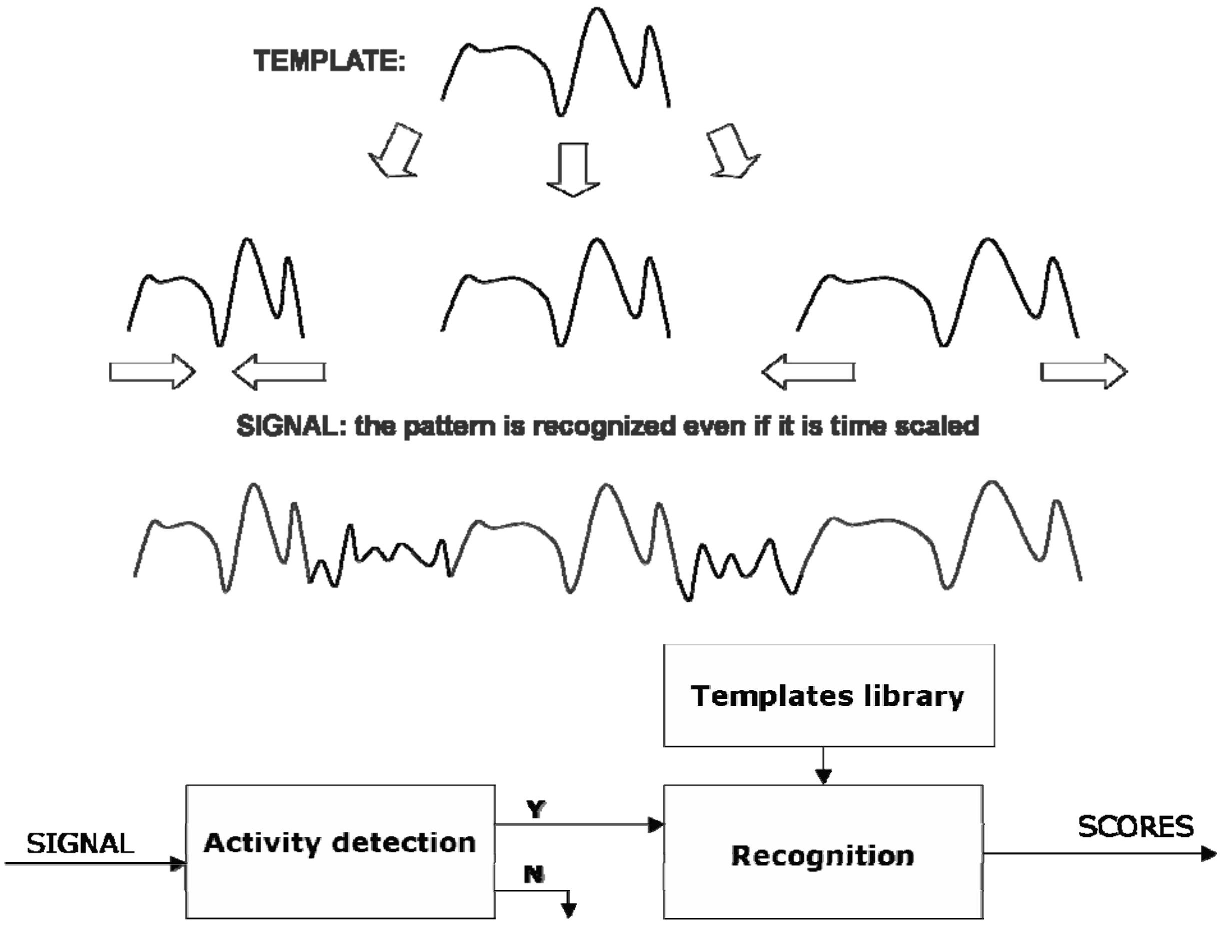


Figure 4: *UPPER PANEL: Time warping technique. LOWER PANEL: Recognition process.*

The recognition algorithm exploit a real-time optimized cross-correlation algorithm. An optimized formula for cross-correlation was also used, thus reducing algorithm complexity, respect to previous works.

Single-channel classification algorithm: The implemented algorithm computes the maximum of cross-correlation coefficient function associated to each sensor channel and each motor activity. When one of such function reaches a certain threshold on a determined sensor channel, the algorithm computes the local maximum of cross-correlation coefficients considering the templates associated to all motor activities. The local maximum is computed in a user-defined time window, as described in **Figure 5**:

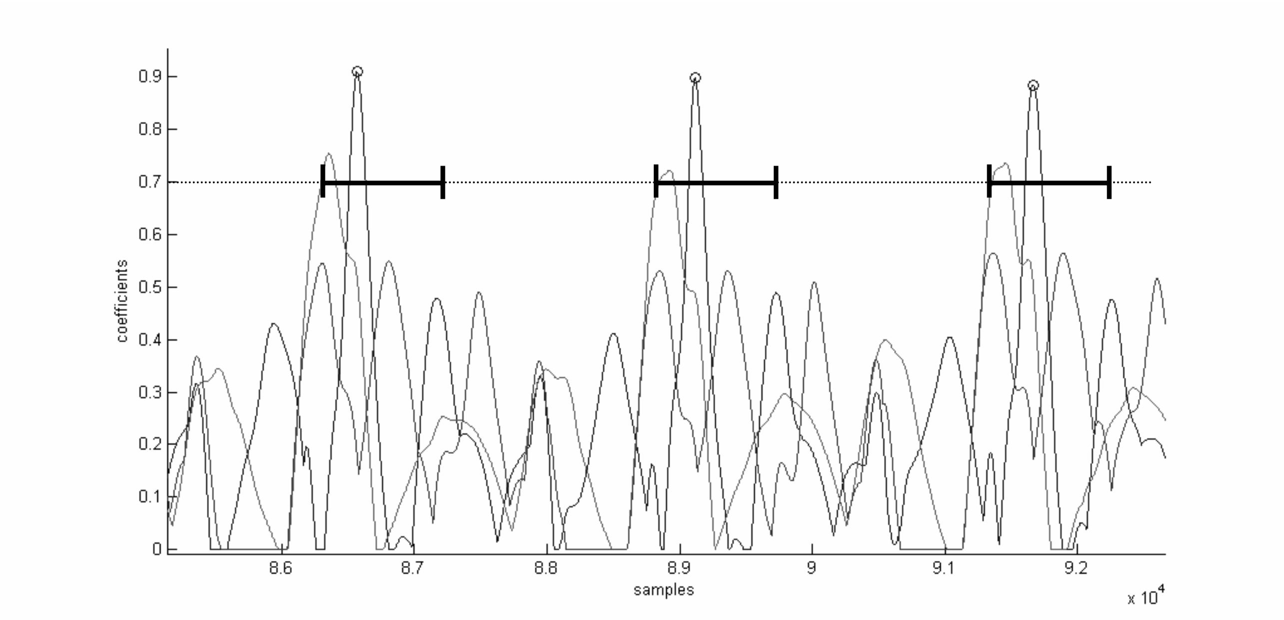


***Figure 5**: Classification algorithm: the defined time window*

Multi-channel classification algorithm: A tree-like classification algorithm design was proposed to obtain a more robust classification combining data recorded by different channels. Such design was particularly useful for the analysis of stand-to-sit and sit-to-stand, activities. The patterns generated during the execution of such activities is in fact particularly poor in characteristics content.

The proposed design provides the combination of the results obtained by different signals recorded on the sternum (see **Figure 6**).

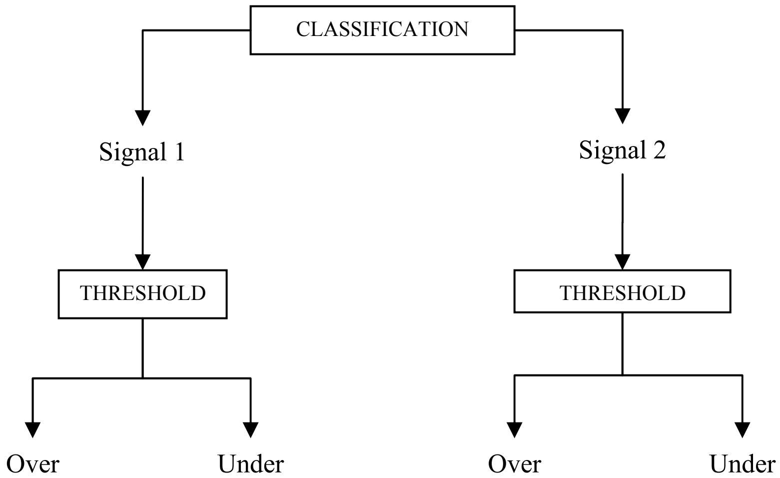


***Figure 6**: Tree classification algorithm*

2.1.4 Prototyping

Regarding the realization of hardware devices, useful in a context of telemonitoring, two possible data elaboration strategies were defined and explored. All devices were designed to be portable and minimally invasive. The results obtained in the algorithm testing phase were also exploited to optimize the design.

In the first “Offline” strategy accelerometer data are processed on a PC, not real-time. In the second “Online” strategy data are processed directly on the portable device and sent to a remote PC station as soon as the results are available. Depending on the complexity of data processing needs, recorded data amount, data transmission rate and data storage size available on the portable devices, one of the two strategies will demonstrate to be the most effective. This work aims in drawing a line between the fields of application of the two possible strategies.

All prototypes were designed to have wireless connectivity and adequate data storage. The technology chosen for data transmission was Bluetooth.

Bluetooth technology guarantees adequate transmission rate and connectivity to other Bluetooth commercial devices (that are being widely available on the market), which could be potentially very useful for the integration of movement analysis with other physiological measurements.

Three different scenarios can be assessed with this technique (as described by the following **Figure 7**). In a first scenario the wireless connectivity is only between the portable device for ADL assessment and the remote PC station. In a second scenario other wireless devices integrate the information collected by the portable device and communicate directly with the PC remote station. In a third scenario other wireless device, including possibly also wireless sensors for ADL assessment, can be directly connected to the portable device (Caselli et al. 2006 [*], Caselli et al. 2006 [**]).

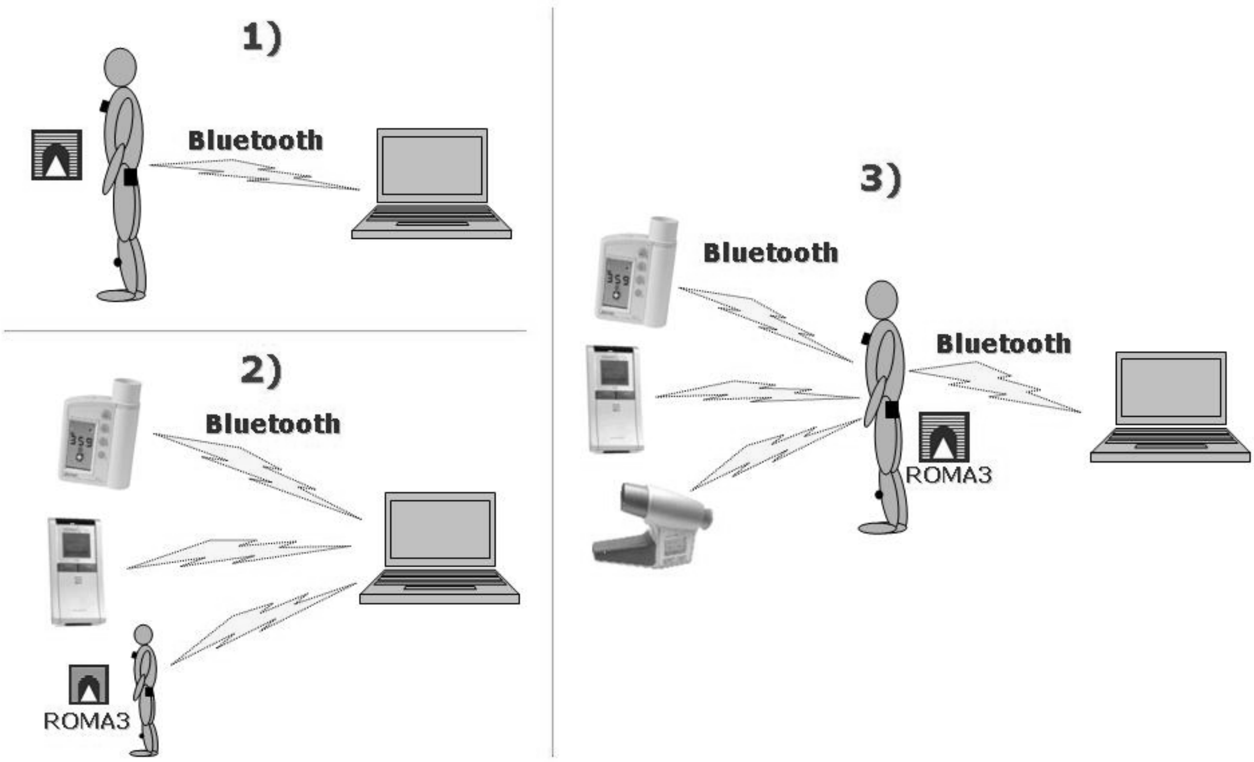


Figure 7*: Different scenarios assessed: <u>Fist scenario</u>: only one wireless transmission of inertial sensors data. <u>Second scenario</u>: other instrument data is integrated: <u>Third scenario</u>: Other instrument are interact directly on patient unit.*

2.2 Upper limbs activity monitoring

2.2.1 Introduction

The use of Human Interface Devices (HID) for arm movement analysis is very spread in literature. The success of such instruments is due to their relative inexpensiveness and to the possibility of easily connect them to a common personal computer, and obtain immediately a visual feedback for the desired motor task.

On other hand such instruments usually interact only with hand and they give no information regarding arm posture. Arm posture is in fact very useful for the study of coordination, movement disorders and sensorimotor learning (Guerfali & Plamondon 1998, Leroux et al. 1992, Seidler et al. 2001).

Several works proposed to use video acquisition techniques in cooperation with HID (Roby-Brami & Burnod 1995, Guerfali & Plamondon 1998, Fukushi & Ashe 2003) for the analysis of arm movement. Video analysis was usually exploited as merely qualitative or, in the best case, only a quantitative measure was extracted by manually elaborating the video sequences recorded.

For such applications, optical marker stereophotogrammetric techniques allow to gain a high accuracy but the cost of such instrumentation, the presence of markers on patient's body, the process of patient preparation and system calibration generally limit their use in research laboratory preventing them from being spread out in clinical practice. Markerless techniques were recently proposed to overcome the limits of marker techniques, but the performance of these techniques still needs to be fully evaluated.

Both video techniques have the limit that they are less utilizable for providing real-time visual feedback for the execution of movement. Thus, in applications in which a virtual feedback is useful, the combined use of HIDs and video techniques seems a good solution.

This work explores the possibility of exploiting markerless techniques to obtain arm posture information, to complete the data acquired by HID, with particular reference to graphics tablets.

Combining video data to a system based on a graphics tablet is a possible solution to maintain all the advantages that an accurate and PC connectable device such like the graphics tablet brings, and to complete the system with arm posture information. A cost effective 2D or 3D movement reconstruction video analysis without optical markers (markerless analysis) is proposed to better adapt the system to a home environment.

The first objective of this work was to obtain an estimation of the performance of such markerless algorithms in this context. A point tracking estimation was obtained using the graphics tablet as reference. Another aim of this work was to provide the graphics tablet with all the necessary tools for home monitoring (i.e.: creating a user interface for visual feedback and task description, and a specialist interface for data elaboration and patient data storage). At a second stage, the work was focused on the techniques exploitable for movement reconstruction.

2.2.2 Materials and methods

The technique used for point (i.e.: image pixel) tracking estimation is the Block Matching technique. This technique computes the movement of a pixel P from a frame to the subsequent defining a Pixel Block around the pixel P and searching on the subsequent frame a new Pixel Block, with equal dimensions, with the most similar color pattern to the old Pixel Block. The new position of the pixel P will be thus represented by the center of the new Pixel Block (see **Figure 8**).

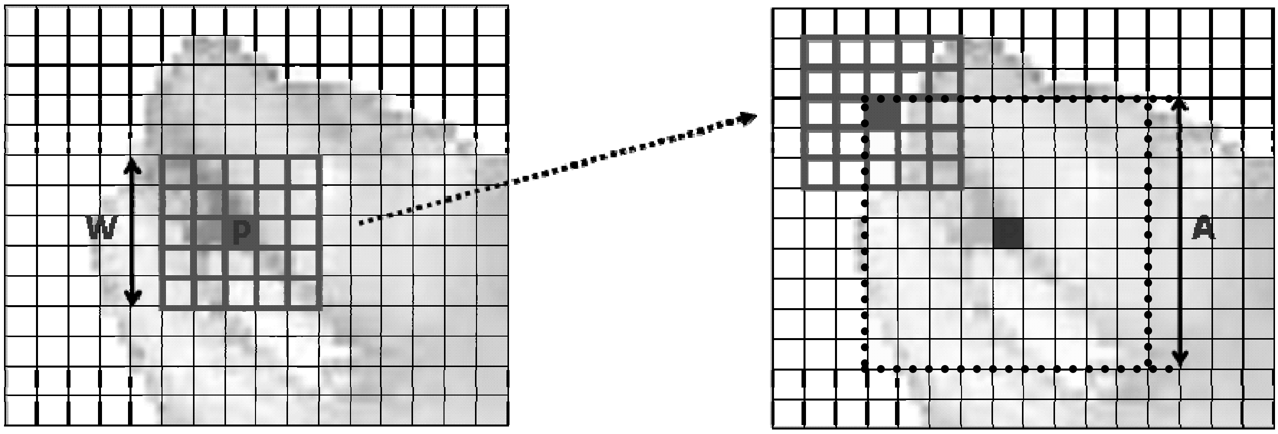


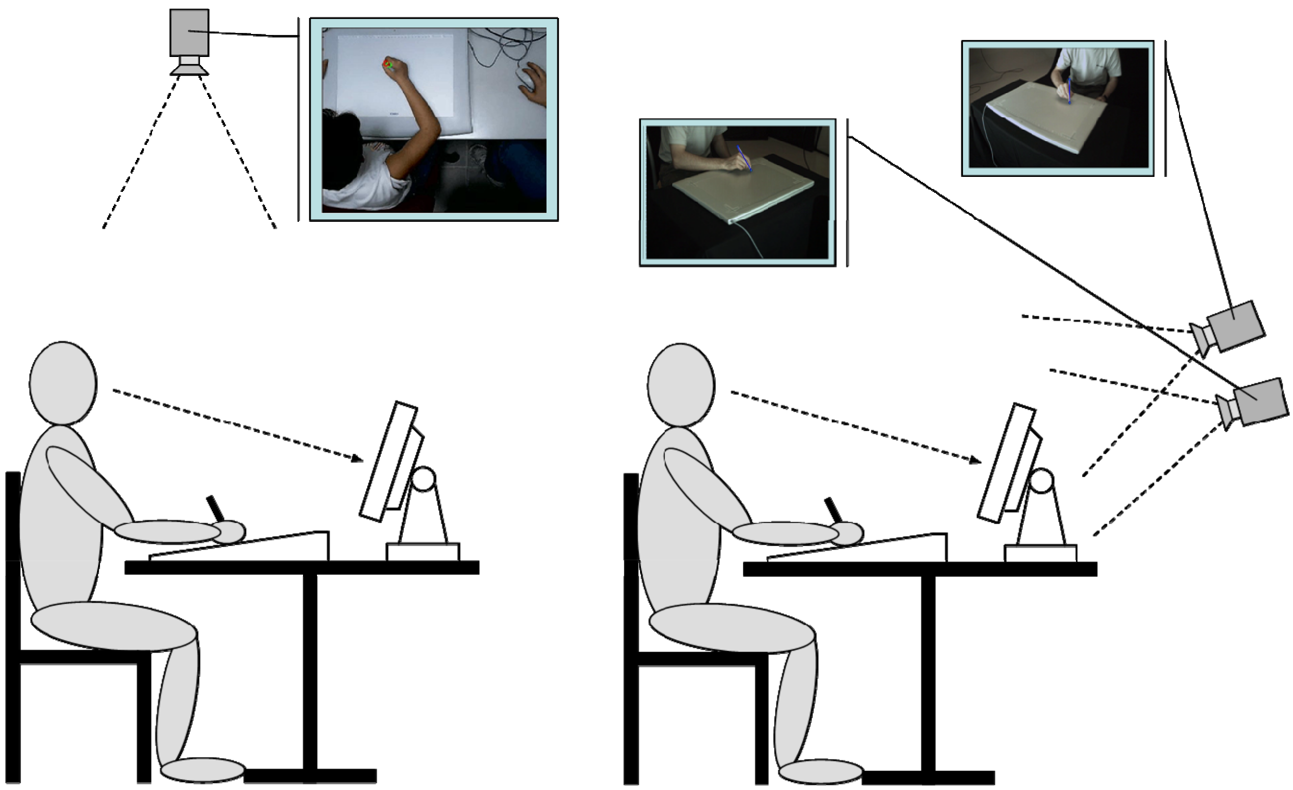
***Figure 8**: Block matching technique: the pixel block P with radius W is compared with all pixel blocks contained in the research area defined by the radius A, which represents all the possible admitted position for the center of block P in subsequent frame.*

In order to determine the rules for the Block Matching, a research area and a cost function are defined. The research area is defined as all the allowed possible positions of the pixel P in the subsequent frame, the cost function is instead defined as the sum of the difference of color associated to each pixel of the two Pixel Block which are being compared

The algorithm used, already presented in literature for different applications (Giunta e Mascia 1999, Goffredo et al. 2004), was designed to obtain a subpixel estimation of pixel tracking.

2.2.3 Collected data

Two different scenarios were analyzed. A first scenario was set up to verify the robustness of the described tracking algorithm respect to image quality (lenses and image size) and to fast movements. The analysis of this scenario is particularly useful to represent the system performance in a context of home monitoring. A second scenario was instead studied to evaluate how accurate the tracking algorithm can be, when using synchronized high resolution cameras and camera calibration tools. This scenario proved to be fundamental to understand what are the real potentialities of the point tracking algorithm.



Protocol for point tracking performance analysis

Test	**Task**	**Camera layout**
Robustness-testing scenario	Fast reaching movements	1 commercial camera
Accuracy-testing scenario	Slow assigned trajectory movements	2 professional cameras

***Figure 9**: UPPER PANEL: System layouts. LOWER PANEL: Tests description.*

Data matching was obtained by tracking with the markerless block matching algorithm the tip of the tablet stylus. The two scenarios can also gave a sufficient estimation of the cost-performance function.

In the first scenario fast reaching movement were chosen as motor task and one commercial camera was placed over the tablet area (see **Figure 9**). The description of the task was provided by a virtual visual feedback on a computer screen. In the second scenario slow movements with assigned trajectory were recorded with two synchronized professional cameras placed in front of the subject. Also in this case the trajectory was represented on a computer screen.

3 Continuous monitoring for lower limb ADLs

3.1 Elaboration algorithms

3.1.1 Introduction

In the last decades, the new opportunities offered by the micro-electronic technologies and the increasing demand of healthcare services are leading to growing interest in wearable sensors technology for monitoring human movement in home environment.

Tele-monitoring and tele-rehabilitation are now fields of great interest where the monitoring of physical activity, mainly of elderly or impaired people, is considered. Among several wearable sensors, accelerometers have been often indicated, in literature, as promising instruments to assess human movement associated to Activities of Daily Life (ADL) (Mathie et al. 2004; Sherrill et al. 2005, Bao & Intille 2004). The use of accelerometers has been proposed for Parkinson disease (Someren et al 1998), chronic pulmonary disease (Sherril et al 2005, Haeuber et al 2003, Steele et. al 2003) or for the assistance of the frail elderly (Mathie et al. 2004), by the evaluation of suitable parameters representative of the human movement. Moreover, accelerometers are proving to be useful for the estimation of energy expenditure and for the analysis of fall risk (Mathie et al. 2004; Chen & Sun 1997; Ohtaki et al 2005).

Several techniques for recognition and classification of motor tasks executed during the ADL, have been developed using data collected by different accelerometer configurations (Mathie et al. 2004, Sherrill et al. 2005, Bao & Intille 2004, Someren 1998, Haeuber 2004). The recognition algorithms presented in literature are often based on statistical parameters such as (Sherrill et al. 2005):

- mean value of the accelerometer signal (as estimator of the body posture) (Ravi et el. 2005),
- standard deviation of the accelerometer signal (as measure of the intensity of motor activity) (Ravi et al. 2005, Lee & Mase 2002, Lyons et al 2005,
- correlation function or correlation coefficient (as index of similarity) (Ravi et al. 2005, Veltink et al. 1996).

Methods aiming at extracting signal waveforms stress the importance of correlation techniques which can be virtually suitable for extending the recognition to a larger number of motor activities.

For example, Veltink, Bussmann, De Vries, Martens and Van Lummel in 1996 showed that, for an accelerometer sensor mounted on the thigh and a given template, the maximum circular cross-correlation coefficients (individual cycles with respect to templates) of walking at different speed were significantly different from the maximum cross-correlation coefficients of individual cycles of ascending or descending stairs. Ravi, Dandekar, Mysore and Littman in 2005 distinguished running and walk from stair climbing by using the correlation between two orthogonal oriented channels of biaxial accelerometers data. The same contributions underlined that with accelerometer sensors it is possible to easily classify body posture by exploiting the low frequency band of signals.

However, less attention has been paid to the study of the relevance of execution speed in the success of the recognition process and to the choice of ideal sensor location. In this paper a study aimed at evaluating these aspects is presented.

One critical aspect of motor activity recognition is the fact that the same motor activity can be executed at different speeds, thus reducing the reliability of the method. In order to overcome this problem, and with specific reference to walking activities, this study proposes a novel statistical data processor that makes possible to cope with the variability of execution speed during the recognition process. The proposed algorithm, instead of handling only one signal template to describe each motor activity, takes into consideration a set of multiple templates obtained by warping through time the single template associated to a given motor activity.

The hypothesis underlying this technique is that the pattern associated to one single motor activity does not change significantly with the execution speed. As far as it was possible to judge, the data collected seem to support this hypothesis.

The computational cost of such algorithm, although higher than other existent statistical methods, can be acceptable for the kind of applications which was tailored for, bearing in mind the low signal bandwidth of human movement accelerations (15-20 Hz) (Mathie et al 2004, Veltink et al 1996) and the processing performance of last-generation micro-controllers and micro-processors. In fact the availability of high processing capabilities directly on sensor unit is starting to be reality (Ohtaki et al 2005, Karantonis et al. 2006), with consequent benefits in terms of sensor intelligence and data storage.

Correlation techniques have the advantage of being a reliable instrument to measure how similar the patterns generated by different motor activities are. Using correlation techniques as a measurement of similarity, this study aims also at determining which signals are more suitable for the classification process. To this purpose a redundant number of accelerometer sensors was used during the tests in order to define the one/s with greater information content.

On the other hand, one important disadvantage of template matching techniques is instead the need to calibrate the system to extract the template set. This calibration typically requires the patient to execute the motor activities in a proper controlled environment.

Trying to avoid such cumbersome calibration, this study also intends to evaluate the possibility of recognizing motor activities using ‘standard’ templates associated to each motor activity, with particular reference to walking activities. As 'standard' template the authors mean a template containing the common signal characteristics associated to the same motor activity. The possibility of using 'standard' templates obtained by an averaging process on a significant control population, is proposed in this study.

As an example of possible application of the proposed algorithm, this work presents the results in the recognition of three walking activities: walking on plain, walking on stairs upward and downward. These activities are obviously basic in the context of ADL. In any case, the technique proposed can be used for the recognition of different activities.

3.1.2 Materials and Methods

a. The proposed Algorithm

The recognition process proposed in this study works in two subsequent steps. In the first step, indicated in the following as "calibration", a complete set of signal templates, associated to different motor activities, is built. The set is formed by using one template per subject, per activity and per sensor channel. The philosophy of the recognition process was to analyze only one sensor channel at once, instead of combining data recorded from different sensors.

In the second step, a recognition algorithm determines which motor activity is being executed by comparing the recorded signals to the signal template previously constructed.

The calibration process allows the construction of signal templates after segmenting the signals into epochs associated to a specific motor activity. The segmentation has been carried on by detecting the activity cycles using foot switches placed under both feet. In order to obtain the template, signal epochs associated to such cycles are interpolated with a polynomial spline (3^{rd}-order algorithm), to obtain sample sequences of equal lengths.

In this process the activity cycles associated to movement initiation and movement termination were discarded. After calculating the mean epoch length, the template related to every subject and every motor activity was obtained by averaging.

It is worthwhile to mention that the use of foot switches does not limit the applicability of the described method but only facilitates the process of template extraction:

in literature there is in fact a number of techniques that can be used for the determination of the time interval of each cycle (Mathie et al. 2004, Veltink et al. 1996).

Unlike other algorithms in the literature, each signal template was at this stage iteratively time-warped in order to obtain a Time-Warp Template Collection (TWTC) constituted by N enlarged or shrunk copies of the original template. Every element of a TWTC was built with a different amount of time-warping. Each TWTC was built with a number of copies and with an amount of time-warping suitable to compensate for the variability in the speed of motor activity execution. For the time-warping process, polynomial spline interpolation was used and two descriptive parameters were introduced: Warp Range (WR) and Number of Warp Steps (NWS).

Such parameters have the following definitions:

- WR: difference between the maximum (d_{MAX}) and the minimum (d_{MIN}) duration of TWTC elements for each motor activity (measured in milliseconds).
- NWS: number of uniformly distributed warp steps used to build the TWTC, i.e: number of elements constituting the TWTC. By definition, if NWS = 1 only the original template was used for the recognition process.

In this study it was always set:

$$d_{MAX} = d_T + \frac{WR}{2}$$
$$d_{MIN} = d_T - \frac{WR}{2}$$

(where d_T is the template duration) and only odd values of NWS were taken in consideration. For deeper insight the described parameters are illustrated in **Figure 1**.

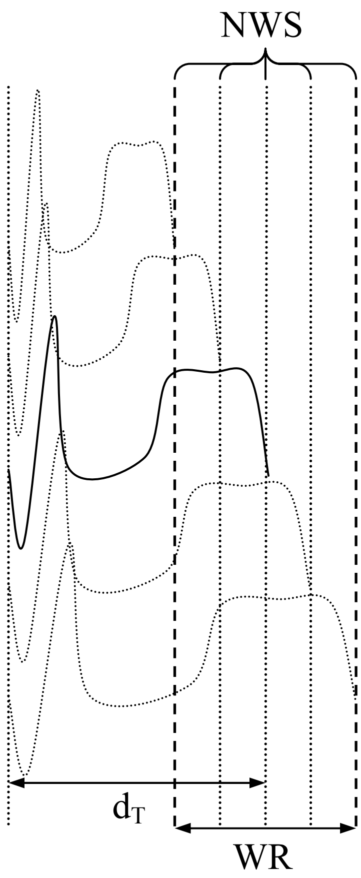


***Figure 1:** Description of time-warping technique (for NWS=5)*

After the time-warping process the mean value of all the elements of each TWTC was removed. The reason for such further elaboration resides mainly in the optimization of the computational cost.

All the TWTC are then compared with the corresponding sensor channel data. The recognition algorithm sweeps each element of the TWTCs determining, for each time t_i, an index of similarity between the element and the signal interval between t_i and $t_i + d_{T'}$ (where $d_{T'}$ represents the duration of time warped template).

The correlation coefficient was chosen as a similarity measurement index between the warped template and the signal interval. Given two discrete signals of equal length (N samples) x and y it is possible to estimate such parameter using the following definition:

$$\rho_{x,y} \equiv \frac{\sigma_{x,y}}{\sigma_x \sigma_y} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - x_M)(y_i - y_M)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - x_M)^2 \frac{1}{N}\sum_{i=1}^{N}(y_i - y_M)^2}}$$

where x_M and y_M represent the mean values of x and y signals respectively. Using this formula, neglecting the initialization (i.e.: the computation of template variance), the algorithm complexity would be equal to $2N+2$.

In order to minimize the computational cost, considering that the mean value of each element of TWTCs was constrained to be equal to zero, the definition of the correlation coefficient can be simplified to the form:

$$\rho_{x,y}^{(x_M=0)} = \frac{\sum_{i=1}^{N} x_i y_i}{\sqrt{\sum_{i=1}^{N} x_i^2 \left(\sum_{i=1}^{N} y_i^2 - N y_M^2 \right)}}$$

Using this formula, the algorithm complexity can be reduced to $N+4$. In fact, once y_M and y-signal sum of squares have been calculated at initial time, it is possible to update the values only by adding and subtracting two terms.

Eventually, the redundancy of information due to the presence of multiple correlation coefficient sequences associated to the same motor activity (collected by sweeping all the elements belonging to the same TWTC), was solved by building a single Maximum Correlation Coefficient Sequence (MCCS). Each MCCS i-th sample was represented by the maximum of the i-th samples of all the sequences belonging to the same TWTC.

The data contained in each MCCS was further processed to obtain only one representative value of correlation coefficient for each activity cycle analyzed. Such values were obtained by a local-maximum-search algorithm. In the following these values will be indicated as Maximum Correlation Coefficients per (activity) Cycle (M3C).

At a second stage, the possibility of avoiding the calibration process in future analyses was evaluated by constructing, for every signal, a unique standard template associated to each considered motor activity. This means that data associated to different participants were processed exactly in the same way as if no calibration had taken place. The standard templates were obtained from the templates belonging to the same sensor and the same motor activity associated to all the participants to the tests.

b. Participants and Procedures

FIRST PHASE: system calibration and testing algorithms. Five healthy consenting participants were recruited for the tests. Tests were divided into 2 sessions: Walk Session (WS) and Stair Session (SS). Signals of WSs were recorded while the participants were walking straight on plain along a 10-meters-long unmarked path. Signals of SSs were recorded on a common 16-steps stairway with 10 cm high and 30 cm long steps. Participants were invited to terminate action at the end of the path or at the end of the stairway, before turning back and starting to walk again.

The recording sessions were designed to obtain a balanced number of samples for every motor activity and to avoid biased execution of the movement by asking the participants to walk for a fixed number of gait cycles. Participants were not informed when data associated to their walk activity was recorded.

Recognition performance was evaluated by dividing data into three classes associated to the analyzed motor activity: Walk Data, Stair Up Data and Stair Down data.

SECOND PHASE: testing speed variability compensation and final layout. The same procedure was applied but participants were asked to execute the whole protocol two times: the first time at low speed, the second time at higher speed. Another recording session was added: participant were asked to sit and to stand up, to stand still and finally to wash and eat. This session was added as control.

c. Experimental Setup

All data were acquired by a gait analysis system (Step-PC® DemItalia) with a sampling rate of 2000 and 12 bits resolution.

FIRST PHASE: system calibration and testing algorithms. A biaxial accelerometer sensor (based on Analog Devices ADXL202 biaxial accelerometer) was placed on medial portion of the right shin with axes disposed on the sagittal plane along radial and longitudinal directions.

A triaxial accelerometer sensor (based on 2 ADXL202 biaxial accelerometers) was placed on the sternum. Sensor axes were disposed along the vertical, antero-posterior and medio-lateral axis of the body. All accelerometer signals were band-pass filtered between 0.2 and 15 Hz.

For the calibration process a set of three foot switches per foot were attached in correspondence of heel, 1st and 5th metatarsal heads. Moreover, in order to have a biomechanical reference of the movement two electrogoniometers were placed on both knee joints.

SECOND PHASE: testing speed variability compensation and final layout. The accelerometer sensor layout was kept similar while electrogoniometers and foot switches were removed (templates extracted during the first phase were used). The participant were wearing their own clothes and shoes.

3.1.3 Results

FIRST PHASE: system calibration and testing algorithms. The performance of the activity recognition algorithm was tested observing the M3C values obtained for each activity cycle. Results were obtained separately for data associated to different motor activity with special focus to signals on the shin.

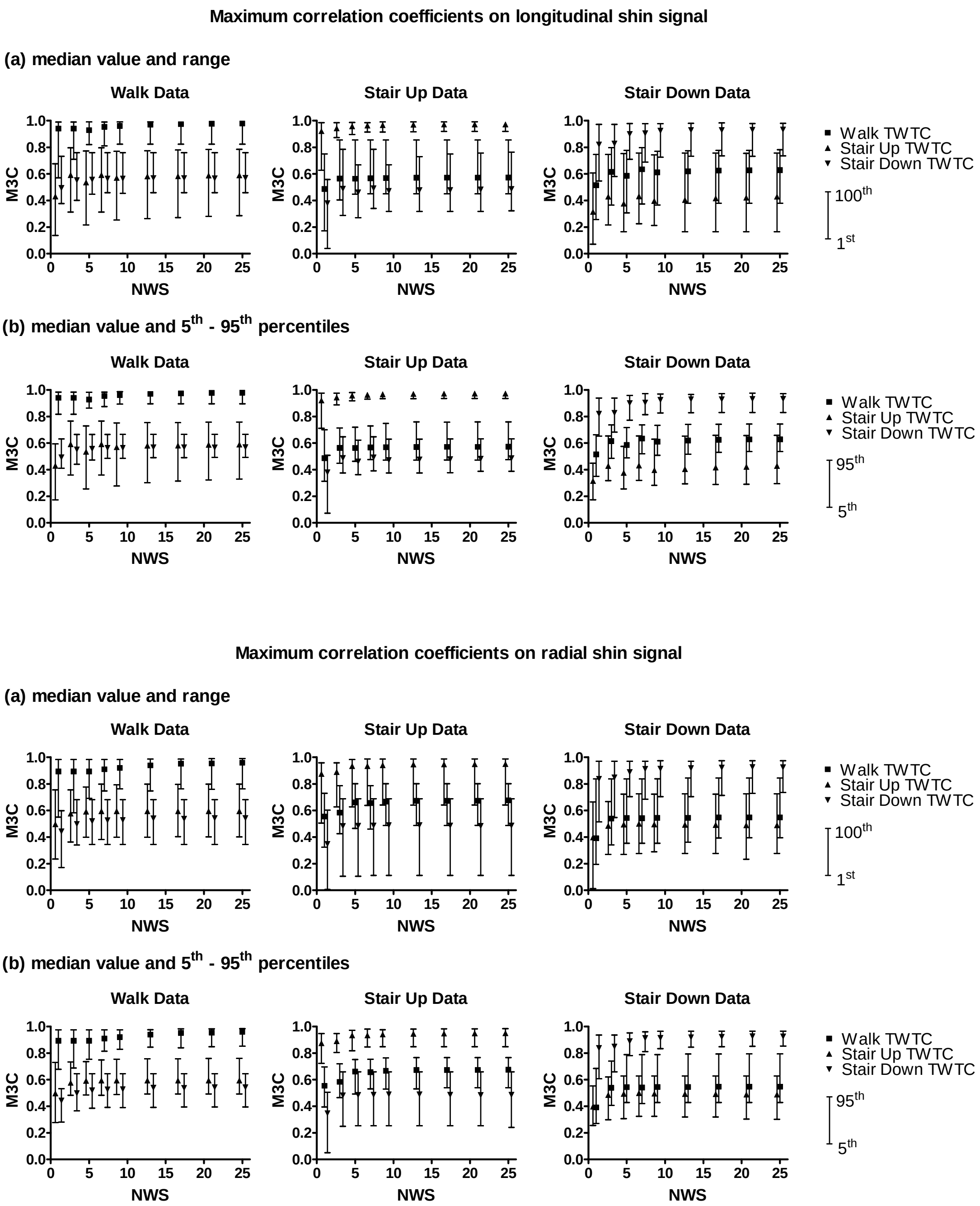


Figure 2: M3C distributions on shin signals for different values of NWS and using one TWTC at once. Each graph represents M3C distribution on data related to one motor activity.

The distributions of M3C values for shin data, calculated by using all the TWTCs (namely: Walk, Stair Up and Stair Down TWTC) are described in **Figure 2**. Each graph represents the distribution of M3C for Walk Data, Stair Up Data and Stair Down Data respectively. The algorithm's settings were: WR=500 ms with NWS spanning the following set: 1, 3, 5, 7, 9, 13, 17, 21, and 25.

It is worth to note that a robust recognition performance can be achieved if M3C distributions appear well separated for each TWTC on same activity data.

The results associated to different NWS describe the improvement in activity recognition introduced by the algorithm presented in this study: while for NWS=1 the obtained M3Cs showed large overlaps, for higher NWS such overlaps always tended to decrease or completely disappear. Moreover it is possible to notice that no significant further enhancement in recognition performance was provided for values of NWS greater than 13. Thus, NWS values greater than 13 bring to a waste of computational time.

The graphs of **Figure 2** clearly show how the longitudinal signal allows better recognition performance than the radial one. In fact overlaps in M3Cs for radial signal are always present while for longitudinal signal do not appear for NWS values greater than or equal to 5 on Walk Data and Stair Up Data.

Such overlaps testify also that it was not possible to achieve 100% score in the classification of activity cycles only by setting a threshold on M3Cs. Nevertheless the graphs contained in sections (b) of **Figure 2** show that: 1) it is possible to correctly classify the 95% of activity cycles setting a threshold at 0.8 (for both longitudinal or radial shin signal); 2) the M3C distributions associated to different TWTCs are separated by a larger gap for longitudinal signal. The cause of the presence of the mentioned overlaps will be explored further in the following.

Higher classification score was achieved by a maximum M3C criterion: each activity cycle was attributed to the activity class whose M3C assumed the highest value.

In this way it was possible to attain 99.3% overall classification score for NWS={1,3} and 100% for NWS={5, 7, 9, 13, 17, 21, 25, 29} using the longitudinal signal; and 99.6% for NWS={1,3, 5, 7, 9, 13, 17, 21, 25, 29} using the radial signal.

Despite the high classification scores obtainable for low values of NWS, it was not possible to achieve robust results in that case. In fact, the presence of low values of M3C (below 0.6) does not guarantee the success in the classification process. Conversely, for NWS values greater than or equal to 13, M3Cs associated to the correct activity were always greater than 0.73 for longitudinal signal and greater than 0.69 for radial signal.

Even in this case, the best results were associated to longitudinal signal. According to this finding and all the other reasons illustrated above, the following discussion will focus only on longitudinal signal.

The overlapping of M3Cs values was further explored by analyzing data with the exclusion of both the first and the last activity cycle of each recording. In this way it is possible to remove from the analysis all the activity cycles corresponding to movement termination or movement initiation that obviously differ from the corresponding template.

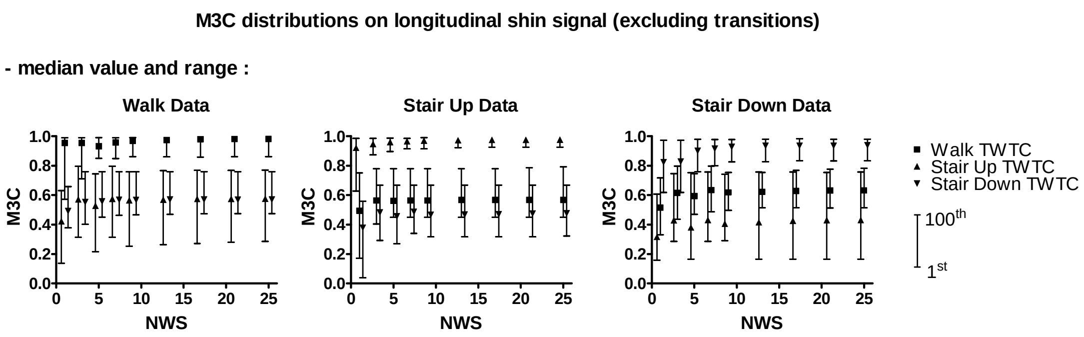


Figure 3: *M3C distributions on longitudinal shin signal for different values of NWS and using one TWTC at once, when transition activity cycles were excluded.*

Figure 3 shows graphs associated to longitudinal shin signal corresponding to 1st and 100th percentile ranges obtained excluding the transition activity cycles. It appears evident that no overlaps appeared for NWS greater than or equal to 9. It is thus possible to classify motor activities only by using a threshold on M3C values if movement transitions were not being considered. Consequently, using a maximum M3C criterion, the resulting classification would be even more robust.

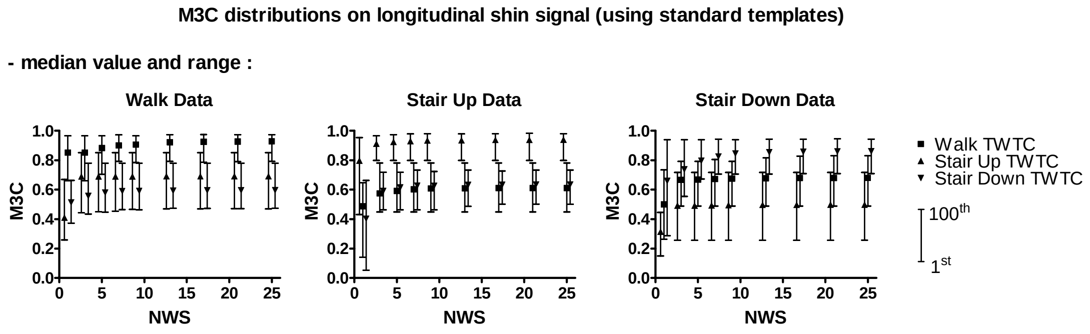


Figure 4: *M3C distributions on longitudinal shin signal for different values of NWS working with one TWTC at once, when standard templates were used.*

The results corresponding to TWTCs related to standard templates (and longitudinal shin signal) are reported on **Figure 4**. The presence of large overlaps on M3Cs makes the classification using a threshold impossible. Using a maximum M3C criterion, it was possible to gain 92.0% overall classification score for NWS={1}, 93.5% for NWS={3}, 98.4% for NWS={5}, 99.6% for NWS={7, 9, 13} and 100% for NWS={17, 21, 25, 29}. The classification appeared to be quite robust for high NWS: M3C associated to the correct activity are always greater than 0.70 for NWS greater than or equal to 13.

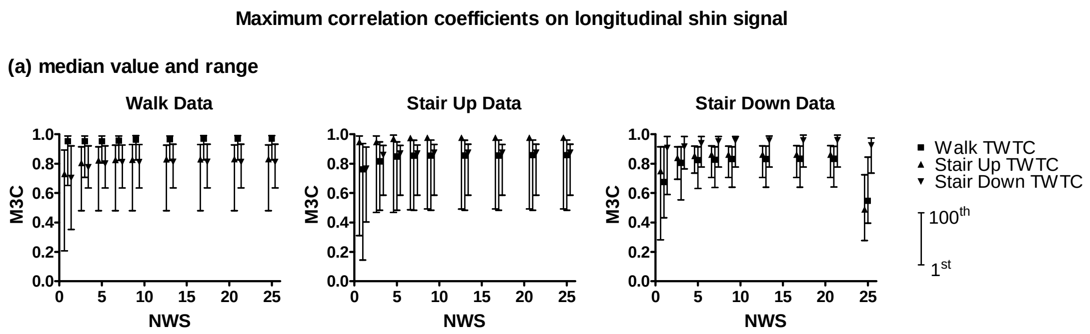


Figure 5: *M3C distributions on longitudinal vertical sternum signal for different values of NWS working with one TWTC at once.*

Figure 5 shows that the M3C distributions of different TWTC were always overlapped in accelerometer data recorded on the sternum in vertical direction. This finding shows how the sternum signals appeared similar in all activities. The classification score, using a maximum M3C criterion, is rather high (>98.4% for NWS greater than or equal to

13), but this results doesn't appear very robust: several M3C values, associated to the correct activity, were lower than 0.59.

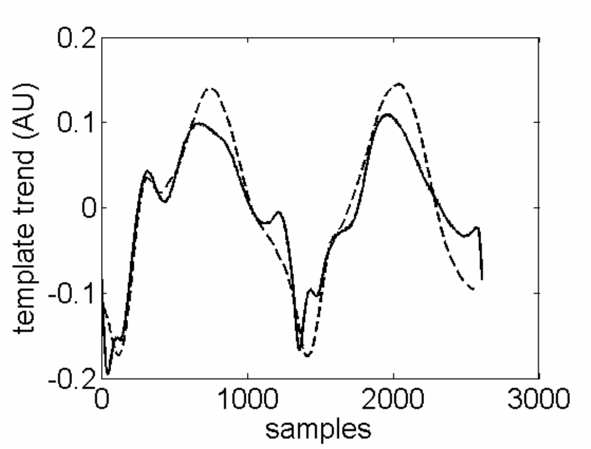


Figure 6: *Difference between Walk and Stair Up templates: the patterns can appear rather similar.*

As a further insight on the similarity among signal of different motor activities, **Figure 6** compares one couple of templates found for Walk and Stair Up activity. In such figure the dash line template was warped to obtain best fit.

SECOND PHASE: testing speed variability compensation and final layout. The objective of the tests is to determine what enhancement of recognition performance can be obtained using the described technique in a context similar to real world, where each activity can be reference sensors are not available and participant are not prepared before the tests. In **Figure 7** and **Figure 8** it is possible to see what enhancement can be obtained using the described technique (exploiting the longitudinal shin signal). It is worthwhile to mention that during the control session no activity was erroneously recognized.

Figure 7: Percent of activity cycles correctly classified, varying the number of time-warping steps

FAST MOVEMENTS:

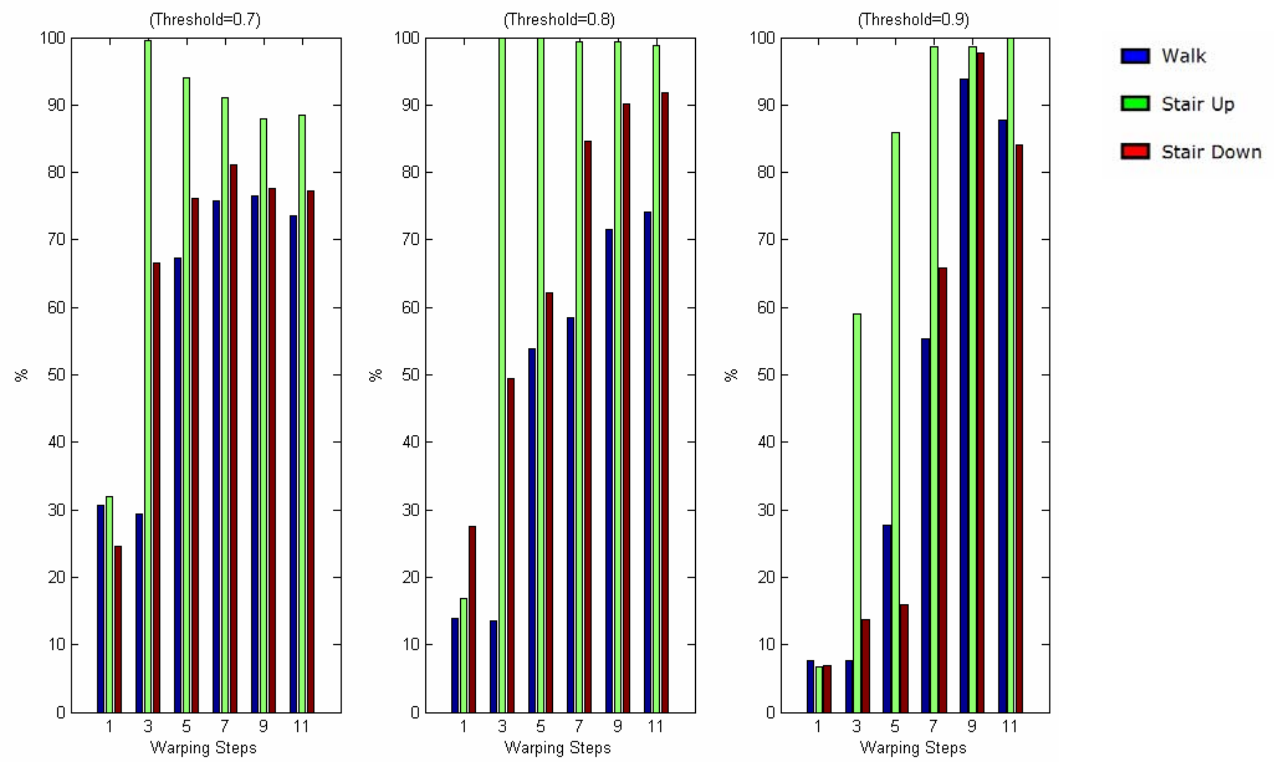
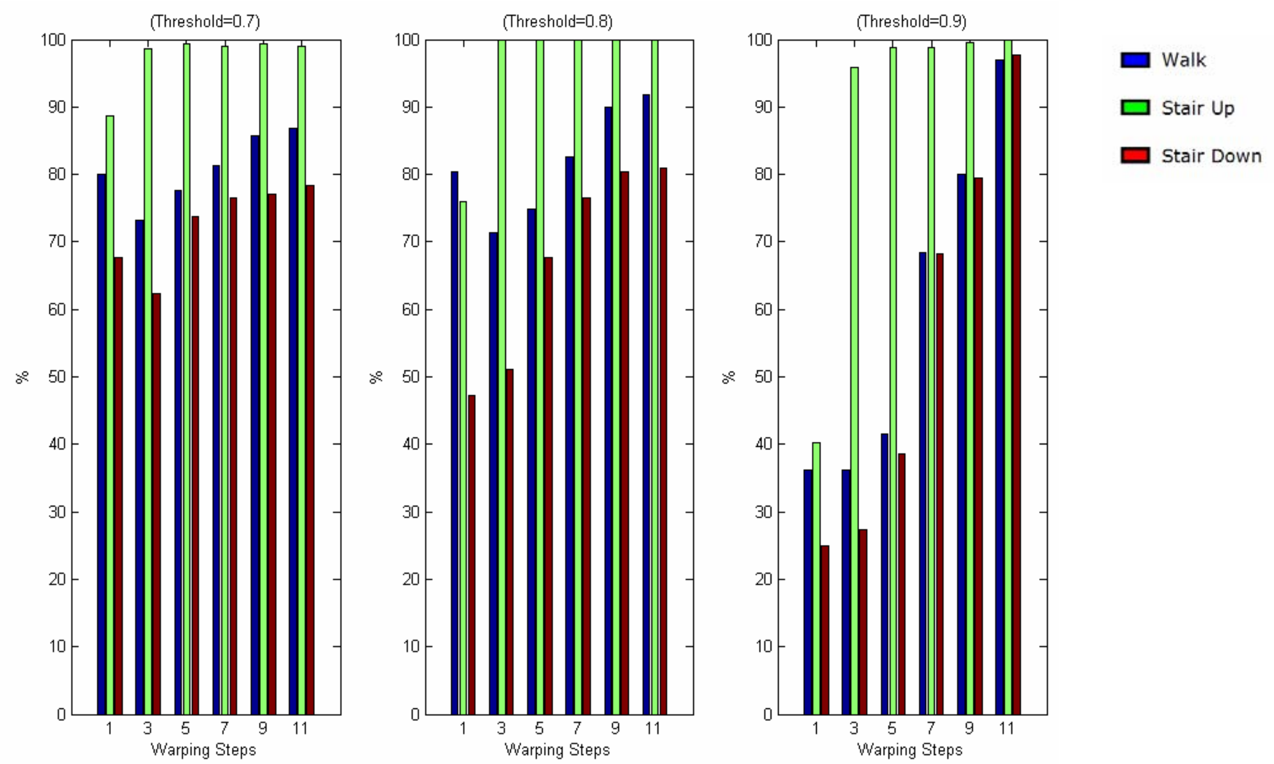


Figure 8: Percent of activity cycles correctly classified, varying the number of time-warping steps

SLOW MOVEMENTS:



3.1.4 Conclusion

The results showed that, using the proposed recognition algorithm, it is possible to obtain an overall score of 100% for the activity classification by placing only one uniaxial accelerometer on the shin in longitudinal direction. Very good (over 99%) overall classification score is also obtainable orienting the uniaxial sensor in radial direction, while accelerometer data recorded at sternum level were not very robust for the classification of the considered motor activity. The authors would like to mention that an accelerometer on the shin can be worn without discomfort for the patient.

The time-warping technique, representing a main innovation of this work, improved both recognition percentage (from 92% to 100% using the standard templates) and the classification robustness (clear separations of M3C distributions and higher M3C associated to correct activity). Moreover, when analyzing activities executed at different speed it was evident the improvement due to the technique. Nevertheless, not always the classification scores were very close to 100%. It is worthwhile to mention that templates were extracted when participants were walking with bare feet, while test done at different speeds were executed with shoes on.

Hardware devices and software tools for home monitoring

Offline elaboration prototypes: (see also Caselli et al. 2006 [*]) The chosen inertial sensors are capacitive accelerometers: Analog Devices biaxial accelerometers ADXL202 (Pulse Width Modulation (PWM) sensor) and ADXL203 (analog sensor), or Freescale triaxial accelerometer MMA7260Q. The capacitive accelerometers can detect both static and dynamic accelerations, they have very small dimensions (around 5x5 mm) and their signal can be conditioned on board.

Accelerometer data is carried to a microcontroller Microchip belonging to the 18F family (for example the Microchip PIC18F252 or PICLF252 proved to have performance suitable for the application needed). If the sensor is analog the microcontroller converts data in 10 bit format, if the sensor is PWM the microcontroller converts data in a 16 bit format, with a resolution dependant on the PWM period. A more sophisticated microcontroller: the Microchip dsPIC30F3013, pin compatible with the previous devices, can also be used to obtain data in a 12 bit format from analog sensors (for a description of the whole measurement process see **Figure 9**).

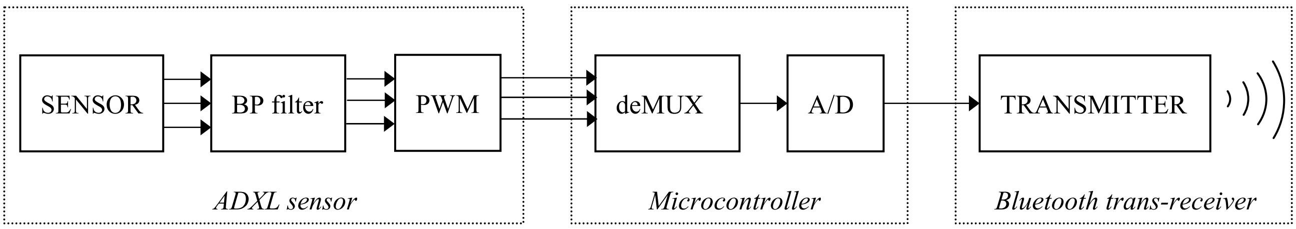


Figure 9: *Measurement process and the role of each component.*

In all cases the microcontroller provides to serialize data and to transmit it to a Bluetooth transmitter/receiver (Panasonic PAN 1560), which communicate with the remote PC station. The Bluetooth module receives also commands from the remote PC station that are received and interpreted by the microcontroller.

Such architecture was evaluated and tested in several acquisition applications. In **Figure 10** one of the prototypes developed is represented:

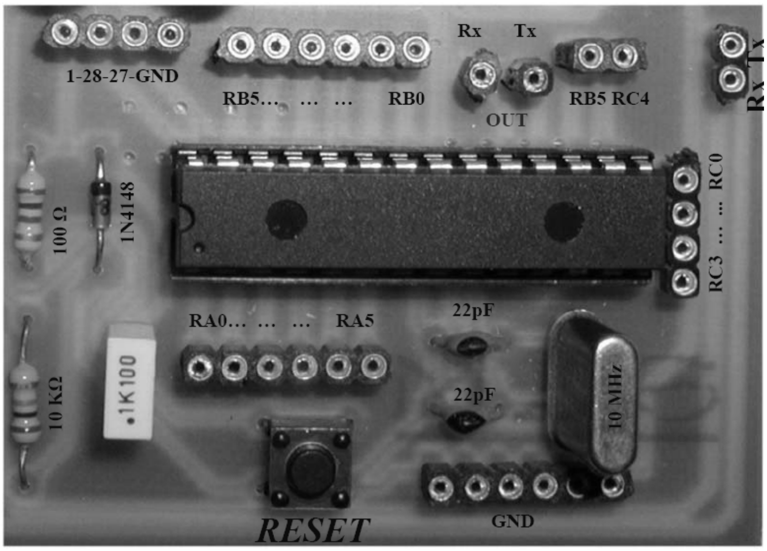


Figure 10: *Picture of one of the prototypes tested. Bluetooth transmitter-receiver is located on the other face of the board*

To give an idea of the performance obtainable with such architecture, the characteristics of the described prototype are summarized below in **Figure 11**:

Prototype description	
Input analog channels	5
PWM channels	3
Transmission rate	115200 bps
Power consumption	**80 mA** (transmission) **30 mA** (idle)
Clock	40 MHz
Weight	40 g
Dimensions	50x21x10 mm
Prototype material cost	<80 € (2/3 of the cost is due to the bluetooth module)

Figure 11: Prototype description, mored details can be found in www.dea.uniroma3.it/biolab/.

Looking at those specifications it is worthwhile to mention that power consumption is not neglectable The reported specifications are related to the SMD (Surface Mounted Device) prototype, whose layout is represented in **Figure 12** below:

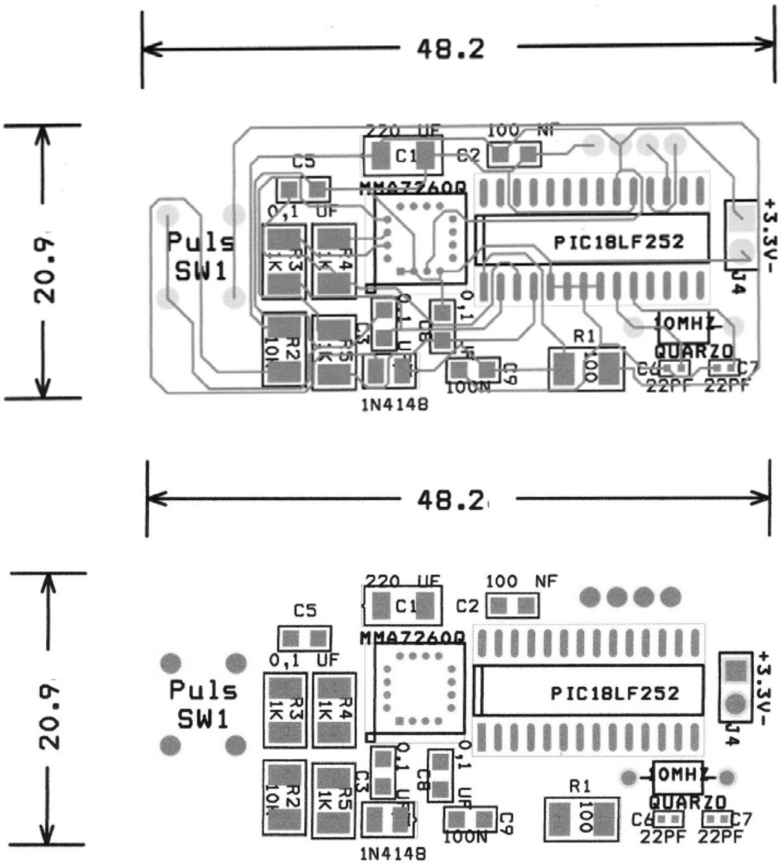


***Figure 12**: SMD Prototype description, mored details can be found in www.dea.uniroma3.it/biolab/.*

The board was designed on two layers. On the first layer were placed the microcontroller, the accelerometer and their accessory components. On the second layer was placed the Bluetooth chipset and the battery pack. Data are sent to a real-time acquisition and visualization application, which stores data in a text file.

The real-time acquisition and visualization application (developed with Visual Basic and Measurement Studio ActiveX controls) can receive data via all the COM port and all the standard transmission baud rate defined in the RS232 protocol. The application developed can automatically handle a variable number of input channels.

The program can also browse for Bluetooth systems present and automatically recognize them. Sensors connected to the Bluetooth device can be also automatically recognized. **Figure 13** shows how this application looks like:

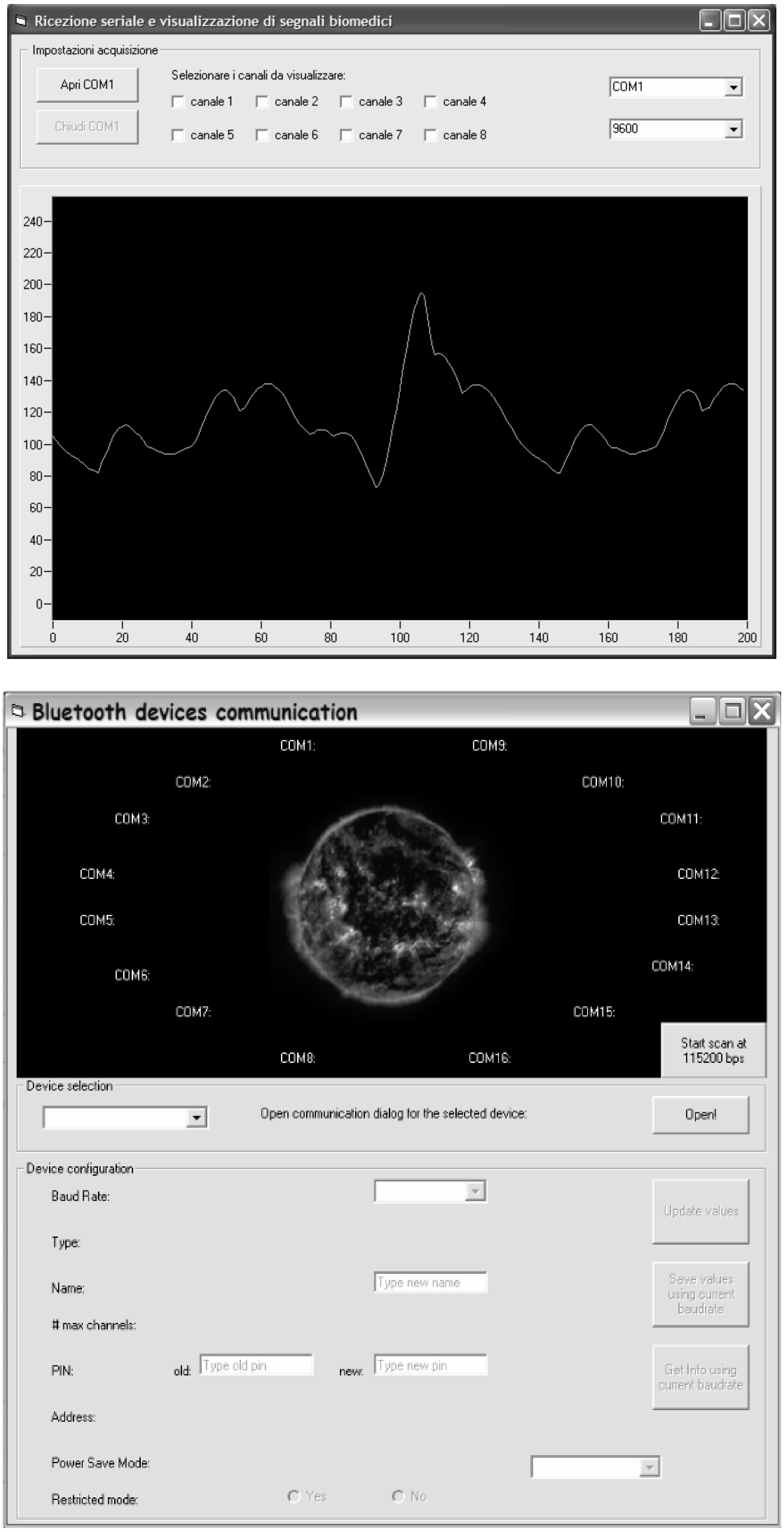


Figure 13: *Graphic user interface for data acquisition and visualization.*

Online processing prototypes: (see also Caselli et al. 2006 [**]) Other prototypes were constructed to implement the ADL recognition algorithm presented in this work. The work was focused on gait. A prototype was designed to recognize and distinguish the activity of walking from climbing and descending stairs. The prototype is based on a Microchip dsPIC microcontroller.

Such prototypes can potentially overcome the power consumption issues raised during the development of the other prototypes, by transmitting only the result of the interpretation or by allowing the storage of data on board in the long term.

In particular the idea dsPIC microcontroller proved to be the Microchip dsPIC30F3013, belonging to the sensor family and endowed with double serial interface and 2kB of RAM (Random Access Memory).

The prototype has the following functions:

- Sample and transmit data at 12 bit resolution and at a sample rate of 50 or 100 samples/s.
- Calculate and transmit in real time the crosscorrelation coefficient of a maximum of 4 templates in total @ 100 sample/s and 16 @ 50 samples/s.
- Low pass filtering for transmitting the orientation of the device respect to the vertical direction.

The tests on the prototype confirm the results obtained when testing the recognition algorithm using a traditional acquisition unit. The tests were conducted testing the device on several participants using a standard template constructed as correlated average of 5 subjects different from the ones taking part to the tests.

The signal is captured by a biaxial accelerometer (the ADXL203 product gives Analog Device) and elaborated by the dsPIC microcontroller, and directly processes it on the wearable unit. Sensor was located on the shin and the longitudinal channel was analyzed.

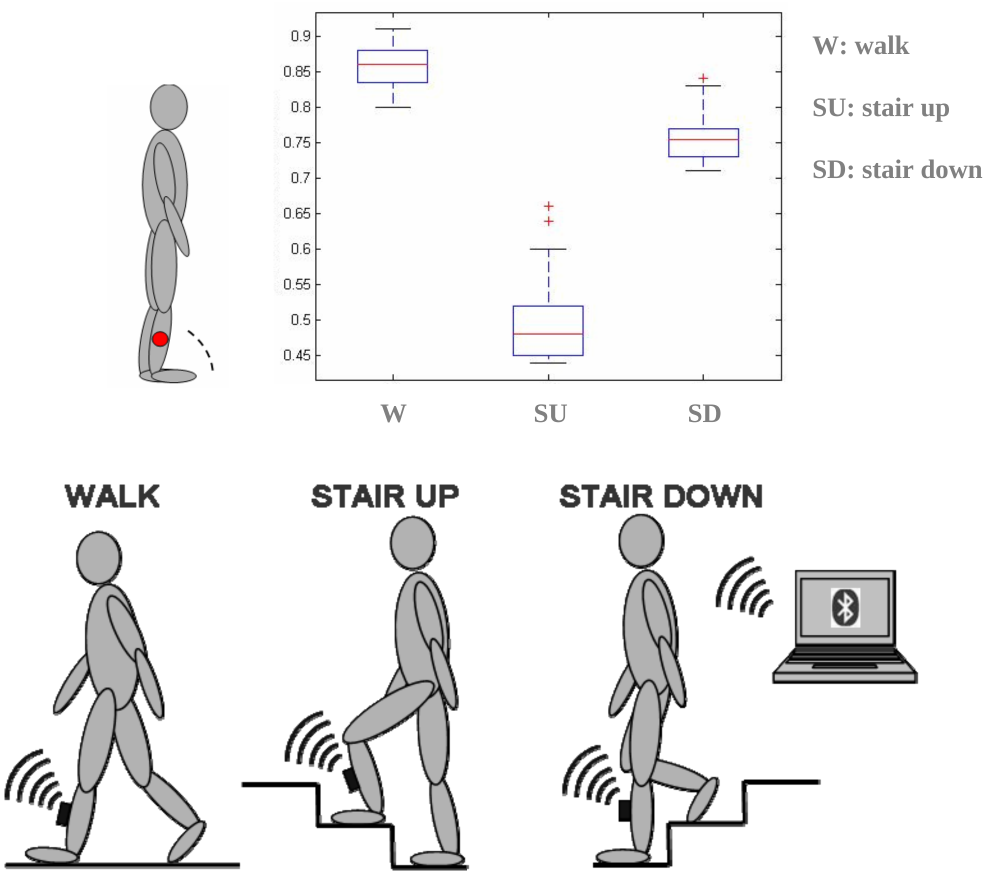


Figure 14: *Sensor location, activities analyzed and distribution of crosscorrelation coefficients obtained.*

The results a sent to a PC for the acquisition and the visualization through a Bluetooth module (Stollmann BlueRS+E). The identification algorithm compared in real time a portion of accelerometer signal with the template of the motor activity (through the calculation of the cross-correlation coefficients), if the value of the coefficient exceeds a threshold the motor activity was considered recognized.

To recognize the motor activity, even if executed at different speeds, the signal was compared to three templates associated to different execution speeds. This technique, as already discussed, uses of a number of duplications of the same template with different durations. The application program for the dsPIC has been written using the MikroBasic for dsPIC compiler produced by MikroElektronika. It is worthwhile to emphasize the fact that the entire system can be reduced to very small dimensions (30x70 mm) using SMD technology.

Data (i.e: the trend of the cross-correlation coefficient) was transmitted with wireless Bluetooth technology. The result collected (see **Figure 14**) put in evidence the effectiveness and the robustness of the algorithm (95,8% considering also the transitions between different activities and 100% not considering such transitions) with respect to the identification of motor activities in real time considering variations in the speed of execution of the gesture.

The dsPIC device demonstrated fast algorithm execution times: 6 ms (equal to the 60% of available time for the real time elaboration), and the memory occupation was 11% for the data memory (RAM) and 28% for the program memory (ROM).

The time length of the three replicates of the original template was chosen according to walk duration on healthy subjects, as reported by the specific literature (gait cycle duration varies from 0,7 to 1,3 seconds; Perry J., 1992).

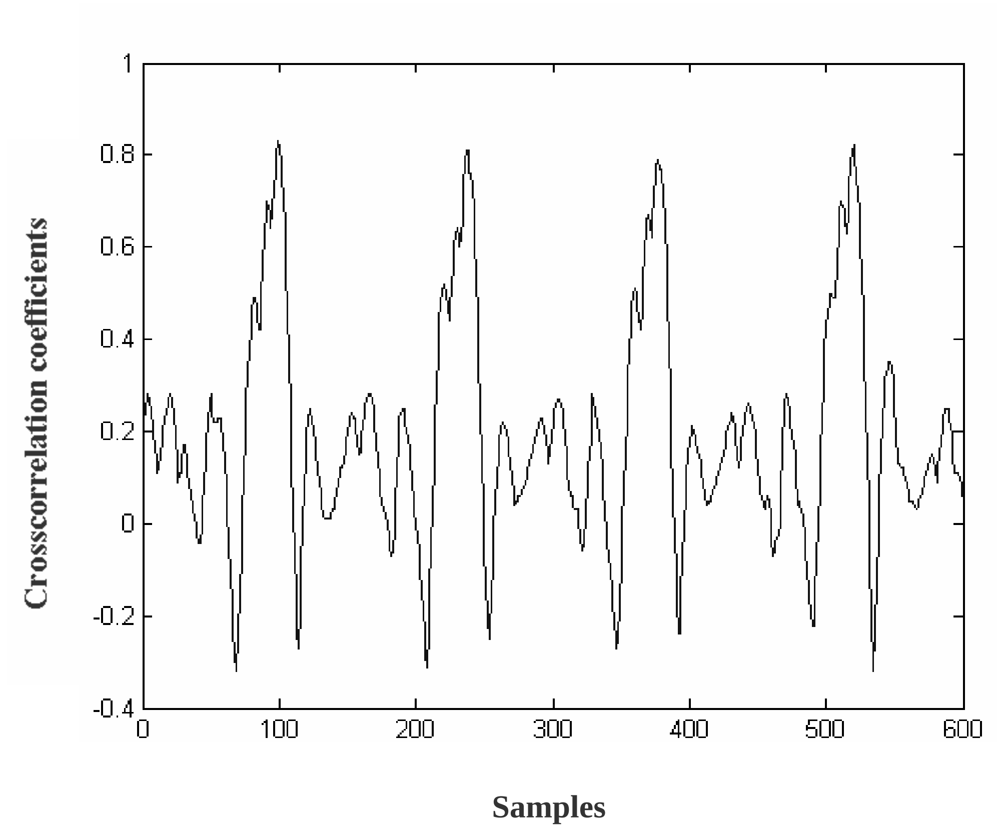


Figure 15: *Example of trend of crosscorrelation coefficients. It is possible to notice the presence of three-lobed peaks in correspondence of each heel strike.*

In **Figure 15** it is possible to observe the typical trend of the transmitted coefficient of crosscorrelation. It is possible to observe the presence of 3 peaks which occur in correspondence of each heel strike. Each peak is due to one different template replicate. Observing on which of the three peaks it is possible to understand if the subject is walking fast (first peak higher), slow (last peak higher) or at a normal speed (middle peak higher).

4 Discontinuous monitoring for upper limbs ADLs

4.1 Combined analysis

4.1.1 Introduction

Arm movement analysis is practiced by exploiting a wide variety of techniques: optical marker systems (Kurtzer et al. 2003, Roby-Brami & Burnod 1995, Harris & Smith 1996, Yang et al. 2002), Human Interface Devices (HIDs) (Guerfali & Plamondon 1998), haptic interfaces (Fukushi & Ashe 2003, Kurtzer et al 2003) robotic manipulanda (Dingwell et al. 2004, Shadmehr & Moussavi 2000) and inertial sensors (Mathie et al. 2004).

Optical marker techniques present high accuracy (declared to be minor than 2 mm by Chiari et al. in 2005) and are usually applied using consolidated and widely spread commercial systems such as Optotrack (Kurtzer et al. 2003, Roby-Brami & Burnod 1995), Coda (Harris & Smith 1996) Elite (Leroux et al. 1992) and Vicon (Yang et al. 2002) (with particular reference to upper limb movement analysis).

On the other hand, the process of patient preparation and system calibration generally limits their use in research laboratory preventing them from being spread out in clinical practice. Moreover the cost of such an instrumentation is not negligible.

Very often it is fundamental to dispose a visual feedback for the description of the motor task and for this reason the motion analysis system is generally interfaced with a calculator provided of graphical output devices such as screens or projectors. This interaction seems more difficult when using marker based systems. Conversely HIDs have the advantage of being thought for such an interaction, are usually inexpensive and present good accuracy.

As an example, the use of graphics tablets for arm movement analysis is rather popular in literature. Many works demonstrated the potentialities of such instruments in the clinical field, both to shed light on arm movement sensorimotor control (Guerfali & Plamondon 1998, Norris et al 2001, Verschueren & Swinnen 2001, Seideler et al 2001, Elliot et al. 1999, Bennet & Davids 1998, Wang & Sainburg 2003, Wigmore et al 2002, Caselli et al. 2006 [***]) and as an instrument to assess arm movement pathologies (Gurd et al. 2001, Gemmert et al. 1999, Erasmus et al. 2001).

As stated above, two main advantages of graphics tablets rely in their ease of use and relative inexpensiveness. These characteristics suggest a broad application field that, in perspective, could include new applications in the monitoring context.

On the other hand, the obvious limit of graphics tablets is that they can record only the position of arm end effectors. In many cases, the information regarding arm posture during tests can be of fundamental importance for movement assessment, as it is the case of pathologic movement analysis (Mussa-Ivaldi et al. 1985, Kiisa et al. 1999, Desmurget et al. 1998).

For this reason, it would be highly desirable to provide the tablet with a video analysis system which could add relevant information on overall kinematics. As a matter of fact, for numerous applications, the high accuracy offered by the latest stereophotogrammetric video systems based on optical markers appears redundant. At the same time, the issues discussed above arise some general concerns regarding their application.

In order to achieve the requirements of easiness of use and unobtrusiveness required for arm movement analysis, many authors are recently proposing algorithms for the analysis of human movement that do not require the use of markers, i.e. markerless. In this way, it would be possible to greatly speed up the patient preparation process, and decrease the constrain subjects' movement.

The importance of obtaining a quicker, cost effective and unobtrusive measure is also testified by the fact that several experimenters felt the need of using movement video sequences, which they used for qualitative assessment or which they elaborated manually to extract quantitative data (Roby-Brami & Burnod 1995, Norris et al. 2001).

Even if, on one hand, motion capture is relevant for studies in biomechanics and for the diagnosis of the musculoskeletal diseases (Harris & Smith 1996), on the other hand, markerless methods are not widely available because the accurate capture of human movement without markers is technically challenging although recent technical developments in computer vision provide a potential for markerless human motion capture for biomechanical and clinical applications. The markerless analysis was applied for example to gait (Ajit et al. 2001, Yam et al. 2002, Wagg & Nixon 2002) and posture (Goffredo et al. 2005) analysis and to gymnastic exercises (Cailette & Howard 2004).

The development of markerless motion capture systems started from computer vision applications like smart surveillance, identification, character animation, virtual reality, and motion analysis (Moeslund & Granum 2001). Recently studies on human motion analysis increased and a great variety of algorithms and systems have been proposed.

These systems vary in the number of cameras used, the representation of captured data, the types of algorithms, the use of various models, and the application to specific body regions and/or to the whole body. Several surveys concerning computer-vision approaches have been published in recent years, each one classifying existing methods into different categories (Wagg & Nixon 2002, Chi-Wei et al. 2003, Cedras & Shah 1995, Aggarwal & Cai 1999, Gavrila & Davis 1996).

While many existing computer vision approaches offer a great potential for markerless motion capture, in biomechanics these approaches are not generally exploited and qualitative tests and visual inspections are most frequently used for assessing markerless motion estimation approaches (Roby-Brami & Burnod 1995, Norris et al. 2001).

Therefore, in this context this work aims at defining a method for assessing the upper limb posture during ballistic movements acquired by commercial cameras. In particular, this contribution intends both to quantitatively evaluate the accuracy of the proposed markerless motion estimation method and to apply it to the upper limb as part of an integrated system for arm movement and arm posture analysis (as proposed in: Caselli et al. in 2005).

The accuracy evaluation is achieved by applying the proposed markerless method to points corresponding to the stylus extremity and comparing the obtained trajectory with the one acquired by the tablet.

On the other hand, in order to use markerless techniques for arm posture estimation, two subsequent steps must be dealt with:

1. track some significant elements on the body surface from the recorded videos obtained by the capturing device(s), and
2. reconstruct body segments and their 3D movement from the tracked elements.

The first phase can be attained by tracking relevant body points or other features, such as lines, contours, shapes. If the points of interest are tracked, the 3D reconstruction is generally achieved by using a number of capturing devices equal or higher than two, that allow triangulation with every point visible by at least two cameras. The overall process can take into account the rigidity of the body segments, so that the triangulation and the tracking procedure can be fairly simplified.

The process of 3D body pose estimation is almost straightforward for model based techniques once the 3D position of at least three non co-linear points of interest for each body segment is obtained, if a model is assumed (Wren et al. 1997, Leung & Yang 1995, Rohr 1983, Cheung et al. 2000, Aggarwal & Cai 1999). If, instead, no mathematical model is hypothesized, the 3D movement of regions of interest are estimated (Jähne 1995, Dufaux & Moscheni 1995) and from them, the entire kinematics is obtained.

Apart from the type of techniques used for monitoring the movement, one question arises: if planar arm reaching movements in rehabilitation practice are monitored through a digitizing tablet, is the technological complexity added by a video capturing system useful to add relevant information for the evaluation of motor ability?

The aim of this work is to provide an answer to this question, by assessing the reliability of the proposed markerless tracking method for upper limb posture analysis. Two different video set-ups are considered and their accuracy are evaluated by comparing data from the tracking method with kinematics obtained by the digitizing tablet.

The reason for using different video set-ups resides on the possibility to assess the difference in movement reconstruction performance when changing the technological complexity of the set-up, in terms of image resolution and number of cameras, in order to establish the most cost-effective layout.

In order to assess the possibilities offered by the proposed technique, the system was tested to show the accuracy attainable in two opposite circumstances in terms of amount of video data recorded and arm movement speed. Thus, two different scenarios were considered: in the first, fast planar arm movements were recorded with one 640x480 video sequence; in the second, slow movements were analyzed with two 1500x996 pixels video sequences.

4.1.2 Materials and methods

The chosen markerless motion estimation algorithm is based on a sub-pixel block matching estimation technique (Giunta & Mascia 1999, Caselli et al. 2005). The algorithm was tested on synthetic video sequences, where it showed a RMSE<0.3 pixels and a satisfactory computational cost (less than 200 ms per frame on a 1.2 GHz processor) at a resolution of 640x480 pixels (Moeslund & Granum 2001). Further results collected on real images by using a controlled trajectory generator showed a RMSE<2.3 pixels which corresponds to 3.6 mm (Bibbo et al. 2004).

Experimental Tests: During tests, participants sat on a chair in front of an office desk and held a stylus. A graphics tablet was set, close to the participant, on the table surface, and a LCD computer screen was placed in front of the participant at a distance of about 90 cm. A graphics tablet Wacom® Intuos I (A3 size, with declared active area dimensions: 457.2 mm width and 304.5 mm height) was used to record the movements, with a time resolution of 5 ms and a spatial resolution of 0.25 mm.

The visual feedback necessary to describe the motor task was presented to the participant on the computer screen, while a set of digital cameras recorded the scene.

Two different scenarios (A and B in the following) were implemented. In A, arm movement was recorded by means of a digital webcam Pc-Cam 750 (Creative® Technology) with an image resolution of 640x480 pixels and a time resolution of 24 frames per second (fps). The motor task consisted in a series of fast reaching movements toward a white circular target appearing on the LCD screen at a random position every 3 seconds.

In scenario B, arm movement was recorded with two digital cameras Imaging MegaCameras SI-3300RGB (Silicon Imaging®) with an image resolution of 1500x996 pixels and a time resolution of 24 fps. In this case, the motor task consisted in a series of movements executed following a triangular shape template visualized on the LCD screen.

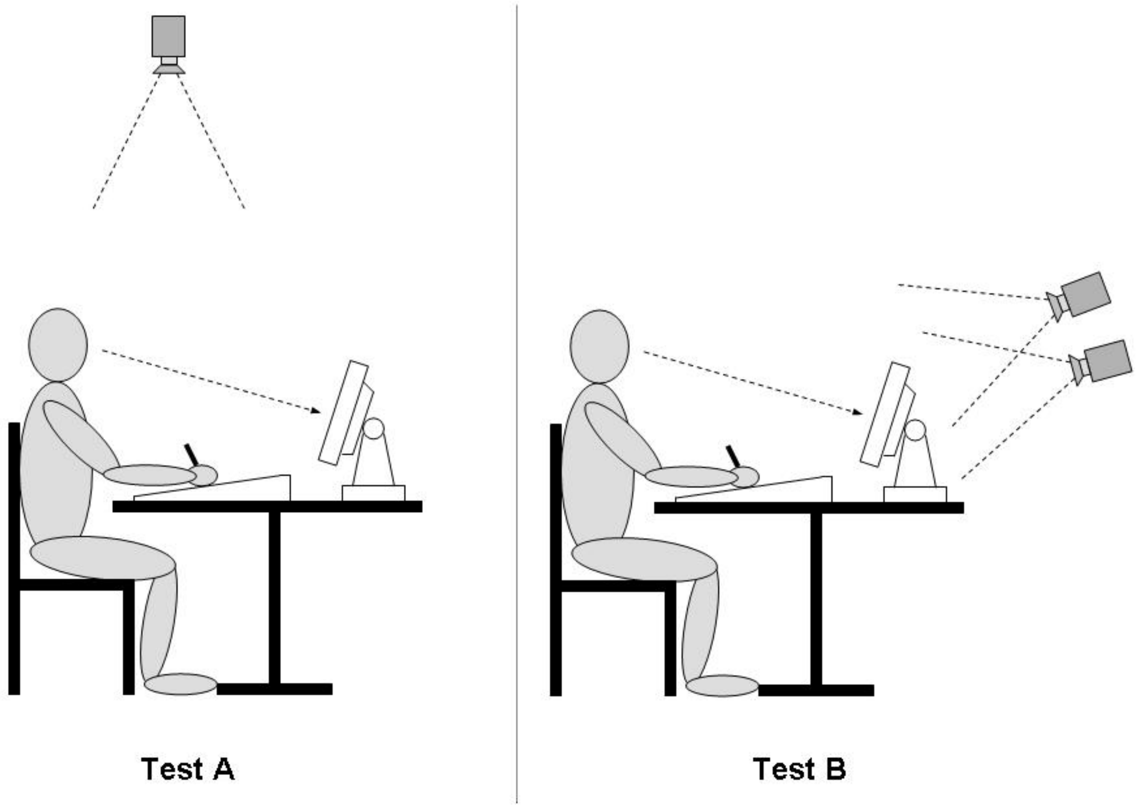


Figure 1: *System layouts in the two different scenarios.*

In A an upper view was preferred for metric conversion needs, while for scenario B cameras had a lateral view with a reciprocal orientation angle of about 90°. The resulting setup configurations are represented on **Figure 1**. It is worth to mention that, since the purpose of the study is to collect information about the whole arm, video sequences were not restricted to the tablet area.

Data elaboration and system calibration: In this section, the proposed approach is described by detailing the theoretical background of image processing, and its application to the combined analysis.

The video markerless technique aims at tracking and reconstructing upper limb movements by analyzing consecutive frames from video sequences recorded during the execution of planar movements with a stylus on a graphic tablet. The procedure for markerless analysis consists in the following two steps (in brackets the corresponding document section):

- calibrating the volume of interest (Camera calibration);
- tracking the relevant points on the upper limb (Markerless algorithm).

In the following the mentioned steps will be described in detail.

Camera calibration: The projection from 3D object space to the camera's 2D image plane consists of an extrinsic and an intrinsic transformation. The first one is an Euclidean transformation from 3D object space coordinates to camera coordinates. This transformation is linear and determined by the position and orientation of the camera with respect to the object coordinate system. The intrinsic transformation is nonlinear and determined by the camera design and construction, including the characteristics of the image sensor and the optical components (Zhang & Chaffin 1999). Camera calibration is the process of determining the parameters of the intrinsic and extrinsic transformations, and allows to transform metric data from pixels to real length measure units (i.e.: millimeters).

In test A, the upper camera view and its negligible image distortions allowed to admit a linear pixel-to-millimetre conversion. The conversion was obtained by using the tablet active surface as calibration object.

In test B a complete stereo calibration method was used. Several different models and calibration techniques are presented in literature (Qingchao et al. 1996, Chun et al. 2003). In this work the Camera Calibration Toolbox for Matlab (Bouguet & Holler 2000, Heikkilä & Silvén 1997) was chosen for its versatility and ease of use. The camera calibration system consists in the elaboration of images containing a planar chessboard at various view angles and distances.

The algorithm can be divided into two consecutive steps: the chessboard corners estimation, and the calibration parameters extraction.

In the first step, the Camera Calibration Toolbox provides a manual solution which prompts the user to click in correspondence of the inner corners of the 4 outer chessboard squares (referred in the following as Reference Corners (RCs)). Then, a corner detection algorithm allows to estimate the position of the remaining chessboard corners starting from the position of the RCs. While being completely unacceptable for an automatic process, this approach makes even the occasional calibration process very cumbersome and error prone (i.e. a fairly good calibration needs about 20 images per camera; considering four clicks per image, this amounts at least to 160 clicks with uncontrolled precision and repeatability).

For these reasons, in this study an automatic procedure for chessboard corners extraction is proposed. The improvement is based on the fact that, analyzing a video sequence instead of a series of images, the difference between subsequent frames is usually of limited amount. Therefore it is possible to estimate the RCs positions in the subsequent frame by applying the same corner detection algorithm. At the same time, using this automatic approach, it was possible to improve the calibration accuracy, as shown below.

The calibration parameters extraction step consists in utilizing the 2D chessboard corners coordinates on each camera and each image in order to estimate the intrinsic cameras parameters (focal length, principal point, radial and tangential distortion coefficients) and the extrinsic ones (rotation matrices and translation vectors with respect to one camera 3D reference system).

As mentioned before, the calibration procedure allows the 3D object reconstruction: in fact the camera parameters are necessary for the determination of the space coordinates (x,y,z) of a point P from the left and right image coordinates of the same point PL=(xL,yL) and PR=(xR,yR).

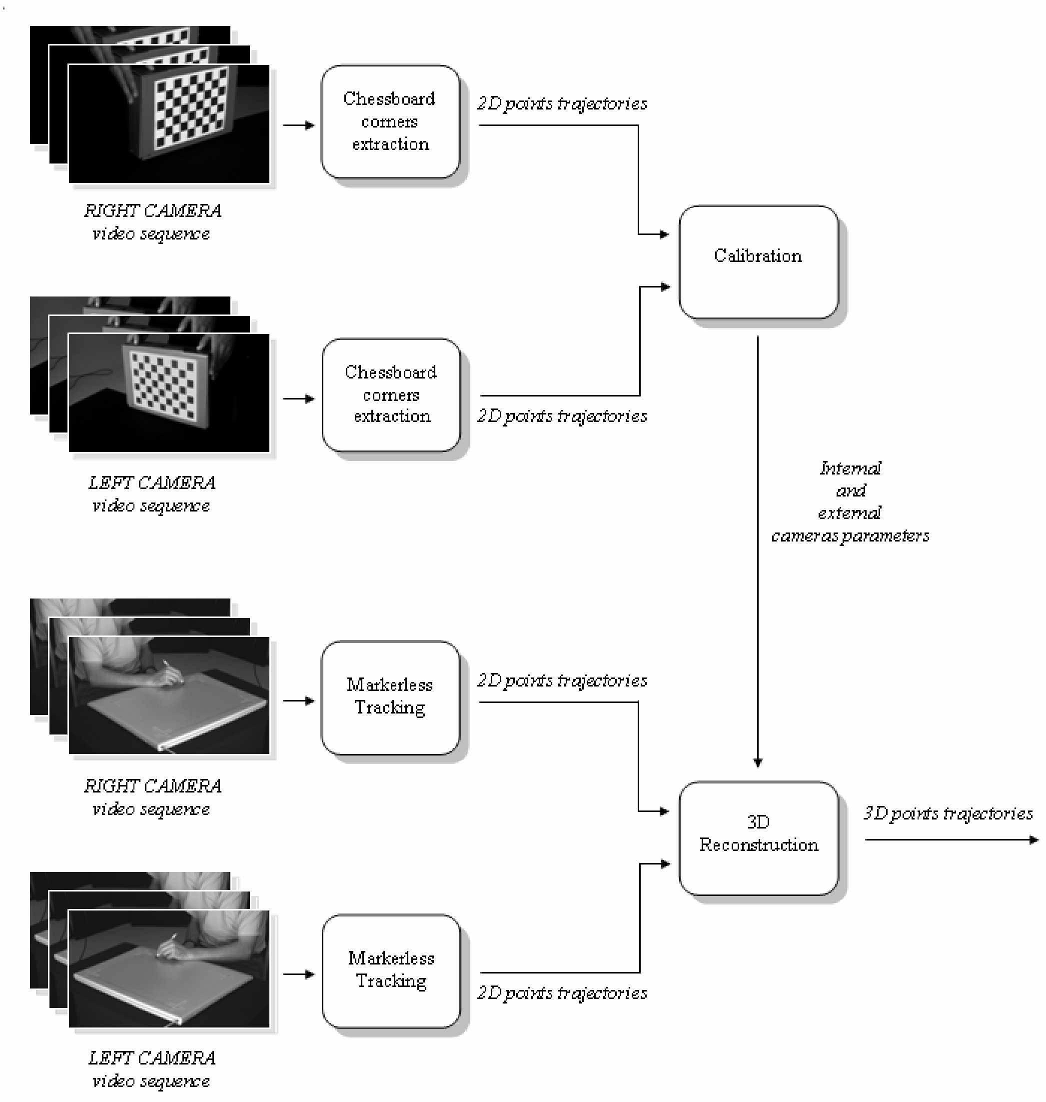


Figure 2: *the proposed 3D trajectory reconstruction.*

Figure 2 summarizes the proposed approach for the 3D reconstruction of the trajectories of points of interest associated to arm movement.

The 3D camera calibration of test B was achieved by analyzing a chessboard (chessboard square dimensions: 28x28 mm) video sequence composed of 170 frames (per camera) with an image resolution of 1500x996 pixels and a time resolution of 24 fps.

The performance of the proposed automatic procedure for chessboard corners extraction was tested by separately processing the same calibration video sequences using the manual procedure and the automatic one. Results showed standard deviation errors in horizontal and vertical image directions equal to (ex, ey) = (0.45, 0.29) pixels when using the automatic algorithm, and (ex, ey) = (0.58, 0.34) pixels while using the manual procedure. On the other end, the calibration process resulted to be over 3 times faster with the automatic procedure.

The following paragraph will describe the proposed markerless algorithm for the estimation of the 2D trajectories of the points of interests in all video sequences.

The Markerless algorithm: The motion estimation technique used in this work, exploits information on the correlation between consecutive frames and relies on a two-phase procedure (Moeslund & Granum 2001): a Block Matching Technique followed by a Fine Interpolation.

The starting hypothesis is that every point of a region of interest is assumed as moving according to a sum of rigid translations; for upper limb planar movements this approximation appears reasonable because the arm motion can be reasonably considered translatory. Therefore, each pixel $\underline{r}$ of the moving area undergoes the same movement, and thus the movement of $\underline{r}$ in $[t, t+\Delta t]$ can be expressed as:

$$\underline{I}(\underline{r}, t+\Delta t) = \underline{I}(\underline{r}-\underline{d}, t) + e(\underline{r})$$

where $\underline{r} = x+jy$ represents the coordinates of the selected pixel, $I(\underline{r},t)$ and $I(\underline{r},t+\Delta t)$ are the frames recorded respectively in t and $t+\Delta t$, and $e(\underline{r})$ accounts for the model error and for the noise; $\underline{d}$ represents the motion vector of the selected element in the frame plane.

The objective of the technique is to estimate the motion vector by a coarse to fine procedure: the coarse estimation of the motion vector, with a standard block matching algorithm, finds the minimum, $\underline{d}^{INT}$, of an integral cost function, $CF(\underline{d},t)$, over the block of dimension W centred in $\underline{r}$:

$$\underline{d}_{\underline{r}}^{INT}(t) = \arg\min_{\underline{d}\in A} CF(\underline{d}, t)$$

where the superscript *'INT'* indicates the integer estimated motion vector and where, considering every pixels of the block W having the same motion law,

$$CF(\underline{d},t)=\sum_{\underline{r}\in W}\left|\left\|\underline{I}(\underline{r},t+\Delta t)-\underline{I}(\underline{r}-\underline{d},t)\right\|_{R,G,B}\right|$$

and A represents the research area, that is the region where the block W is reached in the frame $I(\underline{r},t+\Delta t)$. The Euclidean Norm was chosen as distance criterion. W was dimensioned as (7x7) pixel, and A as (30x30) pixel, which was a conservative choice for the movements in analysis.

In this way, the motion vector $\underline{d}$ was determined, with an accuracy corresponding to an integer number of pixels.

The fine interpolation estimates the fractional translation $\underline{d}_r^{SUB}(t)$ (the superscript *'SUB'* indicates the sub-pixel values) by finding the location of the minimum of the bicubic spline interpolation function obtained using the neighbouring pixels as nodes (**Figure 3**).

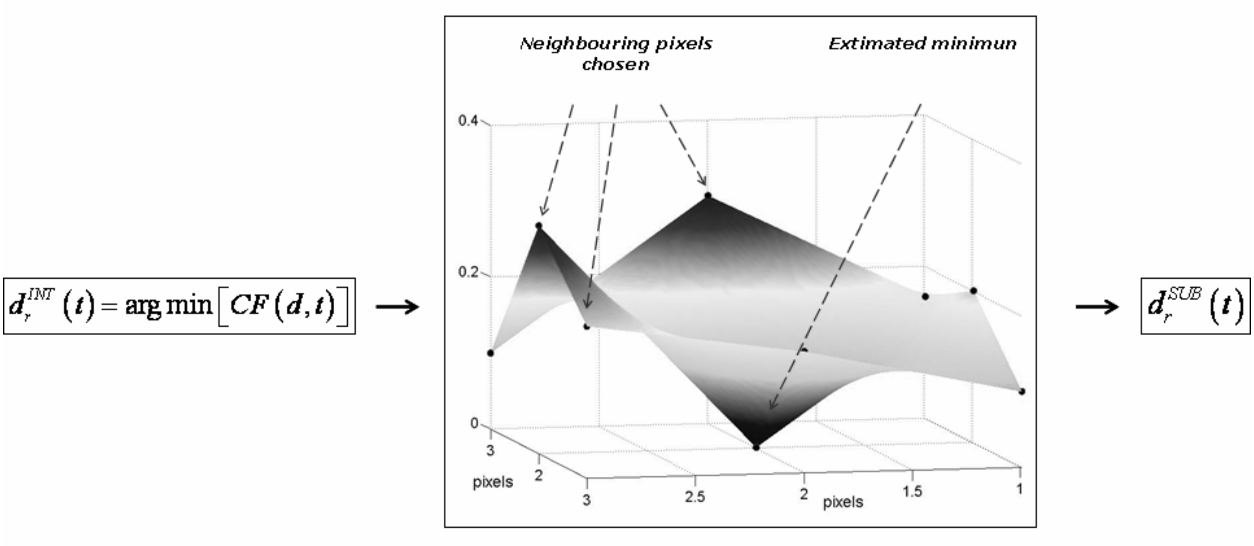


Figure 3: *the proposed 3D trajectory reconstruction.*

Therefore, by applying the proposed motion estimation algorithm, the trajectories of the points of interest on all the camera planes are estimated.

Points of interest used for accuracy estimation were located in correspondence to the hand and the tablet stylus. In particular, several hand points in correspondence to the tablet stylus tip were chosen in order to limit spatial offset between tablet and video data. At a second stage, a simplified arm stick model was considered in order to extract overall arm posture during the execution of movement. Therefore, the points of interest, which the proposed algorithm had applied on, were chosen corresponding to the elbow and wrist and in order to properly match the stick model.

Stylus orientation was also estimated by tracking both stylus extremities with the same markerless algorithm.

Data matching and accuracy evaluation: The graphics tablet was considered as a reference to test the accuracy of the proposed video tracking technique. To this end, the experiments were carried out by applying the proposed markerless algorithm to participant's hand or tablet stylus, and comparing the trajectories with the position of the pen measured on the graphics tablet over time. The different time resolutions between tablet and camera signals made necessary the application of a synchronization algorithm between data obtained with the two approaches, as illustrated below.

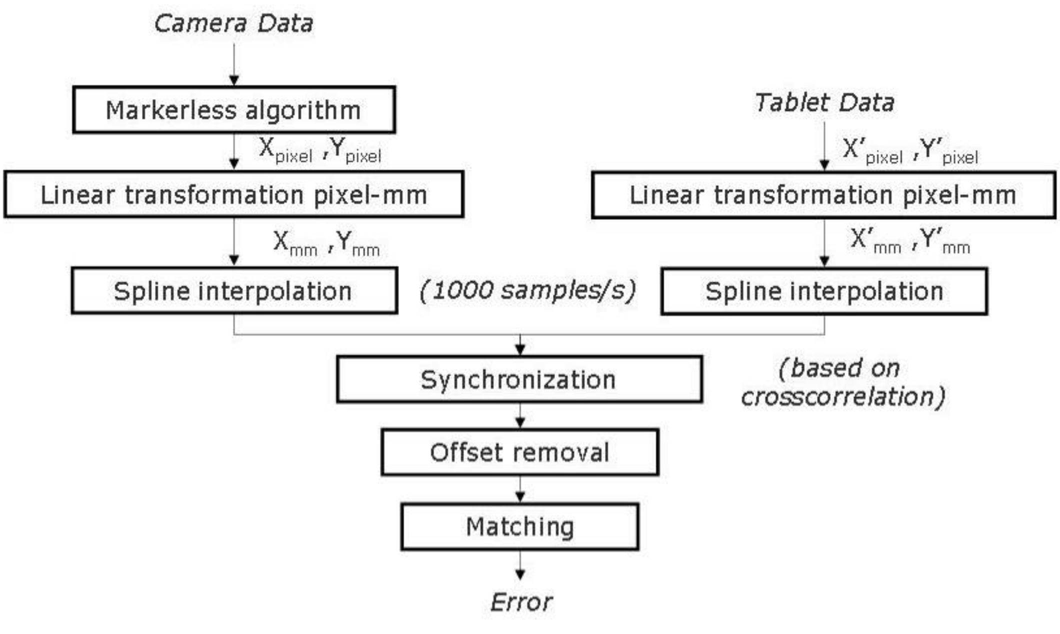


Figure 4: *synchronization technique for fist scenario.*

In scenario A (see **Figure 4**), video data were first processed by the markerless algorithm to obtain a trajectory in pixels. The trajectory data were then transformed into millimetres with the linear transformation described above. A linear transformation was operated on trajectory data recorded with the tablet, in order to convert it from tablet pixels into millimetres.

To obtain a finer trajectory synchronization, both video and tablet data were interpolated through 3rd order B-splines, thus achieving data sequences with 1000 samples per second. The two trajectories were thus synchronized with a crosscorrelation algorithm and subsequently the initial offset was removed.

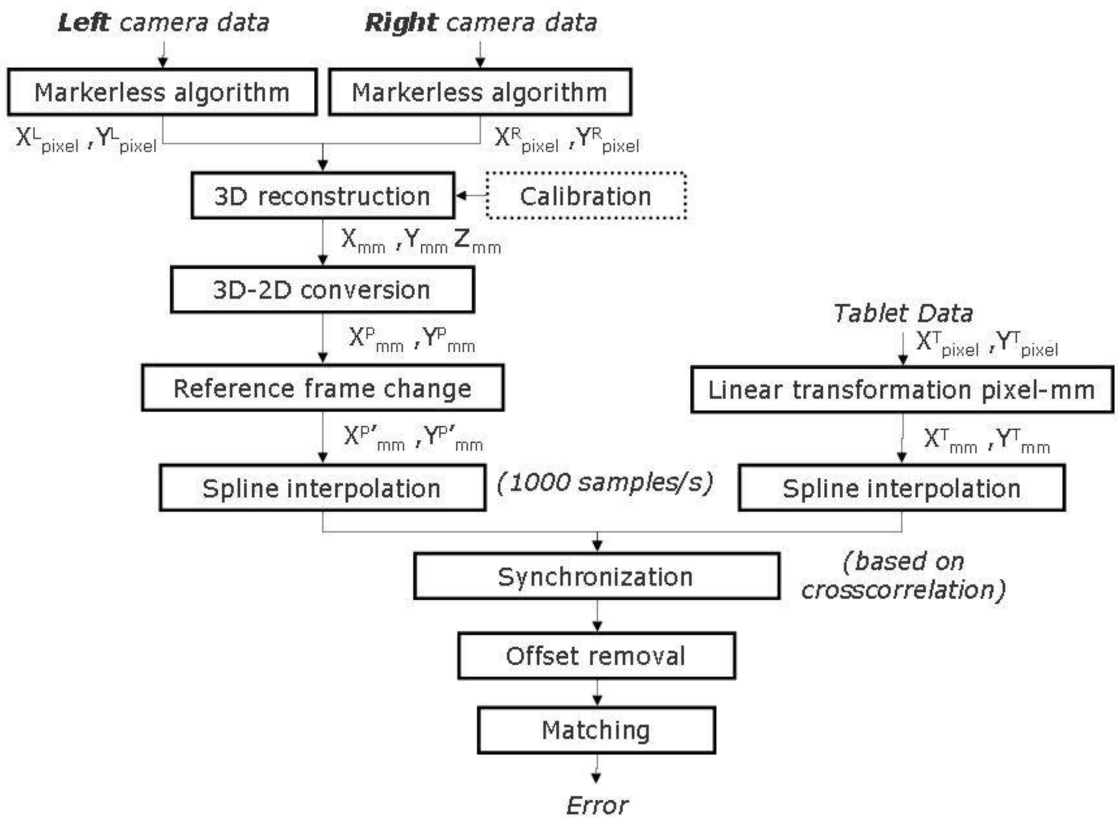


Figure 5: *synchronization technique for second scenario.*

In B (see **Figure 5**) the trajectories of the point of interest on the two cameras video sequences (XLpixel, YLpixel) and (XRpixel, YRpixel) were estimated by applying the described markerless technique, and their 3D position was reconstructed according to the techniques described upwards.

The obtained 3D trajectory (Xmm, Ymm, Zmm) was thus projected on the tablet surface plane to obtain a 2D trajectory comparable with the 2D trajectory recorded with the tablet. Before matching data, it was necessary to change the reference frame in order to transform data from the camera reference frame to the tablet reference frame. The parameters necessary to change the reference frame were obtained by knowing the corner positions of the tablet active area in the camera reference frame.

Tablet data elaboration and synchronization technique in test B were the same as in test A.

Being xt(t) and yt(t) the resampled tablet trajectories coordinates, and xv(t) and yv(t) (see Figure 6 for axes direction and orientation) the resampled video trajectories coordinates, the errors along x and y axis were simply calculated as the difference:

$$e_x(t) = x_t(t) - x_v(t) \qquad e_y(t) = y_t(t) - y_v(t)$$

and the Euclidean error was thus evaluated with the following formula:

$$e_{tot}(t) = \sqrt{\left[e_x(t)\right]^2 + \left[e_y(t)\right]^2}$$

The following three different Root Mean Square Errors were chosen as error estimators:

$$RMSE_x = \sqrt{\frac{\sum (e_x)^2}{l}} \quad RMSE_y = \sqrt{\frac{\sum (e_y)^2}{l}} \quad RMSE_{tot} = \sqrt{\frac{\sum (e_{tot})^2}{l}}$$

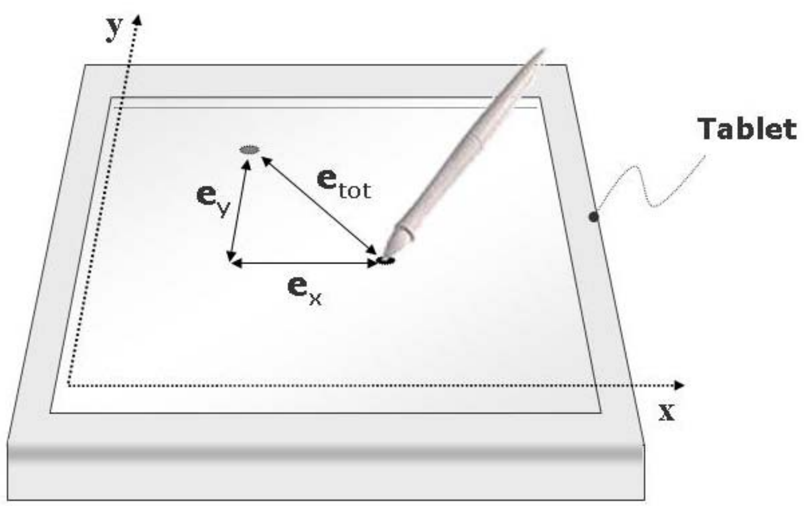


Figure 6: *graphical representation of the errors defined..*

4.1.3 Results and discussion

The results described below were obtained analyzing 700 frames for both tests.

Some of the results obtainable with the proposed method are presented in **Figure 7** and **Figure 8** that show some examples of estimated trajectories for each test.

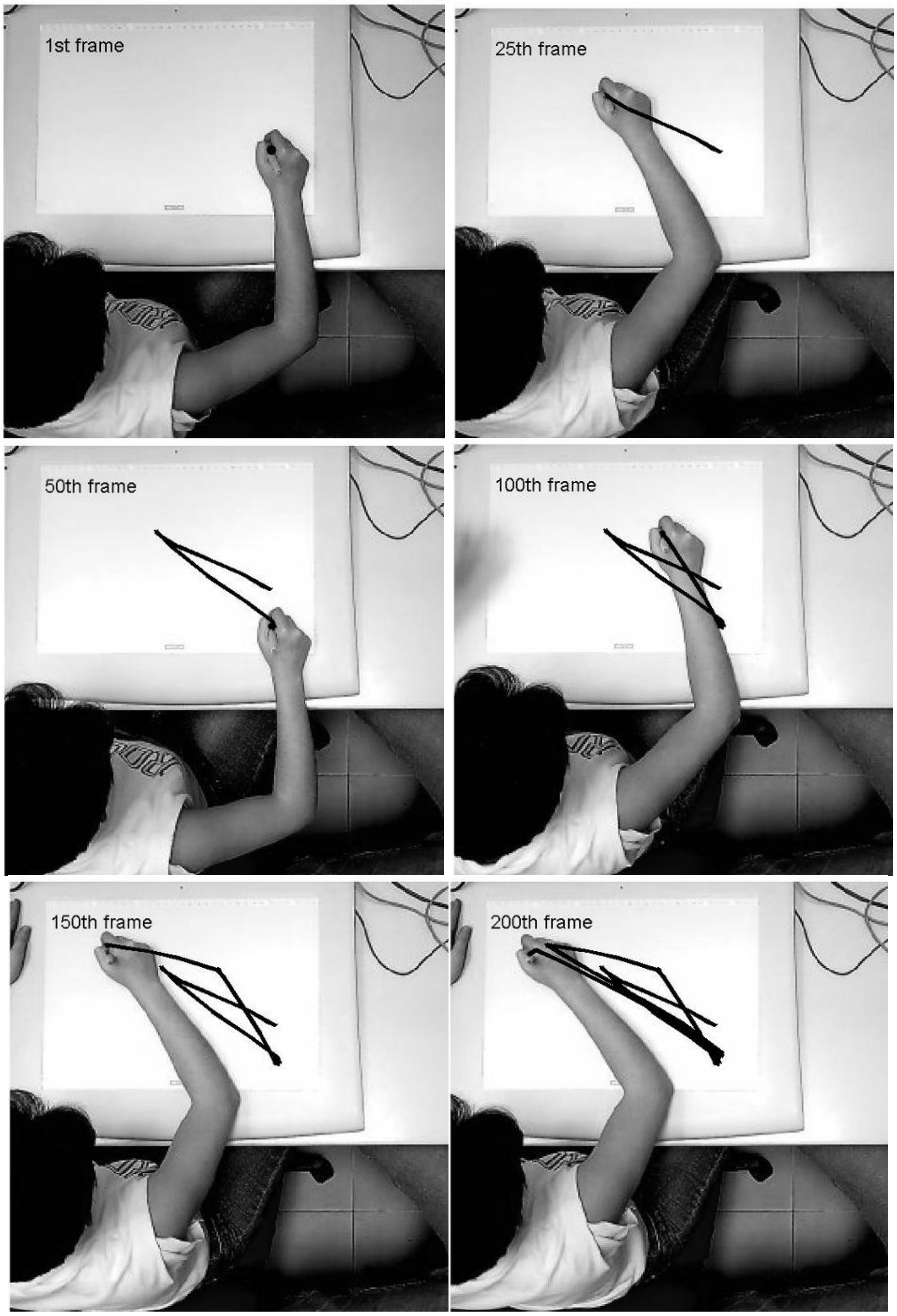


Figure 7: *example of results of the block matching tracking process in the first scenario.*

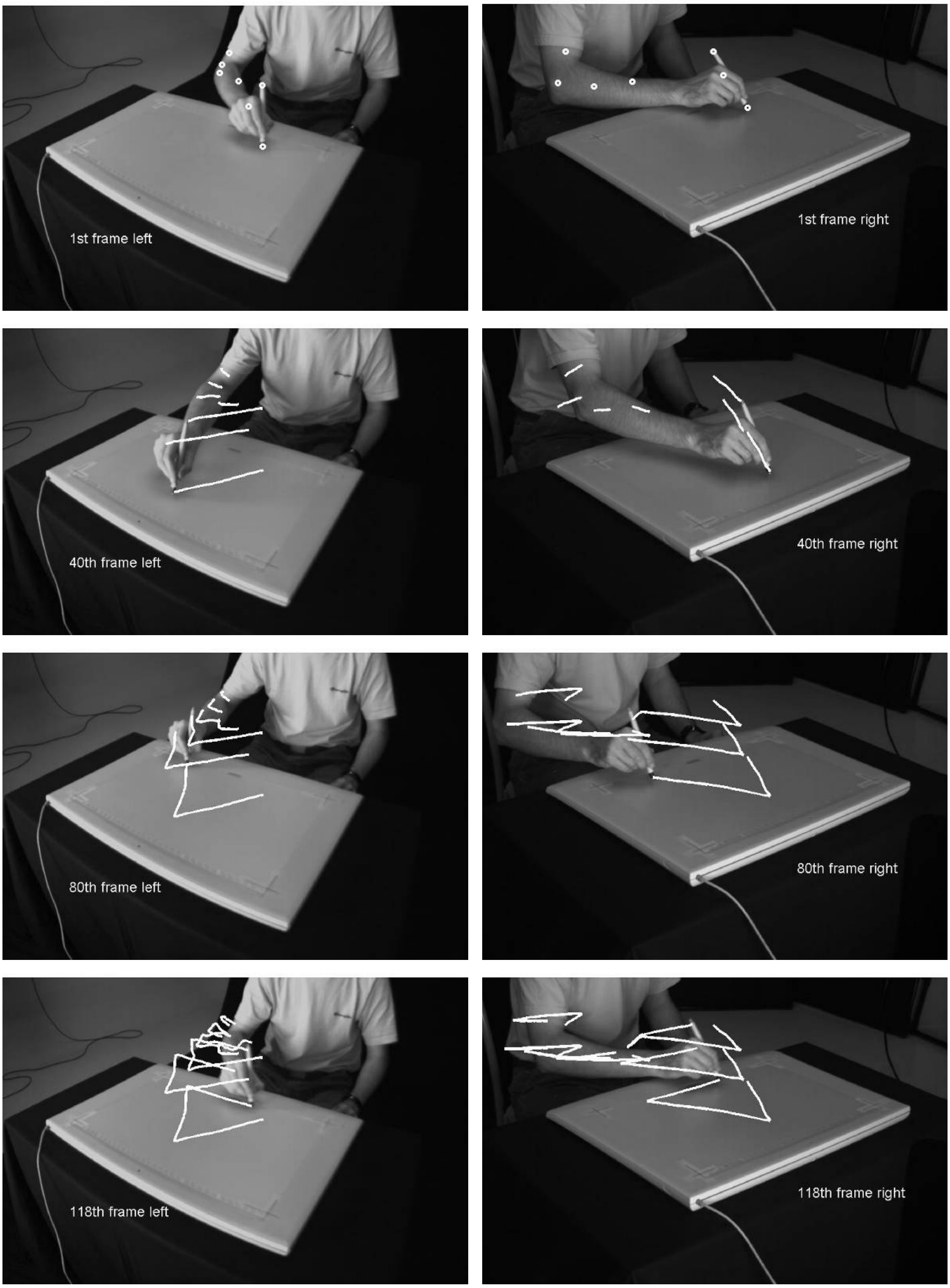


Figure 8: *example of results of the block matching tracking process in the first scenario.*

Figure 9 (upper panel) illustrates the error in trajectory reconstruction obtained in test A by comparing two corresponding sample trajectories extracted from the data recorded with tablet and video.

In the same way, **Figure 9** (lower panel) compares the sample trajectories obtained in test B using the two approaches. It is possible to notice how the trajectory reconstructed with the proposed markerless method contains all the signal characteristics of the reference one, obtained from the tablet, and that no high frequency noise is present.

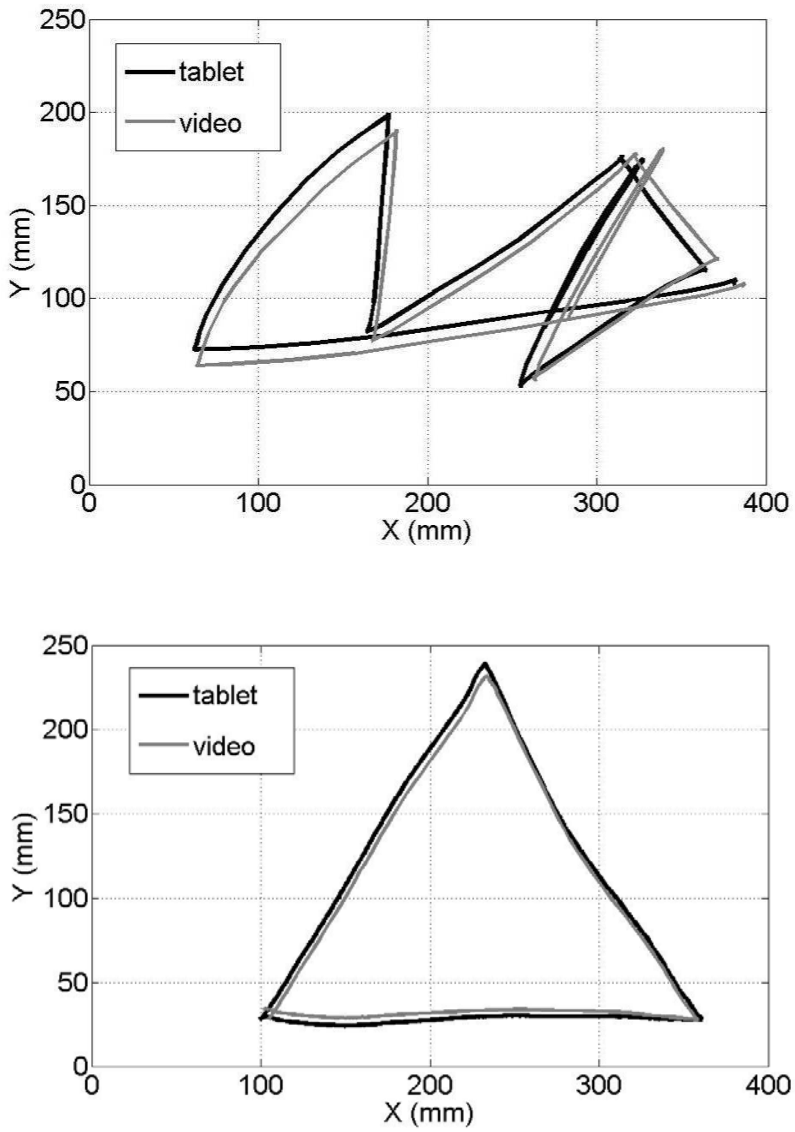


Figure 9: *example of results of tracking process. UPPER PANEL: fast reaching movement tracking. LOWER PANEL: assigned trajectory movements tracked with block matching and 3D reconstruction with camera calibration.*

For a quantitative assessment, **Figure 10** shows the results obtained by comparing the trajectories from the graphics tablet and the markerless system. In test A, the matching of the whole data produced RMSE different for less than 1 cm for each trajectory component (RMSEx = 6.4 mm, RMSE y= 8.7 mm while total RMSE is equal to 10.8 mm). The RMSE appears to be reasonable considering the frame rate, the image resolution and the speed of the task associated to test A (mean movement duration of about 500 ms). On the other hand, in test B, RMSE values appear to be about five times lower: RMSEx = 2.0 mm, RMSEy = 1.8 mm, RMSEtot = 2.7 mm (see Figure 11).

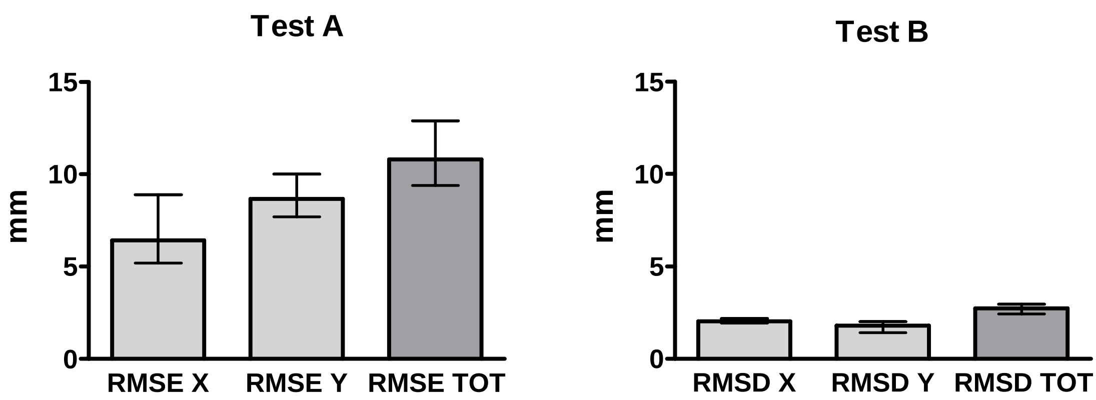


Figure 10: *Errors obtained in the two scenarios.*

It is worth to mention that the errors are not only attributable to the markerless motion estimation technique but also to the calibration steps. In particular, while in test A it was not possible to separate the two contributes (because no camera calibration was performed), in test B, such error appears to have standard deviation components of (ex, ey) = (0.54, 0.30) pixels, as estimated by the Camera Calibration Toolbox.

Further results regard the estimation of the stylus orientation and the exploitation of the proposed markerless method for an overall arm posture analysis. Concerning the first point, the results show a standard deviation error equal to 1.3 mm in stylus length estimation. Moreover, as it can be seen in **Figure 11**, the trajectories of stylus extremities were extracted successfully.

Concerning the second point, upper limb posture was correctly estimated and the 3D reconstruction was possible by using a rigid body model (stick diagram) for the forearm. **Figure 12** shows a possible output of the 3D posture estimation obtained with the proposed approach.

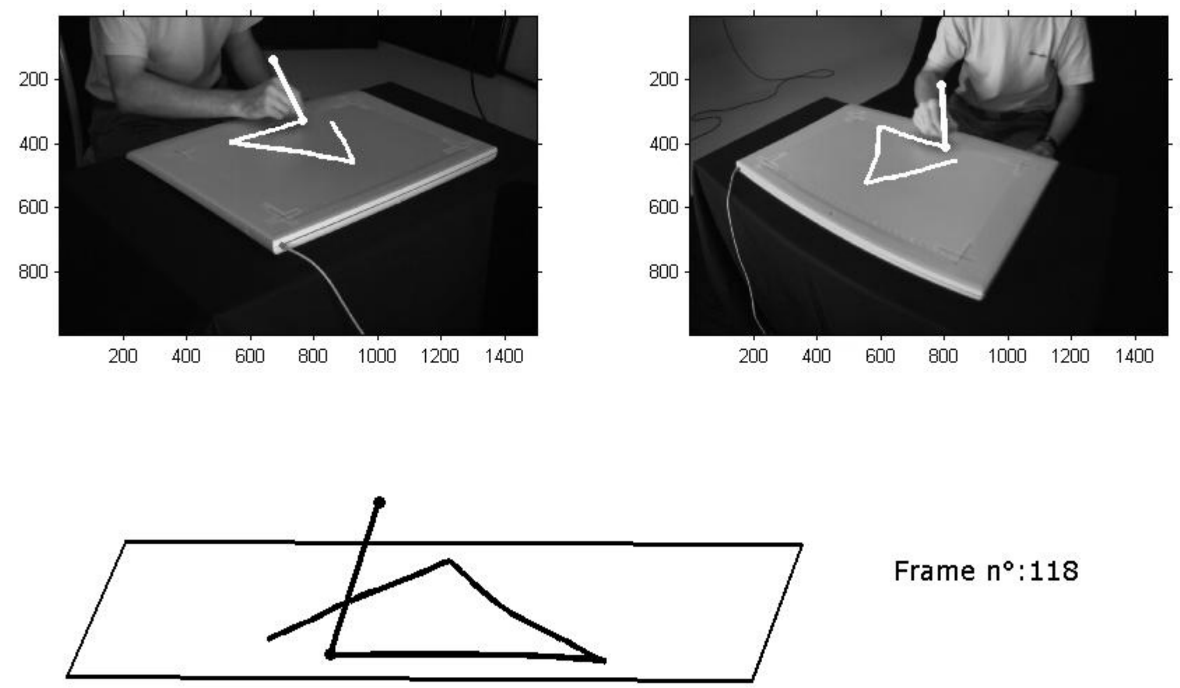


Figure 11: *pen orientation reconstruction.*

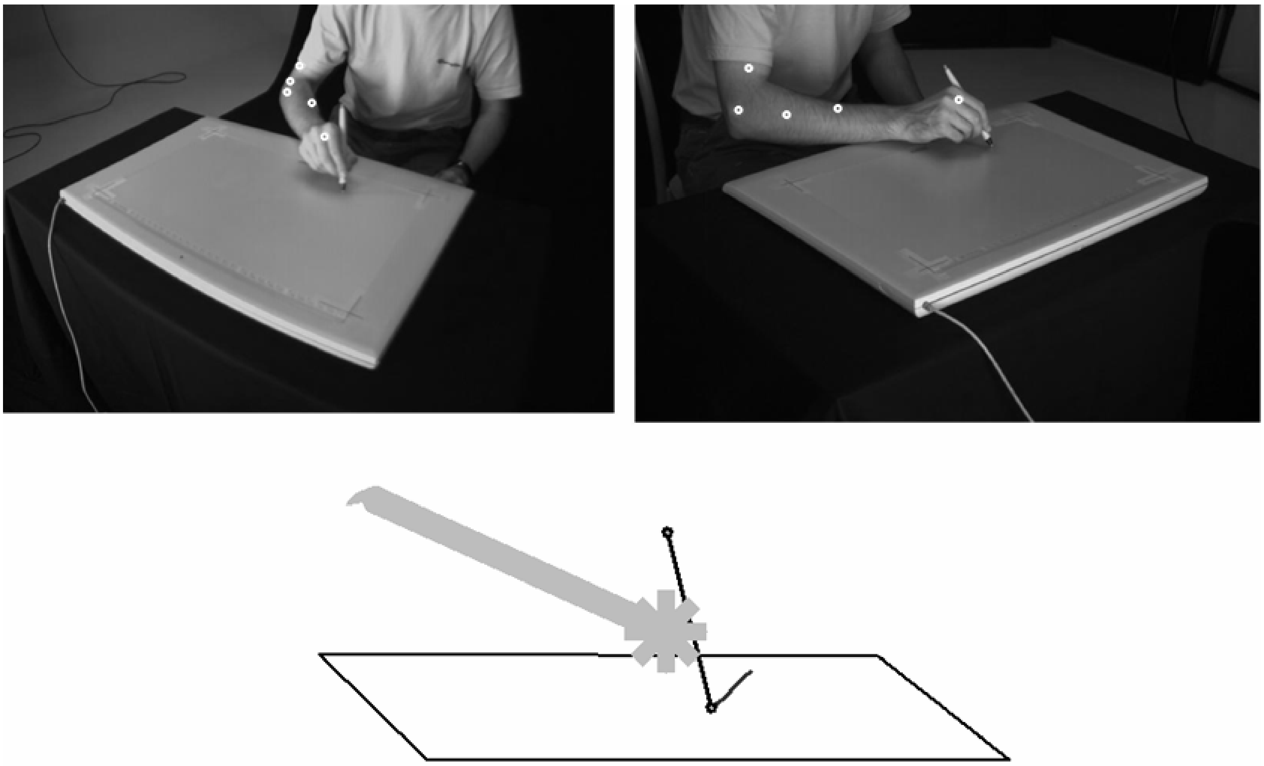


Figure 12: *arm posture reconstruction.*

4.2 Telemonitoring graphic user interface

When studying upper limbs ADLs, it was soon evident the need of having available a set of software tools for conducting the tests and for the subsequent analysis. In order to satisfy this necessity new software applications were designed and implemented. The design was done in collaboration with the Neuroscience Department of the University La Sapienza of Rome. The new tools were designed according to the needs of medical professionals and technicians working in the department.

Two different applications were developed: one application was designed (in C language) for data acquisition and for visual task online representation; another application (written in Visual Basic language) was intended for offline data visualization, elaboration and management.

The first application, destined to home environment, was designed to be simple to use for patients and technical staff. It contains a set of relevant motor exercises that are considered to be useful to assess motor performance, according to specific literature.

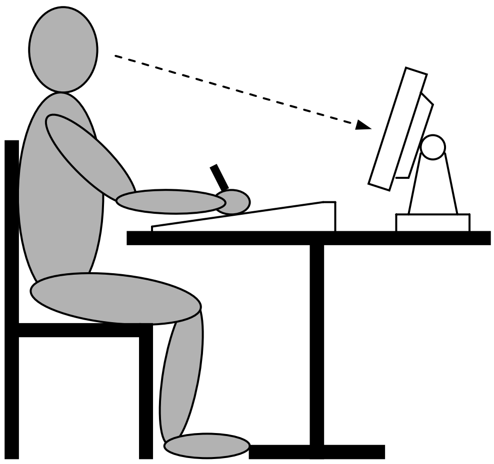


Figure 13: *system layout..*

The scenario of the test is the following: during the tests each participant sits on a chair in front of an office desk and held a stylus. A graphics tablet was placed near the participant on the table surface, while an LCD computer screen was placed in front of the participant at a distance of about 90 cm, as shown in **Figure 13**. Arm posture was neither restricted nor monitored and the hand pointing location was tracked by recording the position of the stylus on the tablet surface.

The device used to record the movements was a graphics tablet Wacom© Intuos I (A3 size). The movements were recorded with a time resolution of 5 ms and a spatial resolution of 0.25 mm. The hand position was represented by a black cross cursor on the computer screen. The screen scaled down the movement executed on the tablet surface with a factor of about 1.5 and had a shape deformation ratio lower than 5%.

The software was designed to execute a collection of tests which are considered to be relevant for movement assessment. The motor tasks which were studied include reaching movements and trajectory tracking. Several distortions and objects can be added to the virtual environment.

A particular attention was devoted to reaching movement. In particular, several kinematic parameters were proposed to assess such movements (Caselli et al. 2004, Caselli et al. 2005). The following paragraph describes the kinematic parameter which is possible to extract.

Characterization of reaching movements: (See also Caselli et al. 2006 [***]) Each movement was automatically revealed by a velocity threshold. Whenever the velocity exceeded the threshold value, a movement validation algorithm was executed in order to discard odd movements and avoid counting the same speed profile twice. A validation algorithm was necessary because the threshold could be reached more than once during the same movement or it could be reached again during post correction or unsolicited movements before the comparison on the screen of the following target.

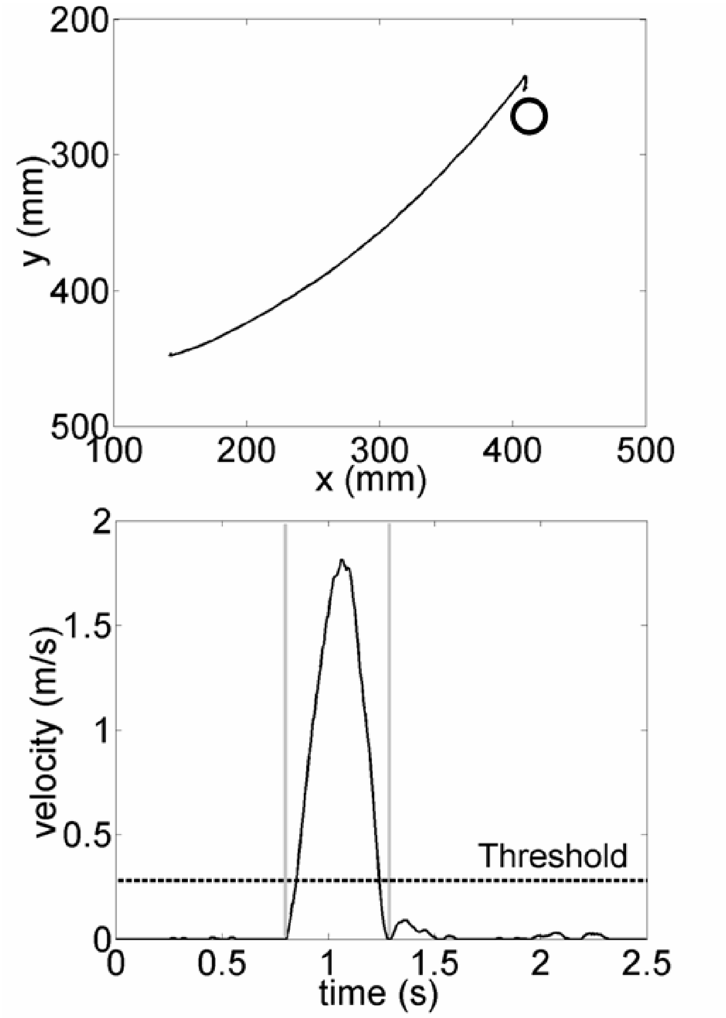


Figure 14: *Movement in the y-x and velocity-time planes.*

Post corrections are motor activations executed to correct final position when the movement has already ended or is about to end; they generally appear when task execution is too slow. The implemented validation algorithm basically discards all speed profiles except the first occurring after the comparison of each target. As the study was concerned with the ballistic component of movement, post corrections due to visual feedback were discarded in the described way. To clarify this procedure, **Figure 14** shows an example of single movement and the corresponding velocity profile together with the threshold used in the validation algorithm. It can be seen how the algorithm discards the post correction.

Several parameters were extracted and analyzed to describe motor performance and movement kinematics (see **Figure 15**):

Duration (ms): Time duration of movement (time elapsed between the farthest samples with velocity not equal to zero).

Peak Velocity (m/s): Maximum velocity during movement.

Position Error (mm): Distance from the final position of the movement and the center of the target to be reached.

Angular Error (rad): Angular difference between the final position and the target seen from the starting point.

Reaction Time (ms): Time elapsed from the appearance of the target to movement initiation.

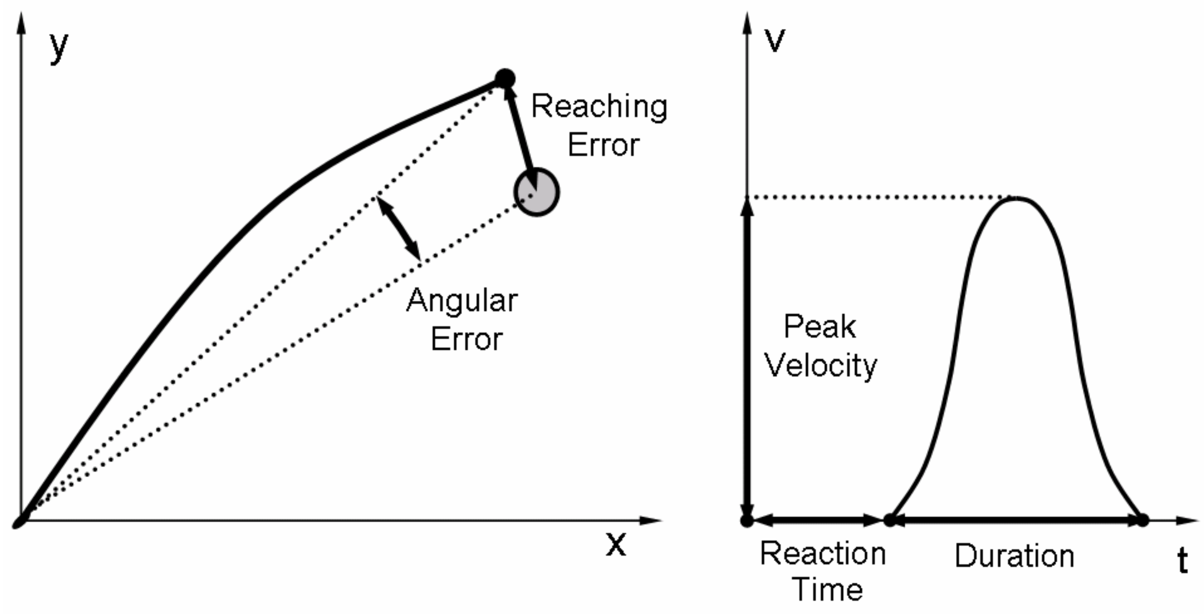


Figure 15: *kinematic parameters defined.*

Reaction Time and Reaching Error were used as indicators of motor performance, while Peak Velocity and Duration were used to monitor variations in movement kinematics. The distributions of these parameters were analyzed in each block of tests and in each of the five trials composing one block.

Mirror distortions (MDs) were studied as a instrument for assessing motor performance. Using such distortions, when analyzing the distribution of angular errors, it soon appeared that the mere value of the error was not sufficient to describe motor performance. In fact, when MDs were applied, some movements were performed toward non-random, wrong directions.

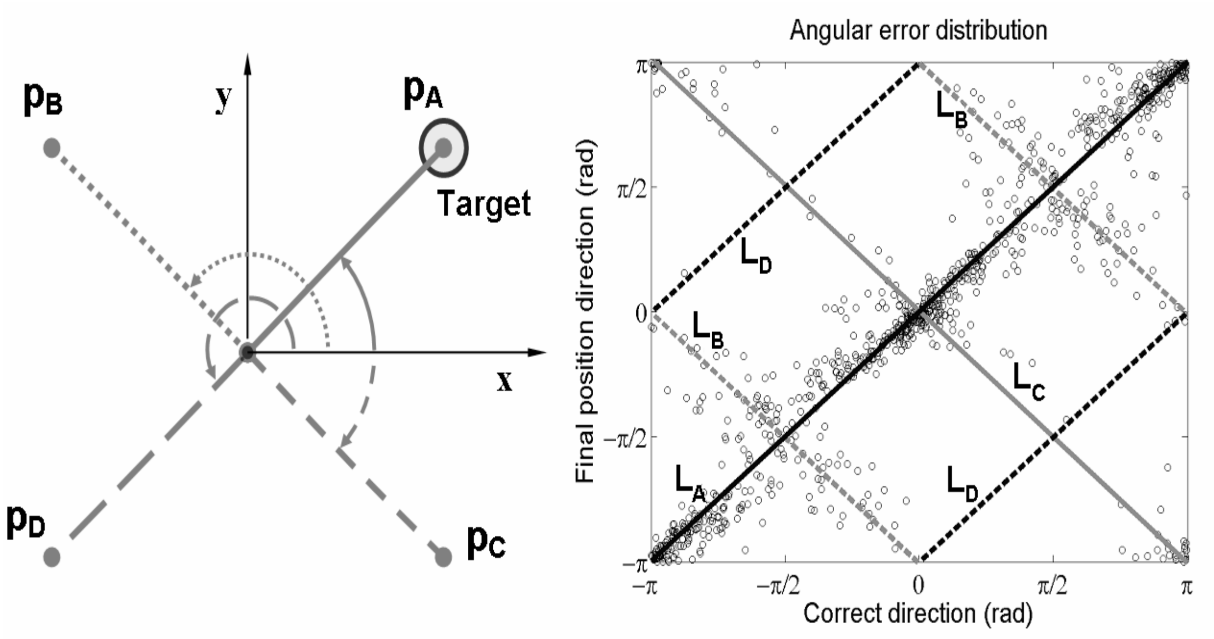


Figure 16: *Error distribution when using mirror distortion.*

It was possible to identify four different categories of movements that are summarized in **Figure 16**, which also represents the target-direction/movement-direction distribution. In this plot, each movement is represented by a point, where:

˜ the X axis corresponds to target direction angle as seen from the starting position;

˜ the Y axis represents the final position angle as seen from the starting position.

Position angles were calculated counterclockwise with reference to horizontal (i.e., lateral) right direction.

In trying to understand the sensorimotor adaptation, it proved useful to distinguish correct movements from those with error induced by MDs. Movements were thus classified into four groups, by a minimum distance algorithm operating on the angular error domain:

1. correct movements, represented by points close to line LA;
2. movements with wrong horizontal component, represented by points close to lines LB;
3. movements with wrong vertical component, represented by points close to line LC;
4. movements with wrong horizontal and vertical component, represented by points close to lines LD.

Each movement was assigned to one of the indicated classes if the distance from the corresponding line was smaller than all the distances from the other lines. Movements with equal distances from the closest classes were not classified.

Task representation and acquisition: The application RecordData, has the two functions: the first is to set, receive and save tablet data, the second is to show an adequate representation of the motor task on the screen.

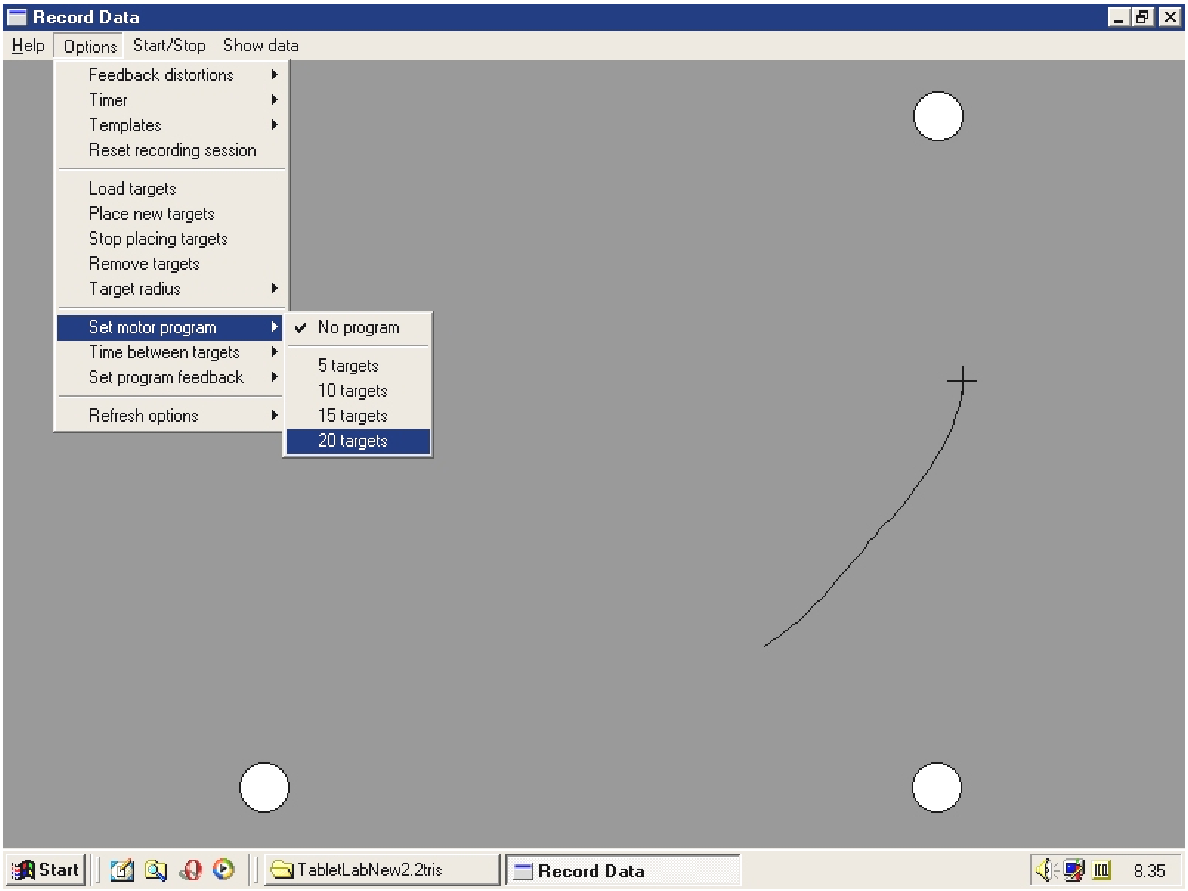


Figure 17: *recording Guided User Interface..*

The pointer is represented on the screen with a cross cursor, which can draw on the screen a curve which can be persistent or appear on the screen for a short time (250 ms). The curve has the purpose to guarantee the visibility of cursor and movement trajectory, even while analyzing very fast movements. The cross cursor doesn't substitute the mouse cursor, which is still available for interacting with the operating system. The whole trajectory recorded can be visualized after the end of the recording session (see **Figure 17**).

It is possible to generate an acoustic signal each time the pressure of the stylus on the tablet is higher than a certain threshold value.

Two different objects can be placed on the screen: targets and templates. Targets are circular white objects that can have different dimensions (with diameters ranging from 0,5 to 4 cm) and can be placed in every point of the screen. This objects can be placed (up to 20) directly on the tablet surface by touching it with the stylus in the desired position. This function is particularly useful when some points of interest are present on physical tablet surface. It is possible to save and load the last target set used, to generate target with random position and to temporize the pop up of templates on the screen. Targets are used when reaching movements are analyzed.

Templates are a set of common trajectories of different shape and dimension, which are commonly used during movement assessment. It is possible to select a line, a triangle, a square and a spiral. These objects are intended for the study of trajectory planning.

It is possible also to apply some visual distortions: horizontal and vertical mirror distortions, horizontal and vertical gain is also obtainable by changing the dimensions of the application window.

Tablet data are recorded in a dedicated format (.TAB), which is recognized by the second application, and contains the information related to the object used during the recording session.

Offline data processing: In the application for offline data processing set of required functions were defined as follow:

- Temporal data representation: x coordinate, y coordinate and pressure.
- Derivative data representation: time trend of speed and acceleration
- Frequency spectrum
- Trajectory data representation
- Zoom instruments
- Spectrogram (time frequency analysis)
- Small database with patient anagraphics, test descripion and other relevant information.

A large part of the work was devoted to the analysis of reaching movements. In particular, the aim was the determination of motor parameters, useful for the characterization of motor performance.

This software tool, developed in Visual Basic, is constituted of different child windows embedded in a parent window:

- Parent window
- Main child window, for temporal and frequency domain visualization, analysis and processing (see **Figure 18**).
- Database windows:
  - ✓ Patients list window
  - ✓ Single patient data window
  - ✓ Single file data view and edit window
  - ✓ File list view window
- 2-dimensional data visualization and analysis window (see **Figure 19**)
- Time-frequency analysis window (Spectrogram)
- Window for kinematic parameters extraction and view

All the functions, options and the instruments implemented can be accessed through a menu bar or a tool bar. It is possible to access to data files by double clicking on the single file (.TAB files). It is possible to open more than one file on the same environment (same parent window).

From the offline data processing application it is possible to remotely launch the acquisition application. When the single recording session is ended data can be automatically transferred to the offline data processing application. Data can be thus completed with additional information, analyzed and archived if necessary.

The main child window can contain the functions (in the time and in the frequency domain) associated to the main kinematic parameters interesting for the movement analysis.

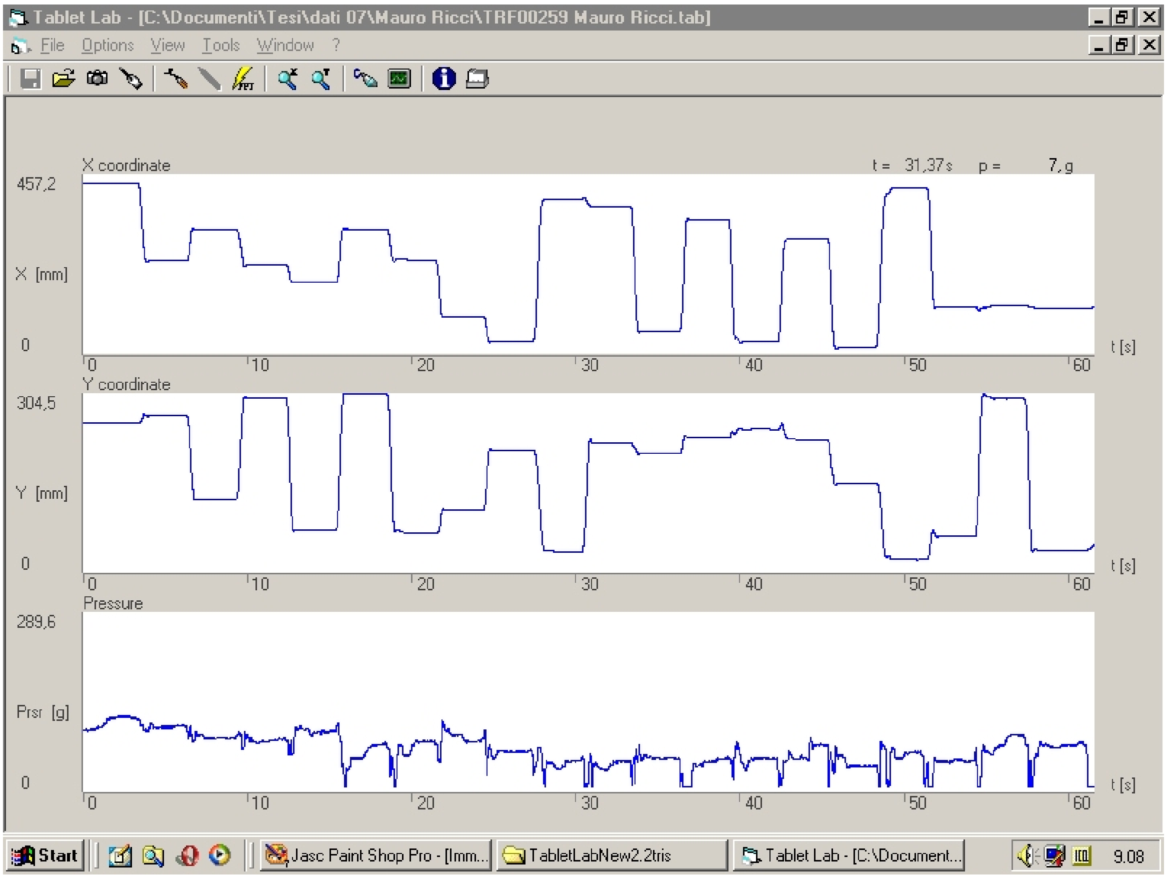


Figure 18: *Main window of data processing User Guided Interface.*

It is also possible to represent data in two dimensions using a dedicated window. It is possible also to view, as third dimension represented by the thickness of the line drawn, the pressure associated to the movement at each time. It is also possible to view the objects present in the virtual environment when the person was executing the test. It is also possible to view local maximums and minimums, and maximum curvature point as well. It is also possible to use a 2-dimensional zoom tool.

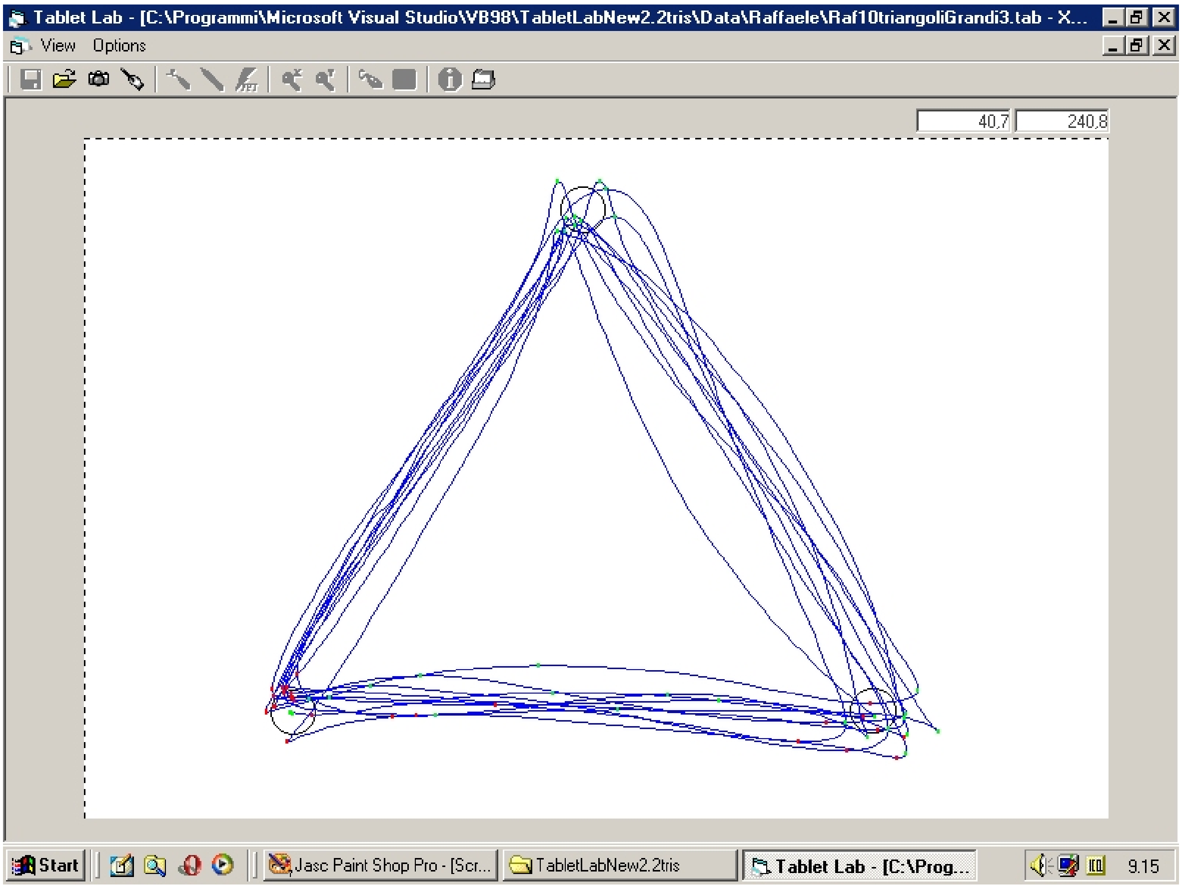


Figure 19: *x-y visualization of the data processing User Guided Iterface.*

Each data file contains all the information regarding the person who executed the movement and regarding the type of test. Those accessory data can be archived and retrieved eventually. The management of such data is done with the database windows.

For reaching movements it is possible to use a tool for the automatic extraction of significant kinematic parameters. It is possible to view the parameters extracted in a table.

5 Conclusion

The results obtained in this work together with the developed systems and the proposed techniques want to be just an example of the possibilities offered by the distance healthcare services. The thesis shows that it is possible to deliver to patients cost effective systems, exploitable for such application.

In particular, the analysis done revealed the impact of execution speed for the recognition of lower limbs ADLs and confirmed that it is indeed possible to recognize and classify the activity, with an acceptable accuracy, by using accelerometers. Moreover results collected show that it is possible to quantitatively reconstruct arm movement by exploiting a ‘markerless’ point tracking algorithm.

Data collected showed also that it is possible to obtain very good classification scores (>95%) for the considered lower limb ADLs, also by avoiding the calibration process for the construction of the template set. The proposed recognition algorithm for lower limbs ADLs recognition allowed to improve the classification score with respect to similar designs presented in literature. While, for upper limb ADLs, the error of the ‘markerless’ technique in reconstructing hand movement during physical exercises showed to be acceptable (root mean square error varying with image resolution from less than 3 mm to 10 mm), even considering that lens deformation cannot be completely eliminated by camera calibration toolbox and considering the fluctuation of the relative position of the tracked point respect to the stylus tip.

The obtained results suggest that probably the variability in movement execution speed is not to be ignored during the recognition of ADLs, at least for the motor activities considered. Simultaneously, the hypothesis that the same patterns can be found in different execution speeds seems confirmed.

The classification scores and the robustness of the recognition algorithm, together with its limited computational load, suggested the development of real-time data processing devices applicable in the tele-monitoring of physical activity.

The developed hardware prototypes appear to confirm such findings, in terms of both algorithm performance and processing capabilities. The overall system has proved to have a satisfying performance for the intended applications in terms of data handling, with a reasonable weight and cost. Power consumption, although acceptable, could be reduced on future design by exploiting next generation transmitters.

These devices allow to limit the information to be transferred (not last reason being the power consumption for data transmission) and to access/visualize the results directly on the patient unit. In fact, the computational load of the proposed algorithm, was proved to be compatible with the processing performance of last generation DSP devices, as shown by the developed prototypes.

As possible further development of this work, it is worthwhile to underline that the possibility of integrating the information collected from different body locations and sensor axes needs to be further evaluated. An appealing topic for future developments would be to explore such possibility, by determining also an optimal classification algorithm, to gain a more robust classification in the long term monitoring, also in pathological conditions.

In addition, the recognition performance could be increased by considering an ‘intelligent’ standard template set, that changes through time adapting to the individual that wears the sensors.

Regarding upper limb ADLs a challenge for future work would be to obtain an accurate estimation of tracking error on the skin and thus to compare the difference between selected points in term of tracking performance. In particular, it would be extremely important to find some classification criterion for an automatic selection of the best-tracking points in the regions of interest.

Regarding the choice of points to track it is worth to mention that, unlike optical markers, the points of interest, which can be tracked by the proposed ‘markerless’ method, can be chosen in a number that can be decided freely by the experimenter, even after the test session, without adding any complication to the overall system. Such possibility could in perspective be exploited to obtain a more robust and detailed estimation of arm posture.

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