POLITECNICO DI TORINO

Master's Degree in Ingegneria Biomedica

Master's Degree Thesis

Development of Machine Learning-Based Algorithms for Assessing Tai Chi Exercise Proficiency in Older Adults

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March 2020

Abstract

In the past decade Tai Chi health benefits such as preventing fall risk, fighting social isolation, depression and improving cognitive capacity in older adults were widely investigated in order to give to physicians the possibility to give evidence-based recommendations to their patients regarding its use in rehabilitation purposes. The goal of the project is to develop a wearable system in order to generate meaningful feedback, to improve exercise performance and continuously monitor safety in individuals participating in a home-based program. This study, in particular, will focus on developing a machine learning algorithm to assess exercise proficiency in individuals performing Tai Chi. To do that thirty two Tai Chi practitioners were enrolled and they were asked to take part in data collection sessions in which, first, their physical eligibility had to be evaluated through a quantitative assessment tool known as BESTest and, finally, they were asked to perform different Tai Chi exercises. To collect data thirteen Shimmer units were put on each body segment of the the body of the subject. Each unit is composed by a 3-axes accelerometer, gyroscope and magnetometer. The beginning and the end of each task performed during the data collection was marked with an event marker so it was possible to keep only the part of the signal related to the tasks.

Before starting the analysis, data needed to be processed. This was made in two main phases. Firstly, data needed to be checked, in order to be sure that each Shimmer unit had recorded properly the entire data collection and, then, check that the applied event markers were in the correct position. Once the controls were over, data were re-sampled and both band pass and low pass filtered. The next processing step was the segmentation of each repetition performed by the subject in each Tai Chi exercise. Depending on the task the number of repetitions could change from six to nine. To achieve this purpose, a semi-automatic algorithm based on accelerometer data was developed and then validated through a graphic user interface realized to check the results of the segmentation.

From processed data, features were extracted and then selected through minimum redundancy maximum relevancy (mRMR) features selection algorithm which ranked them according to their importance and relevancy. Features selected were used to train a Random Forest model able to predict the proficiency level of the analyzed subject. The analysis was carried out using the recorded data and scores assigned, according to a specific visual-scoring system, by a Tai Chi master. Based on five criteria, designed to evaluate a specific aspect of the execution, ranging from 1 to 5, these scores tried to sum up the proficiency level of the subject according to the master point of view.

The achieved results allowed us to draw conclusions concerning the position and the minimization of the number of wearable sensors needed to catch the most significant information reducing the noise added to the dataset by the redundant units. For the exercises present in the protocol the obtained predicted performances, according to the Leave-One-Subject-Out validation process, are generally satisfactory; indeed the averaged accuracy calculated among the exercises is around the 70%.

Acknowledgements

I would like to express my sincere gratitude to Prof. Danilo Demarchi, for giving me the great opportunity to work on my thesis in the Motion Analysis Laboratory of Spaulding Rehabilitation Hospital in Boston and for all the support during these months.
My sincere thanks also go to Dr. Paolo Bonato, for allowing me to work in such an amazing lab where I had the chance to work with incredible people from all over the world, for continuously inspiring me with his work and passion for research, for his guidance and advices and setting my standards as engineer to a high new level.
I wish to express my deepest gratitude to my friend and supervisor Dr. Stefano Sapienza.
The development of this thesis would not have been possible without his support, his competence and his endless patience that have been fundamental to overcome all the personal and technical challenges raised during my stay in Boston and after. Thank you for all the beautiful moments we collected together inside and out side the lab, it would not have been the same without you.
I would like to thank also my second supervisor, inside and outside the lab, Federico Parisi who tolerated my noisy presence, my air drumming in the back office and for being there to help me whenever i needed. I would like to thank all the people that have been involved in Tai Chi project.
In particular I would like to thank Gloria and Francesco for the support given to me in the lab which made everything easier and nicer. Gloria, you are one of the kindest human being i have ever met, thank you for encouraging me with your suggestions and your incomparable smile which helped me more than you think.
I want to thank Giulia and Matteo for being the best travel mates I could ever ask, from now on i will keep with me all the beautiful memories that we collected together during our thesis.
I am grateful to all the people that i met in the lab who gave me the chance to improve my self making me a better person from personal and technical point of view.
This thesis would not have been possible without the unconditional love and support of my parents, Giuseppe and Monica, and my brother Domenico during these years.

Thank you for encouraging me in all my choices and for all the efforts which allowed me to live this wonderful experience.

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Chapter 1

Introduction

1.1 Motivations

In the past decade Tai Chi health and social benefits such as preventing fall risk, fighting social isolation and improving cognitive capacity in older adults have been widely investigated. This was made in order to provide to physicians the possibility to give evidence-based recommendations to their patients regarding the usage of Tai Chi in therapy and rehabilitation purposes.
Nowdays the use of Tai Chi as an alternative and non-pharmacological therapy is becoming more and more popular in treatment of neurodegenerative diseases such as Parkinson disease and multiple sclerosis [1]. People affected by these diseases have to deal with impairments related to their condition like muscle fatigue and loss of muscular tone [2] [3] [4]. Characterized by its mild aerobic exercise, Tai Chi practice allows the subject to restore aerobic capacity, mobility, flexibility and endurance while promoting the conservation of energy through efficient and effective movements. Moreover it represents a tool to preserve cognitive capacity and avoid the insurgence of dementia. Its accessibility from a physical point of view and the related psychological benefits make this martial art the ideal for elderly subjects.
Governments and industries are more and more investing in the development of new portable systems built to manage these age-related and chronic disease in order to reduce healthcare costs while increasing the quality of services. Wearable sensors with their small size, reduced cost, user friendliness and reliability of data distinguished as an ideal tool for the realization of these systems.
Analyzing the results in literature, inertial measurements units revealed to be a widely investigated option, with excellent results, in studies regarding motion detection, gait analysis studies and fall risk prevention. This research focused on the development of a machine learning algorithm to apply in the realization of

a wearable sensor system to monitor practice and the proficiency level of elderly subjects performing Tai Chi.
The opportunity to provide a feedback to the practitioners would allow them to practice at home, monitored by a non invasive user-friendly system capable to make them understand how and in what measure they need to improve their skills and get all the possible benefits from the practice of this martial arts.

1.2 Aim of the Study

Tai Chi exercise-based interventions have been successfully deployed in older adults with balance impairments and shown to have a positive impact on reducing fall risk [5] [6] [7] [8]. Home-based interventions are particularly appealing in this context. Differently from what was done in the past [9] this study will focus on developing algorithms to assess exercise proficiency in individuals performing Tai Chi exercise, using only wearable sensors data.
The final purpose is to develop a wearable system in order to generate meaningful feedback to improve exercise performance and continuously monitor safety in individuals participating in a home-based program.
The fist step of the study is represented by the data collections on thirty two healthy subjects characterized by different familiarity with the exercises proposed in the protocol. All the data have been recorded using a Shimmer platform composed by thirteen sensors applied on the body of the subject, generally at least one sensor per each body segment. Each shimmer unit is a wearable sensor which can provide high quality of data with his integrated accelerometer, gyroscope, magnetometer and altimeter.

Once data collected from the subjects were available, in the second step of the study data needed to be processed in order to retrieve from each exercise in the protocol all the repetitions performed by each subject. Dividing each exercise in repetitions allowed to not lose resolution and, moreover, retrieve a bigger amount of data features necessary to carry on the data analysis.

To perform a reliable analysis of the data two Tai Chi experts were involved in the project in order to develop a set of proficiency criteria and assign a score per each criteria. The evaluation of the proficiency of the subjects involved was made starting from the videos collected in each data collection. The guidelines provided by the two tai chi masters was very important since allowed to identify quantitative biomarkers used to determine the proficiency level of the subject.

1.3 Thesis Outline

In the following chapter, a literature review will be presented regarding the use of Tai Chi as an possible solution for rehabilitation purposes and other benefits related to the practice of this martial art. Later on in the chapter attention will be focused on wearable sensors in particular on their working principles, implication in home-monitoring systems and other potential applications to ensure the safety of the people that are using them.

In the third chapter there will be a detailed description of each step of occurred in the study. In particular, will be analyzed the Shimmer platform used to collect the data collected from the subjects involved. Then the thesis will focus on the description of the data collection protocol followed in the study to give an insight of the choices made to guarantee the coherence of the process used for the set up and data acquisition.
The second part of the chapter will focus more on the data processing. This section was divided in three main parts as follow:

1. Data Correctness evaluation: here all the operation to verify the correctness of data such as the check of length of the recording, correct position of event markers, etc. are described;

2. Data Segmentation: description of the algorithm used to divide each exercise in the protocol in single repetitions;

3. Validation of Segmentation: description of the tool built to check the results of the segmentation algorithm.

The last part of the chapter is dedicated to the data analysis description in which the feature extraction, the feature selection algorithm and data-set will be described.

In the fourth chapter will be presented the results of the analysis carried out. Finally, the fifth chapter will focus on the future development, underlining the achievements and the limits of our work.

Chapter 2

State Of the Art

2.1 Tai Chi

2.1.1 Tai Chi: Introduction

Tai Chi Chuan is an internal martial art and an expression of ancient Chinese culture. This practice develops through the combination of the ancient Taoist philosophical and spiritual tradition and various martial methods. Every movement, every technique is based on the application of the principles Yin and Yang. According to Taoist philosophy, the two basic principles of the universe Yin and Yang, expressed by complementary opposites such as female and male, negative and positive or dark and bright, are inseparable. To avoid situations of imbalance or tension, a harmonic interaction between the two polarities is essential.
The symbol that represents this duality is Tai Chi Tu, the diagram inscribed in a circle, visually represents the infinite alternation of Yin and Yang, in a soft, balanced, mutual form; with a presence of Yin in Yang and vice versa. In the practice of Tai Chi Chuan every movement, every technique is based on the application of these principles and represented through the alternation of two actions such as advancing, backing up, changing weight from one foot to the other and inhaling and exhaling. Understanding this concept is fundamental to move a step forward to comprehend Chinese culture, philosophy and science.
Tai Chi is considered by modern complementary and alternative medicine as a "gentle gymnastics" method, based on slow movements of the trunk and limbs which, associated with a controlled flow of breathing, allow to strengthen the musculoskeletal system, improving mobility of the joints and also soliciting internal organs. A leading role is played by breathing techniques: people interested in learning the practice of Tai Chi Chuan, in fact, are taught to breathe deeply and slowly, promoting a greater supply of oxygen to the cells and helping to reduce stress and tension, both physical as well as psychological. Furthermore breathing correctly

can also increase the elasticity of the lung tissues, the respiratory amplitude and the ventilation capacity of the lungs.
From a bio-mechanical point of view, provides a mild aerobic exercise, improving flexibility (particularly spinal mobility) and promoting the conservation of energy (Qi) through efficient and effective movements [10] [11].

It is a simple and accessible method that promotes physical and respiratory awareness, inducing a state of relaxation and wellness while promoting a better quality of life and many others health benefits that will be discussed in the next section.

2.1.2 Tai Chi: Health Benefits

Tai Chi has gained more and more popularity in the Western countries and its evolution has been catalyzed by its interface with science and medicine, as well as by the growing interest for holistic health and philosophical wisdom from the East.

The research on Tai Chi has advanced steadily since the turn of the century when an article by Wolf and colleagues proclaimed Tai Chi as a tool that may favorably impact the health of older people [12]. In this study, Tai Chi was found to impact numerous biomedical, functional (IADL) and psychosocial well-being variables of frailty shown in Table 2.1.

Table 2.1: Impact of Tai Chi practice on variables of frailty in older people.

Field	**Variables of Frailty**
Biomedical	Strength, flexibility, cardiovascular endurance, body composition
Psychosocial	Depression, fear of falling, self-perception of present and future health, self-efficacy, and perceived quality of sleep
Functional	Indipendence in Daily Living Activities

According to these results, this study set the stage for all the subsequent studies touting whose purpose was to investigate favorable effects on balance and fall prevention, psychological health and chronic health conditions and its merit as an exercise tool to improve the health of older adults.
In the last twenty years it has been demonstrated in hundreds of trials and systematic reviews that, as a non-pharmacological and exercise based intervention, Tai Chi practice finds application not only in the treatment of cardiac, motor and neurological pathologies but also as a tool to fight depression and social isolation and many others factors often common with aging [13]. In 2016 a systematic review by Hutson and McFarlane [14] was published to define general health benefits of Tai Chi practice. In their study Hutson and McFarlane ranked 120 systematic

reviews according to the improvement of the condition of subjects taking part in the study in the following manner:

- Excellent Evidence of Benefit: Preventing falls, osteoarthritis, Parkinson's disease, chronic obstructive pulmonary disease (COPD), and cognitive functioning;
- Good Evidence of Benefit: depression, cardiac rehabilitation, stroke rehabilitation, and dementia;
- Fair Evidence of Benefit: quality of life for cancer patients, fibromyalgia, hypertension, and osteoporosis;
- Preliminary Evidence of Benefit: Multiple Sclerosis, Post-traumatic stress trauma, brain injury and spinal cord injury.

Tai Chi has been recognized as a valid tool to improve dynamic as well as static balance and falls prevention in older or physically compromised adults. Groups of elderly people involved in Tai Chi practice shown an increased muscle strength, improved gait and balance skills, decreased risk of falls [15] , [16] and fear of falling [17] [18].
Parkinson's disease (PD) is a idiopathic and neurodegenerative disease which is responsible of the progressive deficit of the motor control system. This disorder is characterized by tremor, rigidity, postural instability, freezing condition and impaired balance [49]. As an exercise of mid- to high-level balance challenge, TC has been found to be beneficial to persons with PD [19] [20] [21] [2] [3] [4]. In 2016 Kwok et al. analyzed an ensamble of 10 studies and 406 participants to evaluate, from the physiological and psychological point of view ,the effects of mind-body exercises on the outcomes for persons affected by PD [3]. These mind-body interventions demonstrated immediate moderate to large beneficial effects on motor symptoms, postural instability, and functional mobility among individuals with mild to moderate symptoms of PD. Furthermore, as physical activity, Tai Chi can be considered a mild to-moderate form of aerobic exercise suitable in patients with PD to enhance their quality of life, improve depressive symptoms and relive degeneration of motor skills [4]. In literature has been demonstrated that Tai Chi is beneficial for depression, cognitive capacity, dementia, loneliness, social isolation. These latter aspects are very common for elderly people and contribute to define what is called "frailty status in seniors". As reported in the work by [1], preventing and alleviating social isolation through group activities, which promotes social interactions combined with physical exercise, can help to contrast the insurgence of depression, cognitive decline as well as increased admissions to hospital promoting a higher health-related quality of life.
To guarantee the opportunity to have access to this practice in health applications,

simplified protocols have been developed, involving few exercises done independently, so that also older people (too frail to engage in robust aerobic conditioning) or persons suffering from pathologic conditions can learn more easily and thereby benefit from practicing Tai Chi.

In conclusion, the vast field of applications, the great versatility and accessibility make Tai Chi an ideal exercise for recreational or therapeutic purposes regardless of the background from the subject who intends to practice it.

2.2 Wearable sensors for health monitoring

Due to a rapidly increasing aging population and its associated challenges in health and social care, Ambient Assistive Living has become the focal point for both researchers and industry alike. The remote real-time monitoring of a person's health can be used to identify relapses in conditions,therefore, enabling early intervention. Thus, the development of a smart healthcare monitoring system, which is capable of observing elderly people remotely [6] [22].

In recent years, wearable sensors based on miniaturized Inertial Measurement Units (IMUs) are increasingly being used in posturography, fall risk prevention and balance assessment as demonstrated by the high number of papers focusing on these topic [22] [5] [23] [24] [25] [26].

A wearable inertial sensing unit typically includes accelerometers, gyroscopes, and magnetometers.

The tri-axial accelerometers could detect the acceleration of X, Y, and Z movements in a three dimensional space. The underlying mechanisms are that the accelerometers independently measure the respective acceleration in each of the three directions, or the so-called "g-force", as a vector quantity. Based on the detected changes of magnitude and direction of g-force, the direction of linear movements of an object could be obtained A triaxial gyroscope measures its proper angular velocity in a 3D space, and the components of the rate of turn are assessed in a sensor-fixed three-dimensional frame; rotations around three orthogonal axes are commonly defined as Euler angles, e.g., "roll", "pitch", and "yaw".

The magnetometers could provide the direction information or the absolute angular measurements relative to the Earth's magnetic field [76]. The detected vector components of a magnetic field consist of declination (the angle between the horizontal component of the field vector and magnetic north) and inclination (the angle between the field vector and the horizontal surface). Usually, accelerometer, gyroscope, and magnetometer measurements refer to a common three-axes frame fixed to the sensing IMU [25].

In the literature on balance control, fall risk assessment through wearable sensors is a debated topic [24] [27] [26] [8].

In the last decade different studies and systematic review have been conducted regarding balance assessment the fall risk in geriatric populations. In 2013, infact, Howcroft and Kofman in their work [28], defined the possibility to use inertial sensors for fall risk assessment. Then, in 2017 and 2018, two studies have proposed regarding the balance and the fall risk assessment in elderly people through novel sensing technologies such as IMU wearable devices and smartphones [29] [30] [31]. Wearable sensors it is a low cost technology which can provide a huge amount of high quality and reliable data that, if properly processed and correctly interpreted, could be used to evaluate the performance achieved by the user in a more reliable and accurate manner. This is possible since wearable technology is an accessible and user friendly technology which allows to collect data from a larger number of subjects, not necessary in the lab, providing access to a bigger amount of data. In this way it is possible to provide to patients a more personalized rehabilitation protocols.

To reduce the costs of the hospitalization of older people caused by falls and chronic diseases, several campaign and systems based on wearable technology have been released to engage older people in active aging and fall prevention programs.

There is a growing interest in the development of wearable systems specifically designed for the market of "active aging" [22] [7] [8]. These systems may address both healthy and pathological populations. In this context, balance training based on wearable sensors and biofeedback constitutes a promising field of investigation. In some cases, these systems were customized for specific applications in the rehabilitation field, including systems relying on biofeedback [8] [32] [7] .

A further application of wearable technology consists in the development of systems and technique with based on human activity recognition techniques. Existing sensor-based action recognition approaches generally fall into two categories, knowledge-driven and data-driven.

Knowledge-driven approaches start with an abstract model of common knowledge and then implement and apply the model through sensed data. Data-driven approaches first collect sensed data,then exploit hidden correlations between actions and sensor data, and eventually establish a model to classify the actions. Most recent sensor-based action recognition approaches are based on the data-driven "bottom-up" paradigm, which takes various kinds of sensor data as input and utilizes most well-known classification methods to obtain classification results [33] [34] .

Chapter 3

Material and Methods

3.1 Experimental Setup

3.1.1 Shimmer Sensors

To collect data in this study, the third-generation wearable sensor technology Shimmer3,shown in Figure 3.2, produced by SHIMMER sensor Ireland [35] has been used. SHIMMER3 is a wearable sensor which can provide high quality of data with his integrated 10 degrees of freedom through its integrated accelerometer, gyroscope, magnetometer and altimeter. Each of them with selectable range and others general settings [36]. The Shimmer unit is designed to be small, light, robust and user friendly to use in order to be flexible and adaptable depending on the application [37].

Figure 3.1: Shimmer3 sensor unit

During all the data collection made in the Motion Analysis Lab two GoPro's and a set of fourteen Shimmer units have been used. Thirteen of them have been applied on the body of the subject to record the data during the execution each task of the protocol. The last one have been positioned next to the workstation used to set the configuration of the units and monitor the data. This unit was the only one that was providing a real time streaming of the recorded data, this was made in order to have a reference signal used to apply event markers used to determine the beginning and the end of each exercise. The inertial measurements recorded by each unit have been made through Bluetooth with the Workstation (Laptop) as sink in the form of Wireless Body Area Network (WBAN).

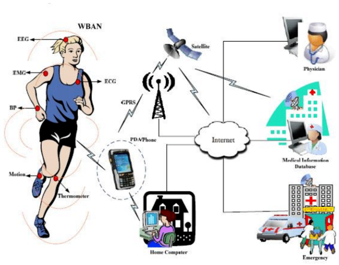

Figure 3.2: Wireless Body Area Network

Shimmer provides a range of advanced and enabling software applications to support users of the Shimmer platform. ConsensysPRO is the software that has been used alongside Shimmer sensors during the data collections. As it is shown in Figure 3.3, Figure 3.4 and Figure 3.5 it allows technician to:

1. Configure Shimmers units for data acquisition;

2. Storage and display of recorded data from a single or multiple Shimmers units simultaneously;

3. Manage the collected data.

In addition to common data processing algorithms, real-time event markers can be applied to the data. Through the software ConsenysPro previously mentioned, event markers in the form of digital values have been applied on data using as temporal reference the signal provided by the unit connected to the workstation in streaming mode. Then the markers have been applied to all the remaining unit.
The possibility to apply event markers during the acquisition was widely used in order to label each single exercise performed by the subject during the data collection. In particular, a couple of markers for each exercise have been applied to subsequently recognize only the portion of the signal which contained the activity of interest.

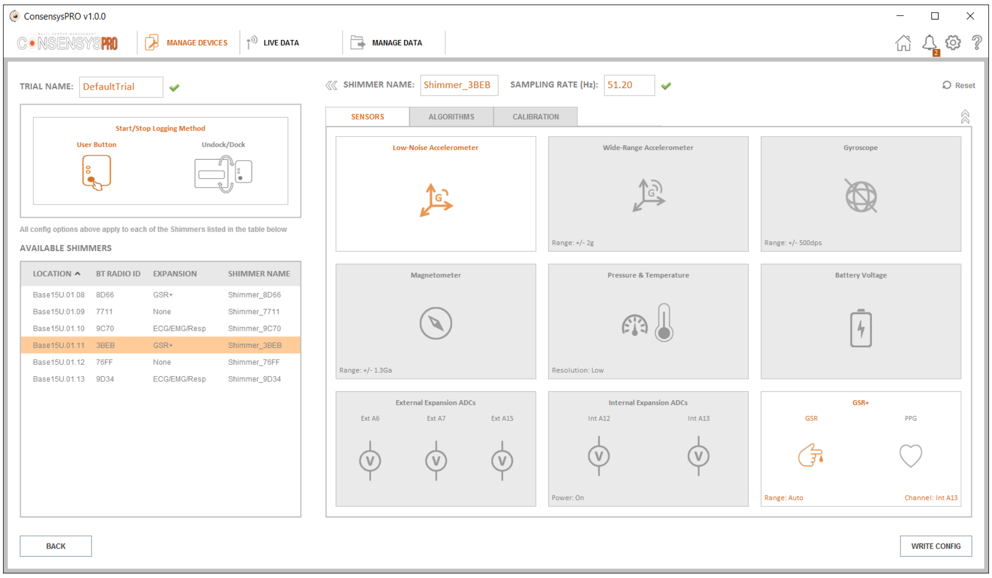

Figure 3.3: ConsensysPro mock up page used to set the configuration of Shimmer units.

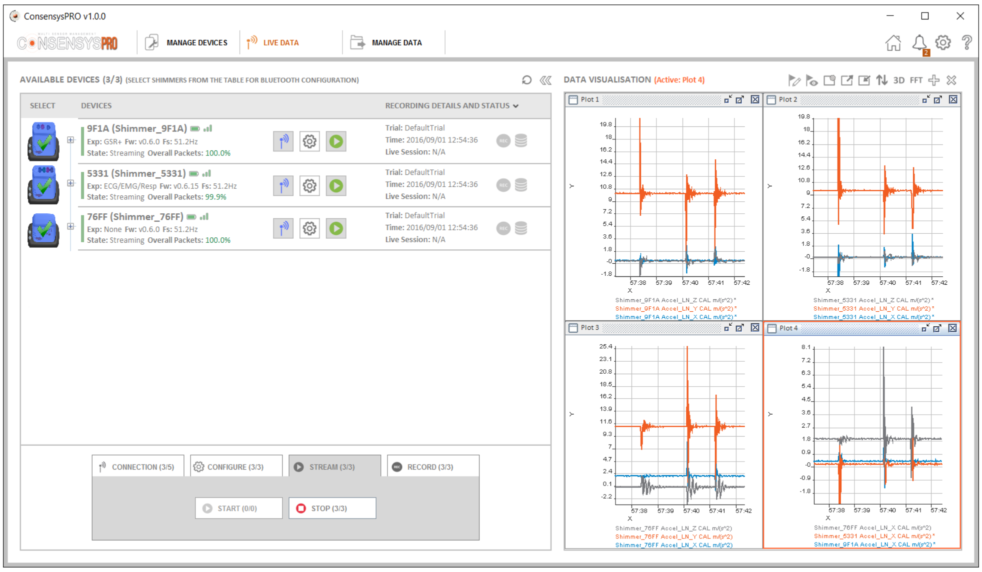

Figure 3.4: ConsensysPro mock up page used to storage and display of sensed data from a single or multiple Shimmers units.

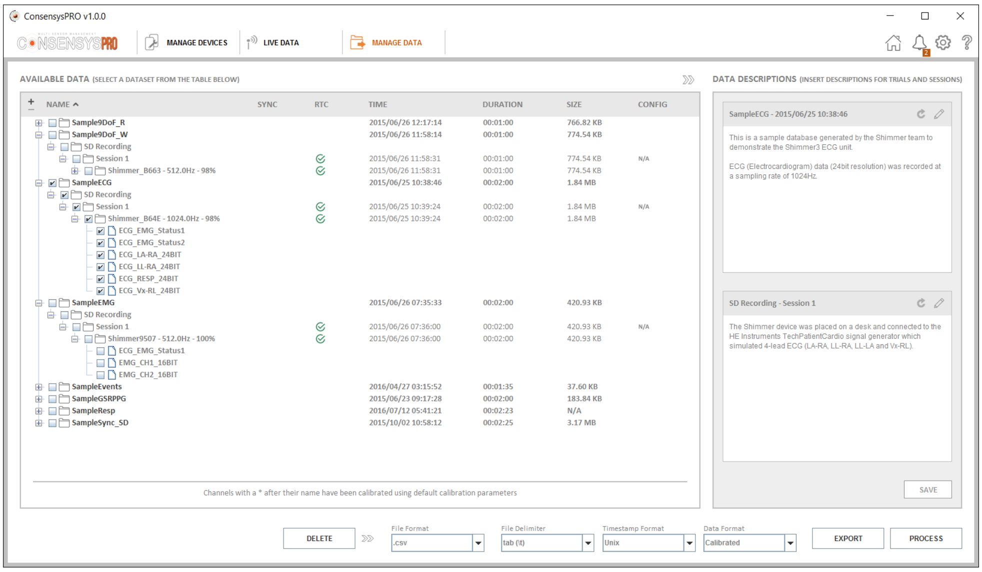

Figure 3.5: ConsensysPro mock up page used to manage the collected data.

3.1.2 Data collection protocol

In this section will be presented the protocol and the procedures followed by the staff of the Motion Analysis Lab for all the data collections related to the thirty two subjects that have been enrolled in the study. During the data collection both engineers and physicians were involved.

- **Shimmer Sensors Set Up** Before of the beginning of the data collection Shimmer units needed to be prepared properly to collect data in a proper manner. Each unit needed to be turned on and configured according to the range chosen for this study. The chosen configuration, for each shimmer, is summarized in Table 3.1 and it has been kept the same in every data collection.

  Table 3.1: Shimmer units configuration

Settings	Value
fs	100 Hz
Accelerometer	± 4 g
Gyrocope	± 2000 dps
Magnetometer	± 1.3 Gs

  Once all the 14 units had been turned on and configured the record session started.

The Shimmer unit called "PushButton" was the only one the has not been applied on the body of the subject since it was the only one connected via Bluetooth to the workstation, in streaming mode. This was necessary in order to apply the event markers on the signal during each phase and exercise of the data collection. All the markers applied on the PushButton unit would have been automatically applied on all the other 13 units during the downloading phase.
Although all shimmers involved in the session were programmed to be synchronized, at the beginning of the data collection a simple shake of all of them was performed in order to have a reference signal on every unit. The shake was performed to check, during the data processing phase, the true correct synchronization of the units. .

- **Consent form and cognitive evaluation of the subject**

  In this first part the subject had a short interview with the physician in charge of providing informations such as: the aim of the study, use of the data, benefits and risks of the test. Moreover, the physician had to ask a series of simple questions to assess the cognitive eligibility of the subject. The assessment of cognitive and physical eligibility have been made according to the criteria approved by the ethic committee which authorized this study.
  If the subject was declared eligible, thirteen Shimmer3 unit, previously turned

  on, synchronized and already in recording mode, were applied to the subject body using elastic belts and Coban [38] bandage in order to fix them on the corresponding every body segment. The placement of each unit has been made through the instructions provided by the physicians in order to put the same unit in the same position of the body, keeping always the same orientation independently from the subject. The positions of the units, shown in Figure 3.6,all on the right as well as left side of the body, are the following: chest, trunk, back, ankle, shank, thigh, upper arm and wrist.

- **Initial Reference**

  Once the shimmers were placed on the body, the subject was asked to stand in the middle of the laboratory for thirty seconds in order to have a reference position per each unit before the beginning of the following part. As it was for the reference signal due to shake of the sensors, having a reference position in space was very helpful to perform the successive controls on the correct orientation of the sensors on the body.

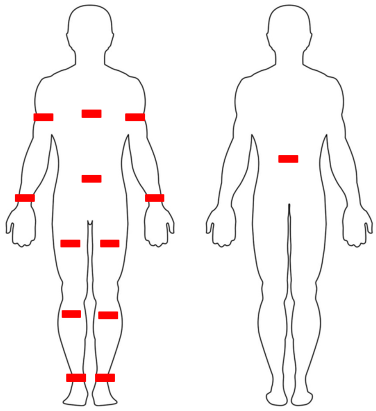

Figure 3.6: Position of the Shimmer units on the body segments of the subject.

- **BESTest**

  To evaluate the physical eligibility of the subject the BESTest have been used by clinicians. BESTest [39] is a quantitative assessment tool first developed in 2009 for clinicians to differentiate balance problems into six underlying systems that may constrain balance. It has thirty six tasks that evaluate performance of six balance systems:

  1. Bio-mechanical constraints;
  2. Stability limits/ verticality;
  3. Anticipatory and postural adjustment;
  4. Postural responses;
  5. Sensory orientation;
  6. Stability in gait.

  Each exercise has been described to the subject before the execution. Depending on the task the evaluation has been assessed measuring the stability the time needed for the performance and assigning a score.
  The physicians used the total aggregation of the scores, obtained from the execution of every exercise included in the BESTest, to determine the physical eligibility of the subject. To easily identify each task performed by the subject, the tasks of the BESTest have been marked on the data applying an event marker through the Shimmer software.

- **Tai Chi**
  Once the BESTest has been completed, the status of the battery of each unit

on the body of the subject has been checked to ensure the complete recording of the session. After the check, the Tai Chi part was ready to start.
Before performing each exercise in the protocol, the subject was asked to watch the video of that specific task executed by one of the two Tai Chi masters involved in the project. The subject has been allowed to watch the video as many times as he/her needed to practice it. Once ready, the video was stopped and the subject has been asked to repeat the exercise up to an established number of repetitions, 6 or 9 depending on the exercise.
As for the BESTest the beginning and the end of the exercise was marked on the data applying an event marker through the Shimmer software used also to configure and manage data at the end of the data collection.

This was repeated for six different Tai Chi exercises previously chosen by the Tai Chi master:

1. Raising the Power;
2. Push;
3. Grasp the Sparrow's Tail;
4. Wave Hands Like Clouds;
5. Brush Knee Twist Step;
6. Golden Rooster.

Push, Grasp the Sparrow's Tail, Brush Knee Twist Step and Golden Rooster have been performed in two versions, either with right or left foot forward. Wave Hands Like Clouds and Raising the Power instead, since they are the only two symmetric exercises in the protocol, they were performed only one time . Every Tai Chi session have been recorded also using two GoPro in order to provide to the Tai Chi master the frontal view and the lateral view of the execution.

3.1.3 Description of the Exercises

To better understand the tasks previously mentioned and main principles of Tai Chi, in this section a short description of the exercises included in the protocol will be given. Tasks performed on both sides will be described only one side since the coreography is the same and the execution reversed.

- **Raising the Power (RTP)**
  This movement starts from standing position with both hands lying along the body. Then arms float up to the shoulder level as the knees bend. After that elbow sink towards the chest as the leg straighten. Particulary important in

this exercise is the alignment of the head over the torso and the torso over the lower limbs when the subject is sinking and rising.

- **Push (PUSH)**
  The description regards the execution performed on the left side. The subject starts in standing position with the left foot forward and both hands out to the front. As the subjects moves his weight onto the back leg, he lets his hands drop. The front foot rises a little bit while the hands circle up. Then the body moves forward along with the hands and during the weight shifting the back heel is lifted up. In terms of coreography, this exercise was not considered hard to perform by the subjects however it requires a very good fluidity in the movements being careful to not lose the alignment of the torso over the lower limbs during the weight shifting.

- **Grasp the Sparrow's Tail (GST)**
  The description regards the execution performed on the left side. This exercise starts with the left foot forward, the weight shifted backward on the right leg and the waist rotated about 90 degrees respect to the feet. Right hand and left hand are positioned in front of the body respectively next to the chest and the waist , aligned along the center line of the body. As the subject turns the waist into the front foot, the left hand comes up while the right hand gets closer reducing the distance between the palms. When the rotation is completed the right forearm goes down in order to go back to the starting position while the left hand follows the rotation of the waist until the movement is finished.

- **Wave Hands Like Clouds (WHLC)**
  The starting position of this exercise requires to stand up on both legs, with the waist turned on the right, the right elbow lifted up to the shoulder with the palm of the right hand (or back hand) facing down and the left hand (or front hand) besides the right hand, in the opposite position, with the palm facing up. So if the subject is turning from his right side to the left side his right hand drops, meanwhile, he will start shifting his weight to the left with both hands coming across the body. The movement performed by the right hand is called "scooping the water" while the movement performed by the left hand "Watching the cloud" since the performer has to look to his hand during the execution. Both these movements are performed while the waist is turning to the left and the weight is shifting from the right leg to the left. Once the movement of the waist is completed this first transition is replicated turning, this time, from left to right, with the right hand performing "Watching the cloud" and the left one "scooping the water". In the execution of this exercise principles of balance and yin and yang can be observed, infact, the movements of the limbs are always synchronized but always opposite in terms of position

and direction of the upper limbs in order to represents balance and armony during the performance.

- **Brush Knee Twist Step (BKTS)**
  The description regards the execution performed on the left side. The movement starts in standing position with left elbow lifted up to shoulder and left hand open up with the palm towards right. Right hand instead, lies along the body with the pal open to the left. This position is a representation of yin and yang principle since left hand and right hand are in opposite positions and they are facing opposite directions. From this position the left leg steps out meanwhile left hand moves down and right hand goes up. In this part of the execution The waist is rotating and the weight is shifting from the right leg to the left one so it is very important to not lean either forward or backward losing consequently the alignment of the body. Once the rotation of the waist is completed the right hand pushed forward while the elbow and the wrist is as high as elbow and shoulder. Left hand instead, pushes down and out beside the left knee. Then the movement starts again. This exercise was recognized by the subjects and the Tai Chi master as the most difficult one in the protocol since it requires familiarity with the intricated coreography, synchronization of the movements, balance and fluidity to move from previous movement to the next one.

- **Golden Rooster (GR)**
  The description regards the execution performed on the left side. Starting from the standing position the left foot and the left hand are moved forward in order to make possible the weight shifting of the body. As the body moves forward, right leg and right hand are lifted up simultaneously while the left hand goes down. The subject stand on one leg for a moment before going back to the starting position. In the execution of this exercise is very important the concept of alignment of the body fundamental to keep the balance when the leg is lifted up.

3.2 Data Processing

In this section will be described all the controls and manipulation performed on data to obtain the final dataset used in the section of data analysis.

3.2.1 Data Correctness Evaluation

After every data collection, data have been downloaded from each Shimmer unit on the workstation and then imported into Matlab. Before starting with the extraction of signals, between the event markers applied during the data collection, a series of controls on the downloaded data needed to be done.

The check list is here reported:

- **Length of the recording**

  The first control made on data is checking the length of the recording retrieved from each individual sensor applied on the body of the subject. This was done in order to identify if one or more sensors stopped recording during the data collection and which related data has been lost. This control has been performed checking the time interval between the first and the last marker applied, during the data collection, on the signal recorded by the pushbutton shimmer unit.
  This unit has been chosen since it has been used as reference to apply the event markers, moreover, the technician could visually check that the unit was actually recording through the streaming of the data. The duration retrieved between the first and the last marker of every individual sensor has been compared to the one retrieved by the pushbutton shimmer unit. A record with a lower duration has been identified as an "incomplete data" and furthermore analyzed to verify which part of the data collection went lost.

- **Synchronization of the units**

  Although all the units were synchronized through the UNIX Epoch time [40] the control about the synchronization between them was performed using the reference signal related to the "shake" performed at the beginning of the data collection. Performing the cross-correlation between the signals of the shake it has been possible to detect, if present, the delay between data. The control of this aspect was fundamental since the event markers have been applied through a process that relies on the correct synchronization of the units.

- **Saturation of the sensors of the unit**

  Saturation of sensors was controlled checking if the signal had values over the range of the initial configuration, see Table(3.1).

- **Presence of all the markers related to all the exercises performed by the subject**

  This check was necessary in order to correct any mistake made by the technician during the application of the event markers. In particular it was important to detect if any markers were missing. If one or more were missing they have been manually positioned in order to not lose some of the exercise actually performed by the relative subject.

- **Positions of the markers on the signals**

  Once the number of markers has been controlled, the position of markers on the signal needed to be checked in order to avoid the loss of part of the signal for that specific exercise.

After making sure of the correctness of data each signal was resampled at a new sampling frequency of 30 Hz. All the available data have been low pass filtered using a Chebychev filter with 4 Hz as cut off frequency and a bandpass filtered using a Chebychev filter with 10 mHz and 4 HZ as cut off frequencies. These cut off frequencies have been obtained evaluating the power spectral density estimation of the signals. In Figure 3.7 and Figure 3.8 have been reported the power spectral density estimation performed on the acceleration data related to the sensor placed on the right wrist on subject TCOA09 performing the exercise raising the power.

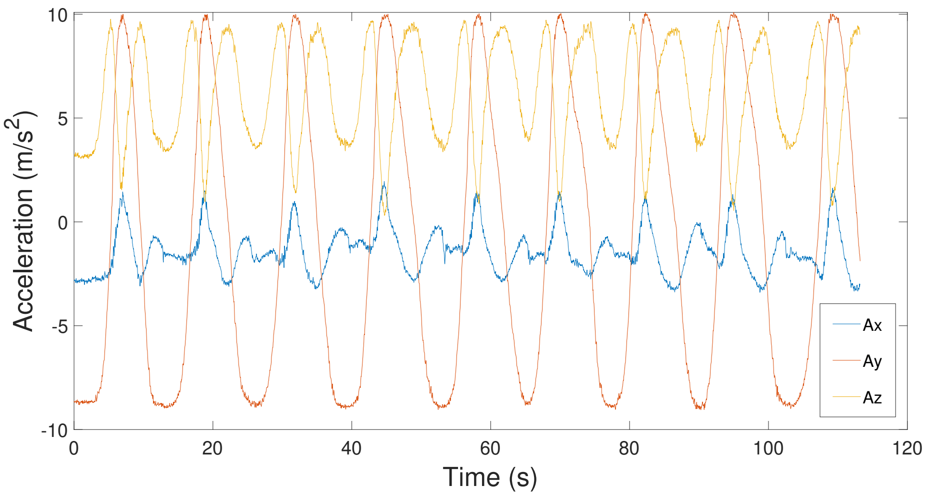

Figure 3.7: Rght wrist sensor acceleration components of the exercise Raising the Power performed by subject TCOA09.

3.2.2 Data Segmentation

The second part of the data processing was the separation of each repetition made by the subject in every exercise during the Tai Chi phase of the data collection. This operation was repeated for all the individuals that took part in the study. Dividing every task in repetitions was necessary in order to retrieve a bigger amount of data to use in the features extraction and, concurrently, better characterize each subject.
To split the signal in repetitions was developed a semi-automatic algorithm based

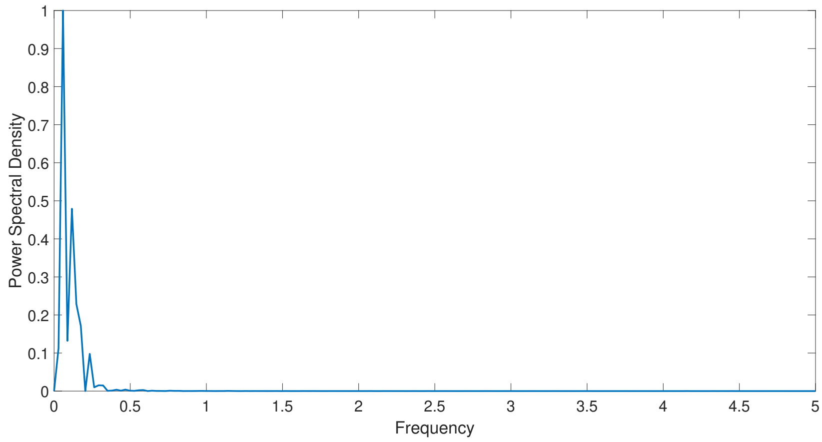

Figure 3.8: Acceleration data related to the sensor placed on the right wrist on subject TCOA09 performing the exercise raising the power.

on data recorded by the accelerometer. Depending on the exercise performed, the number of repetitions that the subject was asked to make were:

- 6 (for exercises named "Golden Rooster" and "Wave Hands Like Clouds");
- 9 (for exercises named 'Raising The Power', 'Grasp The Sparrow's Tail', 'Brush Knee Twist Step' and 'Push').

Generally, the first and the last execution of the movement have been discarded since it was possible to recognize relevant discrepancies such as the different starting or ending position of the body if compared to the other repetitions. Efforts were made to guarantee at least 4 out 6 repetitions for "Golden Rooster" and "Wave Hands Like Clouds" and 7 out of 9 for 'Raising The Power', 'Grasp The Sparrow's Tail', 'Brush Knee Twist Step' and 'Push'. The choice about which and how many repetitions to exclude has been left to the technician.
This latter acts in the segmentation algorithm in several occasions, in particular the user has to choose the:

1. Exercise to segment;
2. Body segment unit to use for the segmentation;
3. Signal to use to retrieve the indexes of repetitions;
4. Repetitions to be kept and to be deleted;
5. Confirm the results, choose another signal or choose another sensor.

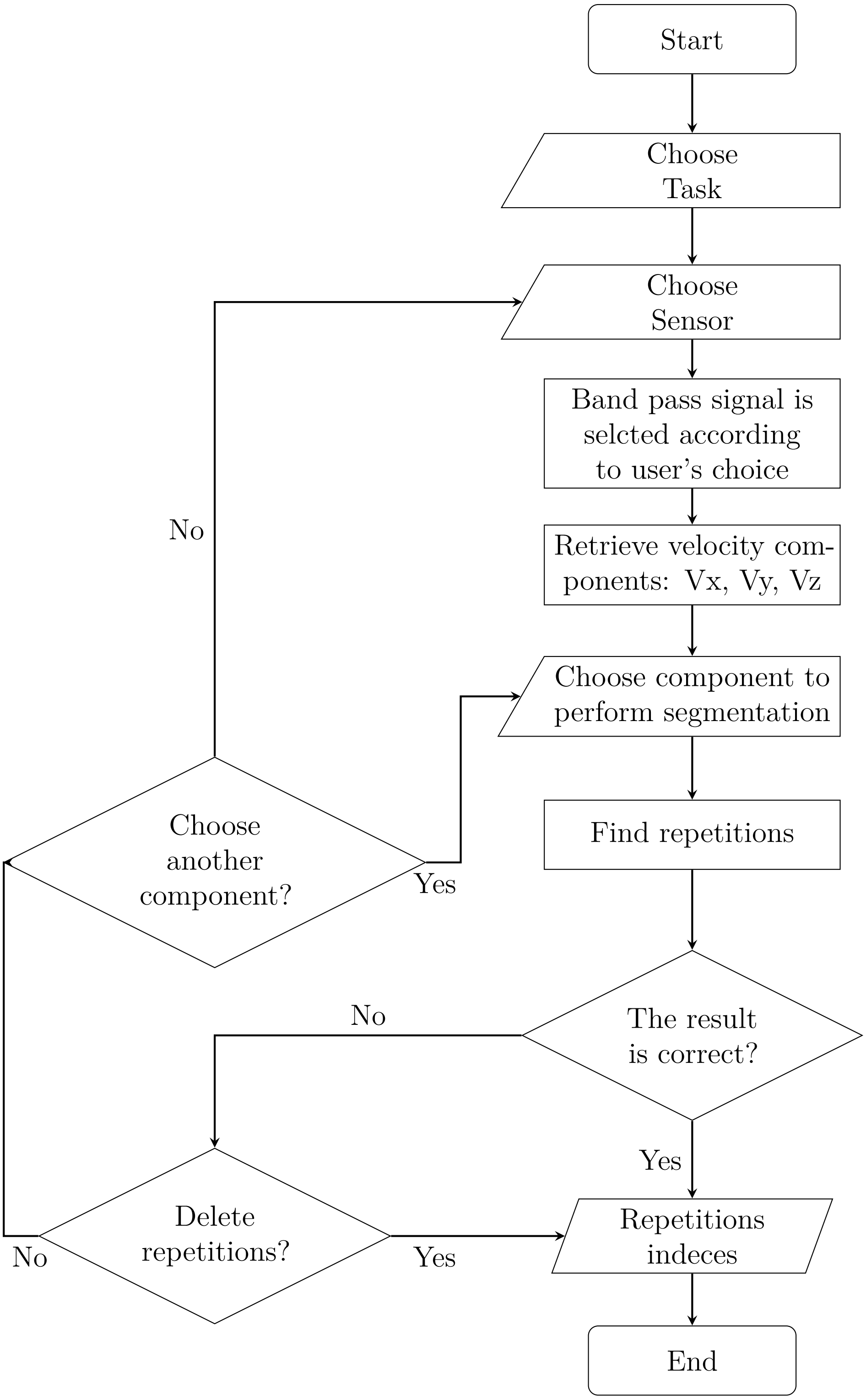

Figure 3.9: Flow Chart Segmentation Algorithm

The algorithm developed follows the steps reported in the flowchart in Figure 3.9. The exercise and the sensor used to perform the segmentation are selected by the user. The choice of which body segment to use has been made looking at the video record of the execution of the tasks in a way that it was possible to identify which body segment was involved at the beginning and at the end of the movement. According to these settings the band pass filtered accelerometer signal of the task is selected by the algorithm. Starting from the acceleration components a_x, a_y,a_z , the components v_x, v_y, v_z of the velocity, as the ones shown in Figure 3.10, Figure 3.11 and Figure3.12, have been obtained.

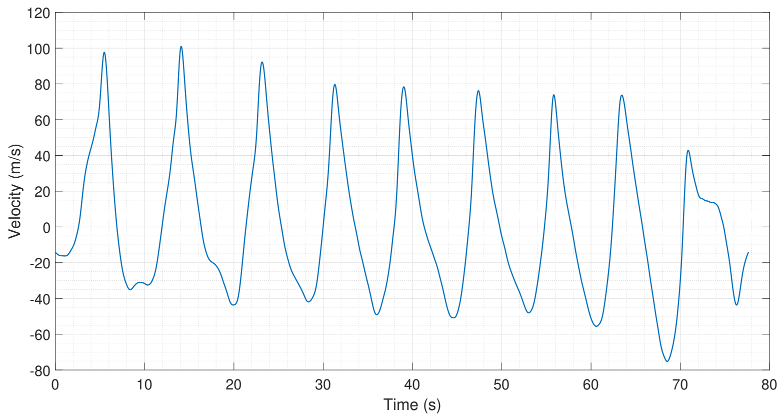

Figure 3.10: Velocity component along X axis retrieved from acceleration data

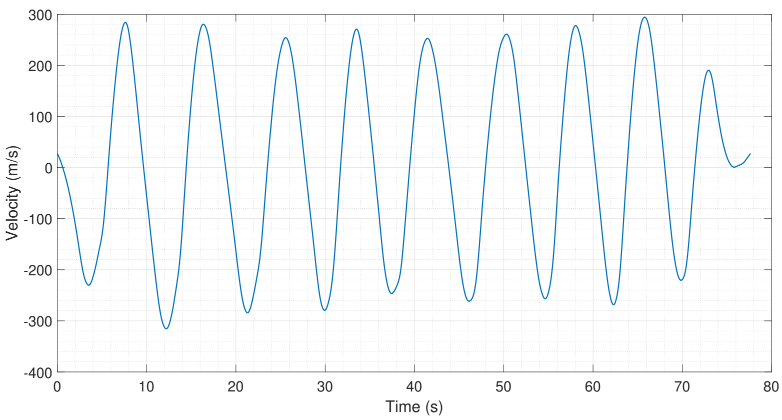

Figure 3.11: Velocity component along Y axis retrieved from acceleration data

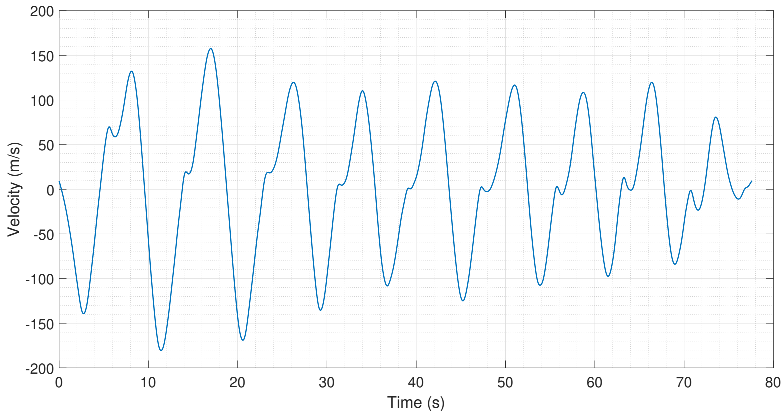

Figure 3.12: Velocity component along Z axis retrieved from acceleration data

Once the components are available, the user has to choose which one allows to better identify each repetition. The chosen component, used to segment a particular exercise, has been used also to segment the same exercise, for every subject, in order to be coherent in the process applied to find the repetitions. An example of the velocity component chosen to perform the segmentation is shown in Figure 3.11. In this case the component along the y-axis has been chosen.

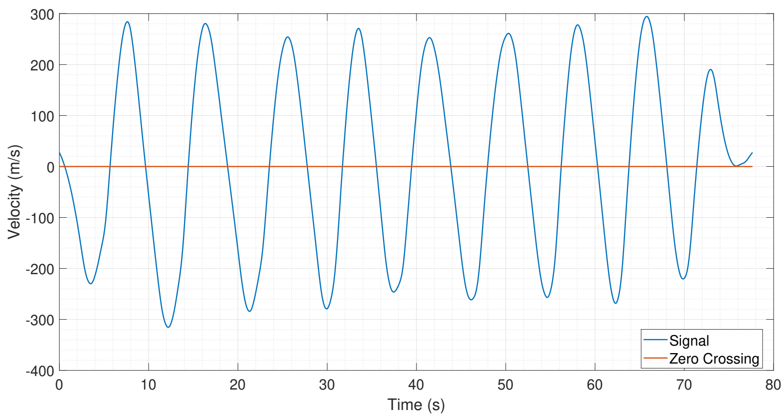

Figure 3.13: Chosen component used for segmentation

Since the execution of the movement is repeated for a fixed number of times, the signals of acceleration retrieved by the Shimmer unit are characterized by a repetitive pattern, this is valid also for the signals of velocity. In particular, looking at these last ones, it can be detected the moment at which the movement

is beginning and the moment at which the sensor begins to go back to the starting position. In Figure 3.13, these two conditions can be identified on the signal when it is equal to zero.
Since the aim of the segmentation is to find the beginning of each repetition the algorithm is interested in zero crossing points related to this position, as it is shown in Figure 3.14.

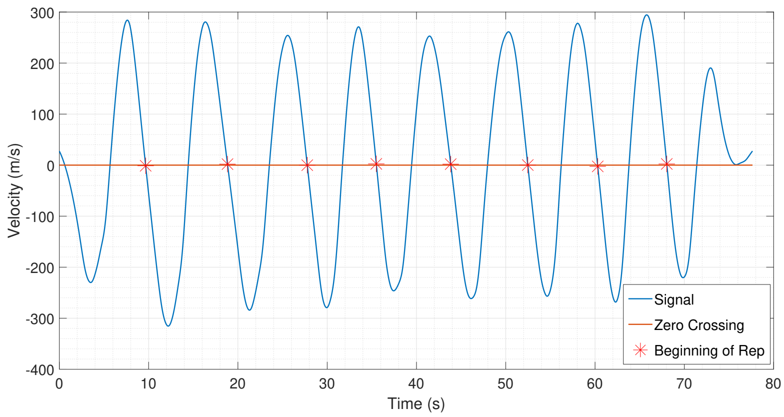

Figure 3.14: Detection of the beginning points of each repetition on the chose component for the segmentation.

A possible problem related to this approach is related to the presence of multiple zero crossing due to the noise or to a wrong movement. This issue has been avoided through a threshold by which the detection of zero crossing is interrupted for a fixed number of samples.
Once the result of the segmentation is ready as it is shown in Figure 3.15, Figure 3.16 and Figure 3.17 , the user has to decide whether or not confirm it.
If the result is not satisfactory the use has three main options:

- Delete some of the obtained repetitions;
- Change the component of the velocity used for the segmentation;
- Change the body segment to use for the segmentation .

The described approach was applied to all the exercises performed by each subject enrolled in the study.

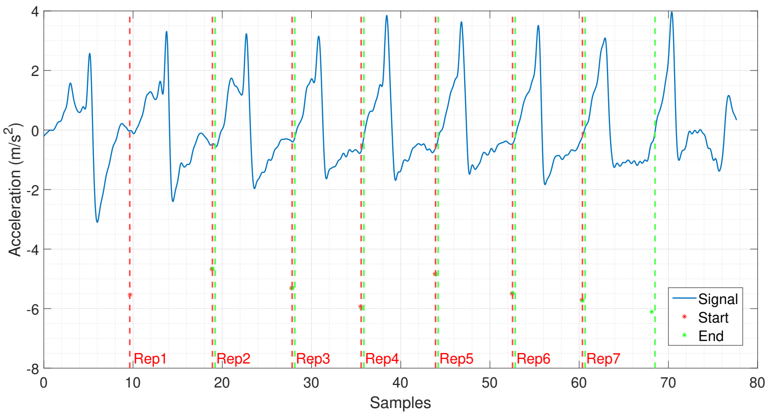

Figure 3.15: Acceleration component along X axis with the segmentation result.

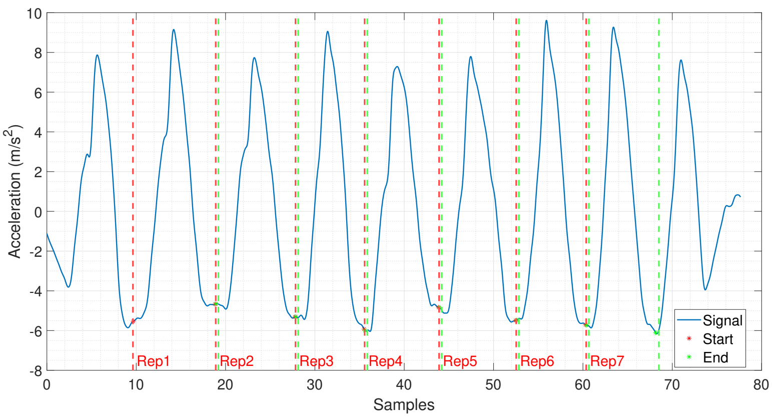

Figure 3.16: Acceleration component along Y axis with the segmentation result.

3.2.3 Validation Of Segmentation

To verify the results obtained in the segmentation a graphic user interface (GUI) was developed. In Figure 3.18, it can be seen the mock-up of the inzializtion of the graphic user interface. The GUI has been organized in order to be as much user friendly as possible.
Looking to the second mock-up, shown in Figure3.19 it can be seen that the interface has been divided int three main window: the two on left dedicated to the visualization of the signals of the sensor chosen for the segmentation and the one on the right dedicated to video of the execution of the task performed by the

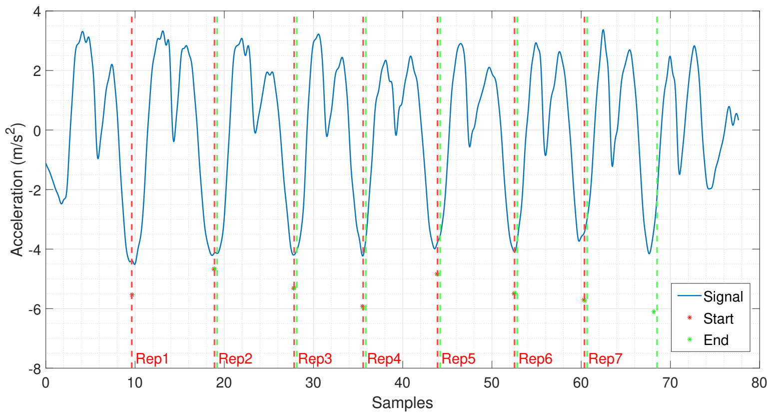

Figure 3.17: Acceleration component along Z axis with the segmentation result.

subject intended to verify. Moreover a series of pushbutton has been added, on the top right of the interface, in order to start, stop and move along the execution.
To reduce the computational efforts, the video record of the performance has been converted from RGB to black white. A pointer, synchronized with the video, has been set on the signal in order to allow the user to check if each repetition on the signal matches the corresponding repetition on the video. This tool allowed to review the results provided by the segmentation algorithm, previously explained being sure to consider a repetition the correct portion of data.

Figure 3.18: Front page GUI

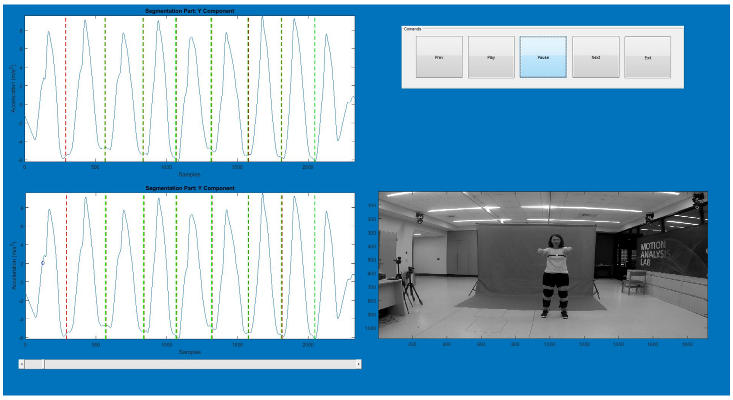

Figure 3.19: Checking results through GUI

3.3 Data Analysis

3.3.1 Proficiency Level Estimation

Given that the ultimate purpose of this study is the development of a wearable system which monitors the performance of the individual using it, the criteria for assessing the proper execution of the exercises are pivotal. This section is concerned with the description of the analysis of the data which have been collected in the previous sections.

3.3.2 Scoring Criteria

Tai Chi is a Chinese martial art which is profoundly linked to Taoist philosophy. During the course of its history, several schools of thought have been developed in order to establish the correct way of performing and concepts at the basis of its practice. A thorough comprehension of the aforementioned concepts, together with the evaluation process behind the performance of an exercise by a Tai Chi expert. In this regard, two Tai Chi masters have been required to develop a scoring system for the performances of the individuals who have taken part in the study.
The system which was established is based upon 5 criteria, each of them of equally importance and having a possible range of values extending from 1 to 5. The aforementioned criteria are given/listed below:

1. **Gross Competency (GC) :**
   This criteria evaluates the ability shown by the subject to perform correctly the choreography of the different exercises present in the protocol.
2. **Expression of Yin-Yang (YY) :**
   In the practice of Tai Chi every movement is based on the application of

Yin-Yang principles, that is mean that expressing Yin-Yang in the dynamic of the execution has an important role during the assessment of the scores. A clear example of this aspect during the performance is represented by the alternation of two actions such as the weight shifting from the passive leg to the active one, the synchronization of the breathing with the movement and the position of the joints.

3. **Alignment and Posture (AP) :**
   Structural alignment and posture are a key criterion, with many subcomponents. One of the most important alignment principle is verticality. This aspect focuses on the importance to keep the alignment of the body segments during the movement so that the head is centered over the torso, the torso rests over the hips, hips centered over the base of support and each knee joint over the central axis of the corresponding foot.

4. **Flow and Dynamic Integration (FD) :**
   This criteria takes into account the slowness, the coordination and the ability to shift smoothly from the previous position to the next one. Ideally the sequence of movements should appear as a unique and simultaneous movement trying to preserve as much as possible the balnce.

5. **Range of Motion (ROM) :**
   Range of motion evaluates both the amplitude of movements of the waist and limbs and the stiffness of the body. An execution characterized by rigidity will get a lower score compared to a flexible and fluid execution.

Both the Tai Chi masters have been involved in the creation of the scoring system previously described. Furthermore he assigned the scores used for the analysis of the data. During the scoring process, the individual's prior experience in practicing Tai Chi has not been taken into account. Furthermore, it has been decided to use a favorable scoring system by discarding any potential disadvantage, due to possible execution errors.
The performance has been evaluated by observing the physical exercise on both sides and providing an average score based on the two performances. In addition to the 5 evaluation criteria, movement score (1) and total score (2) have been taken into account. These two criteria are respectively calculated as (1) the sum of the scores which have been obtained for the 5 criteria in the single exercise and (2) the sum of every score obtained in the entire set of exercises. Although the evaluation system consists of the (5) above-mentioned criteria, during the analysis phase only the Gross Competency parameter has been used. The reasons behind this decision are manifold. The first reason is associated with the aim of the system, hence the generation/creation of a feedback regarding the performance. It has been reckoned that the evaluation of this aspect cannot disregard the proper execution of

a choreography. Moreover, after a cross-analysis concerning the Gross Competency parameter and other indicators, such as alignment and posture, flow and dynamic integration, range of motion, a nearly constant correlation between score assigned to the Gross Competency parameter and the others has emerged, as it can be seen in Figure 3.20, Figure 3.21, Figure 3.22 and Figure 3.23. This result/outcome has made it possible to define — at least in a first approximation — the Gross Competency as an adequate criterion for estimating the proficiency of an individual who practices Tai Chi.

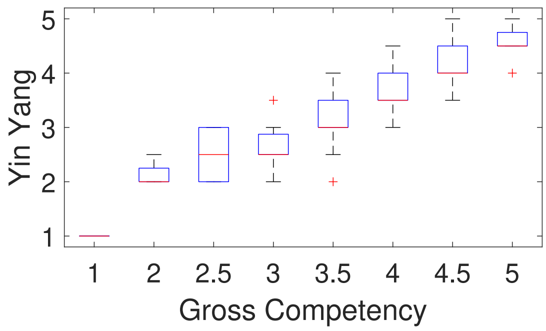

Figure 3.20: Boxplot between scoring criteria Gross Competency and Yin Yang

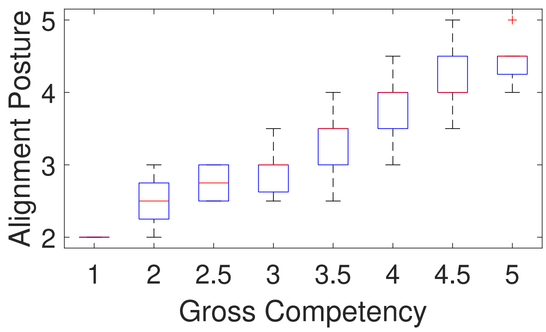

Figure 3.21: Boxplot between scoring criteria Gross Competency and Alignement and Posture

The Yin-Yang parameter represents the attitude and the emotional state of the individual during the execution of task and although it is a fundamental principle for the philosophy at the basis of Tai Chi, it has been discarded. This decision

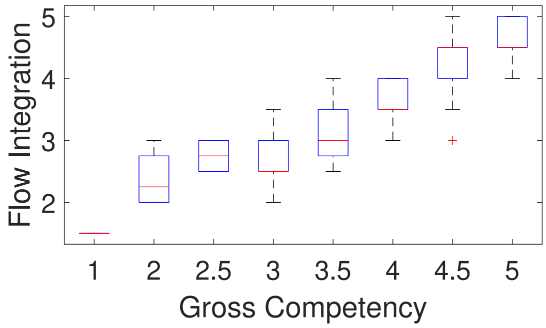

Figure 3.22: Boxplot between scoring criteria Gross Competency and Flow Integration

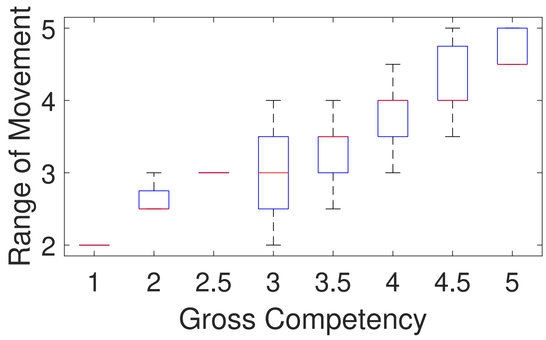

Figure 3.23: Boxplot between scoring criteria Gross Competency and Range of Movement

has become necessary on account of the difficulty to identify significant features to perform its evaluation starting from the data collected by the inertial detectors.

3.3.3 Features Extraction

After defining the previously mentioned scoring system, a set of features has been extracted from the collected data from the 32 individuals who have taken part in the study. Every excerpted feature has been calculated along the three axes of each Shimmer unit for the low pass filtered and band pass filtered signals extracted from the accelerometer and gyroscope.
The data which have been obtained from the magnetometer have been discarded

due to electromagnetic interference caused by the various devices located in the lab during the data collection. The data collected from the accelerometer and the gyroscope have been employed in order to obtain the orientation of the Shimmer units applied during the performance. The extracted features, listed in the Table 3.2, have been selected in the light of the reading material concerning balance evaluation and motion detection studies. Mean value was extracted in order to characterize general posture, for the accelerometer as well as for the gyroscope data. The range was included as well since it showed to be related to level of the proficiency of the subject. In particular, subjects characterized by a low proficiency generally had a lower range compared to the the subjects with a high proficiency score. RMS and entropy were both calculated since, both features had been chosen in several previous studies showed their efficacy in this kind of application, with entropy measuring the regularity and unpredictability of fluctuations in the data. Features in the frequency domain have been also calculated for both accelerometer and gyroscope data. These features have been use to better characterize the execution of the movement, infact these features allows to detect the different behaviour between the movements performed by different body segments. Different values of dominant frequency and energy will be assigned, to different body segments, according to the proficiency level of the subject.
An auxiliary set of features has been obtained exclusively from the data collected by the accelerometer. More specifically, the cross correlation has been calculated between the sensors located on the upper limbs and lower limbs for the purpose to evaluating the symmetry and the synchronism of the movements on the two sides of the body. An additional discrepancy, which is tangible between the individuals who have a different level of proficiency, is a greater regularity and smoothness of the signal from the individuals that recorded better performances. For evaluating both of these parameters an ensemble of features has been concerned, such as (maximum value, root mean square value and the range of values), which have been derived from a signal which is known as jerk and defined as the derivative of the acceleration.

The ensemble of features which has been previously described, has been calculated for every repetition of every exercise, performed by every individual for a definitive dataset composed of 1909 elements and 1805 features.

3.3.4 Dataset Description

This section concerns with describing the characteristics of the dataset and the actions which have been performed on it prior to feature selection. So as to ensure a further simplicity of notation and a greater readability, the name which refers to the exercises will be hereafter abbreviated as reported:

- Brush Knee and twist Step (BKTS),

Table 3.2: Features extracted for the proficiency evaluation

Sensor	**Features**
Accelerometer, Gyroscope and Orientation	• Maximum Value; • Root Mean Square Value; • Mean Value; • Range of Values; • Entropy; • Energy at Dominant Frequency; • Dominant Frequency; • Ratio between total energy and energy in first peak; • Ratio between energy in the first peak and energy in secondary peaks.
Accelerometer	• Magnitude Maximum Value; • Magnitude Root Mean Square Value; • Jerk Maximum Value; • Jerk Range of Values; • Jerk Root Mean Square Value; • Velocity Maximum Value; • Velocity Mean Value; • Cross-Correlation between low pass filtered data of wirsts and ankles.

- Golden Rooster (GR),
- Grasp the Sparrow's Tail (GST),
- Push (PUSH).
- Raising The Power (RTP),
- Wave Hands Like Clouds (WHLC),

Table 3.3 shows the number of individuals who have completed each exercise of the protocol. The Brush Knee and Twist Step, and Golden Rooster exercises are the only two tasks which are performed by a lower number of individuals compared to the total. This occurs because of the difficulties intrinsic to the choreographies. On one hand, the BKTS requires indeed a great synchrony of motion from the lower and upper limbs, as well as the capability of shifting successfully the body-weight from the active leg to the passive leg. On the other hand, the GR requires a firm stability of the lower limbs, since the choreography includes balancing on a leg at a time.

Table 3.3: Number of subjects that actually performed the relative task in the protocol

TASK		Number Of Subjects
BKTS	**L**	25/28
	R	23/28
GR	**L** **R**	25/28
GST	**L** **R**	28/28
PUSH	**L** **R**	28/28
RTP		28/28
WHLC		28/28

Although 32 subjects have been enrolled in this study, only 28 subjects have been scored by the Tai Chi masters so the analysis has been conducted only on these last. Table 3.4 shows the distribution of the various individuals in their belonging class for the different exercises. It is possible to notice the evident imbalance between the classes with a general overcrowding of classes 4 and 5 and classes 1, 2 and 3.

Table 3.4: Distribution of subjects in each class and divided by task.

CLASS	BKTS	GR	GST	PUSH	RTP	WHLC
1	0	0	1	0	2	2
2	0	2	3	4	1	1
3	10	1	5	1	3	2
4	11	17	11	9	9	9
5	2	5	8	14	13	14

In this regard, the BKTS exercise represents the sole exception, for its difficulty of execution has determined a greater number of individuals in classes 3 and 4, at the expense of classes 1 and 2, which are lacking in individuals.
This limited number of individuals, compared to the number of the classes, along with the method of validation which has been adopted (Leave-One-Subject-Out) has required the dataset intervention in order to deal with imbalance issue of the classes. This problem has been addressed in two different modalities:

1. **Deleting classes populated by a single subject;**

   This option has been chosen because the application of the Leave-One-Subject-Out method would not have ensured a correct prediction of the class of belonging of any individual since other samples belonging to that class would have been missing. In doing so, a structural limitation of the dataset has been prevented from having an adverse effect on the predictive performances of the model.

2. **Merging in a single class, those consecutive classes populated by a small number of subjects;** The classes populated by a number of individuals which is greater than 1 (however significantly lower than the classes with a greater population) have been merged into a single class, so as to have a number of individuals which could be compared to the remaining classes. The consecutiveness of the classes has been imposed in order to avoid the merging of classes which are extremely different.

An application of these two operations is the exercise Grasp the Sparrow's Tail (GST), in which class number 1 is eliminated and classes 2 and 3 are merged to create a single class composed by 8 individuals, comparable with classes 4 and 5, respectively populated by 11 and 8 individuals
The elevated number of sensors applied during the data collection has made it possible to obtain a significant amount of useful data for the evaluation of the proficiency. However, since the central concern of this study is the development

of a wearable system, attempts have been made to reduce the number of sensors used to perform the prediction. The said operation has been performed in order to discard the ensemble of data derived from non-relevant entities in the execution of a particular exercise. Selecting the correct configuration of shimmer unit is crucial in order to ensure a successful analysis, since it defines the subset of data which will be provided as input for the feature selection algorithm and subsequently to the predictive model. Generally speaking, a reference configuration composed by 5 inertial detectors located on the wrists, the shanks and the chest has been maintained so as to have a detector for every body segment. However, in some exercises which are characterised by a unilateral execution, e.g. the Golden Rooster (GR), the relative arrangement on the body segment has been changed by using exclusively the detectors located on the active side of the body.
Finally, the individuals which are lacking of the data deriving from one or several detectors, belonging to the chosen arrangement on the body segments have been discarded from the analysis.

3.3.5 Features Selection

The feature selection stage in a machine learning problem consists in the process by which a subset of relevant features to be used, to train the predictive model, is selected. The main aim of the feature selection algorithm is to reduce the dimensionality of the data, reduce overfitting, provide faster and more cost-effective predictors and improving prediction performance.
To reach this goal, a specific feature selection algorithm, developed by Peng et al. [41] and known as "Minimum Redundancy Maximum Relevance (MRMR) Algorithm" was used. Minimum Redundancy Maximum Relevancy is a filter based algorithm that ranks features through the forward addition scheme built on two different parameter known as relevancy and redundancy both based on mutual information score Eq. 3.1 $I(X,Y)$. The aim is to penalise a relevancy of the features by its redundancy in the presence of the other selected features. The mutual information quantifies the similarity of two discrete random variables X and Y :

$$I(X,Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \left(\frac{p(x,y)}{p_1(x)p_2(y)} \right) \tag{3.1}$$

where $p(x,y)$ is the joint probability distribution function of X and Y , and $p1(x)$ and $p2(y)$ are the marginal probability distribution functions of X and Y respectively.
In the following description will be applied the following notation to identify the relationships feature-feature and feature-class for the same instance k of the dataset:

- f_i, f_j represents the features i and j where i,j= 1,2.......N and N is the number of features in the dataset;

- $I(f_i, f_j)$ represents the mutual information between features i and j;
- c represents the target class label;
- $I(f_i, c)$ represents the mutual information between feature i and target class c;
- S identifies the subset of features and $|S|$ is the number of elements present in S.

In order to be sure to rank features correctly two conditions should be met. The first one is the maximum relevancy condition:

$$D(S, c) = \frac{1}{|S|} \sum_{f_i \in S} I(f_i; c) \tag{3.2}$$

and the second one is the minimum redundancy condition defined as:

$$R(S) = \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i; f_j) \tag{3.3}$$

Peng et al. [41] defined the quality of the feature to include in the subset through two parameters: MID and MIQ. These functions quantify the importance of a feature using a heuristic algorithm and both returns score. A large score value indicates that the corresponding predictor is important .The two simplest combinations of these two parameters are reported:

$$MID = \max \Big[D(S, c) - R(S) \Big] \tag{3.4}$$

$$MIQ = \max \left[\frac{D(S, c)}{R(S)} \right] \tag{3.5}$$

The MRMR algorithm ranks features according as follows:

1. The first feature is selected according to the largest relevance value Eqs.3.2 in Ω and added to the empty subset S;
2. Find the features with nonzero relevance and zero redundancy in the complement of S, Ω_S. If present select the feature according to the largest relevance and zero redundancy. If Ω_S does not include a feature with nonzero relevance and zero redundancy, then select the feature that has the largest MIQ value with nonzero relevance and nonzero redundancy in Ω_S.

3. Step 2 is repeated until the redundancy is not zero for all features in Ω_S. In this way the first features included in the subset S are those one that are not correlated but are carrying information;

4. in this step the feature that has the largest MIQ value, with nonzero relevance and nonzero redundancy in Ω_S, is selected and added to the set S;

5. Step 4 is repeated until the relevance is zero for all features in Ω_S;

6. The remaining features with zero relevance are added to S in random order.

$$\min_{f_i \in \Omega_S} \left[\frac{1}{|S|} \sum_{f_i \in S} I(f_i; c) \right] \tag{3.6}$$

$$\max_{f_i \in \Omega_S} \left[I(f_i; c) \right] \tag{3.7}$$

The combination of Eq. 3.6 and 3.6 according to Eq.3.4 and 3.5 result in two selection criteria in the following formulas Eq 3.8 and 3.9:

$$\mathrm{M}ID = \max_{f_i \in \Omega_S} \left[I(f_i; c) - \frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i; f_j) \right] \tag{3.8}$$

$$\mathrm{M}IQ = \max_{f_i \in \Omega_S} \left[\frac{I(f_i; c)}{\frac{1}{|S|^2} \sum_{f_i, f_j \in S} I(f_i; f_j)} \right] \tag{3.9}$$

An example of the ranked features according to MRMR algorithm is shown in Fig. 3.24. In this figure, the score used to rank each feature was normalized respect to the maximum value.

3.3.6 Data Visualization and Dimensionality Reduction

In order to facilitate visualization of data points in space according to the selected features, 3D Sammon mapping has been used. Sammon mapping is an non-linear approach that allows to represent data originally in a high-dimensional space to a space of a lower dimensionality.
The main benefit of using this technique is the facilitation of the visualization of points in the lower space preserving, in the representation, the inter-point distance of the high-dimensional space. Starting from the visualization the distribution of data points according to to the features seleceted, it is possible to evaluate the quality of the extracted features representing the differences between subjects with different level of proficiency. Furthermore, it allows to assess the efficacy of the feature selection algorithm looking at the overlap between different clusters. Since

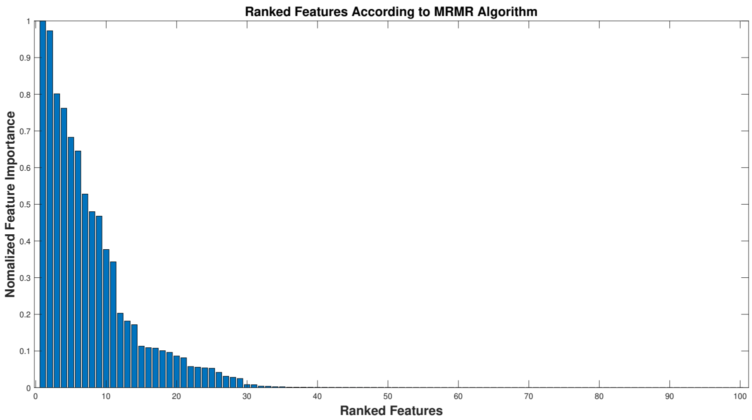

Figure 3.24: Ranked features according to MRMR Algortithm. The scores provided by the algorithm have been normalized respect to the maximum value.

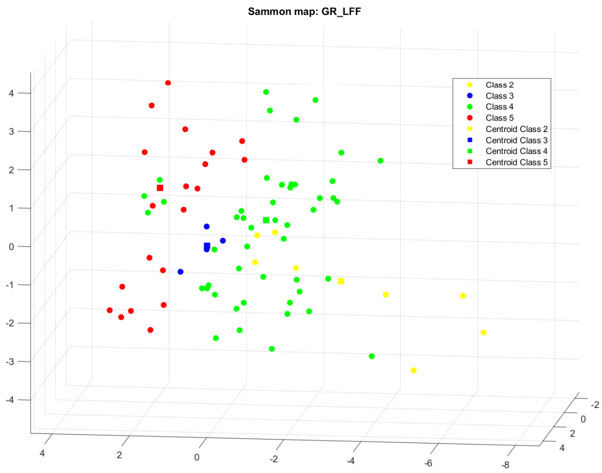

Figure 3.25: Sammon Map for Grasp the Sparrow's Tail with right foot forward.

the purpose of the algorithm is the estimation of the proficiency level, a pattern between classes should be observed.

In Fig.A.10 is shown the exercise Grasp the Sparrow's Tail performed with the right foot forward. Looking at the distribution of clusters and data points it can be seen that although the clusters are not very well separated it is possible distinguish all the classes in a well defined order, and recognize the pattern previously mentioned. Data points belonging to the cluster, colored in blue and representing class 3, are the most scattered ones, this is mainly due to the fact that a single score was given

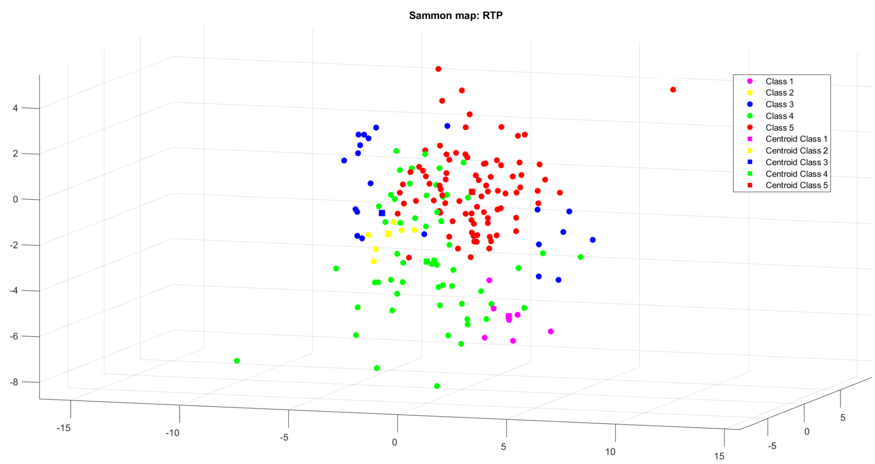

Figure 3.26: Sammon Map for Raising The Power before merging subjects from different classes.

to evaluate all the repetitions for the same subject so, especially for the middle classes, one or more outliers can be present.

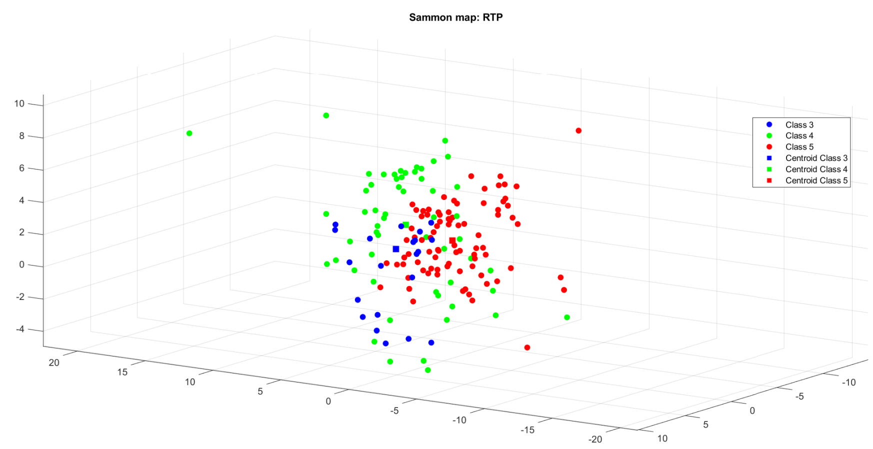

Figure 3.27: Sammon Map for Raising The Power after merging subjects from different classes.

Sammon map visualization was also used to decide wether or not merge subjects from different classes. In Fig.3.26 and Fig. 3.27 classes 1 and 2 are populated only by one subject. According to what was explained previously, in the dataset description section, classes composed only by one subject should be deleted. However if data points of these classes are closed one to the other could be useful merge them in a single class that represents the low level of proficiency. In this case it can be seen that points of class 2, marked in yellow, are close to blue points of class 3 while data points of class 1 are too far. This observation allowed to use the subject in class 2 increasing the number of subjects of class 3. A further observation can be made on the overlap of clusters in Fig. 3.27, indeed it very difficult to see the the separation between them. This can be reduced to the fact that the scores provided by doctor Peter Wayne are related to his experience in Tai Chi practice and not on quantitative data used to assess the quality of the performance so discriminate a class 4 from a class 5 could not be an easy task.

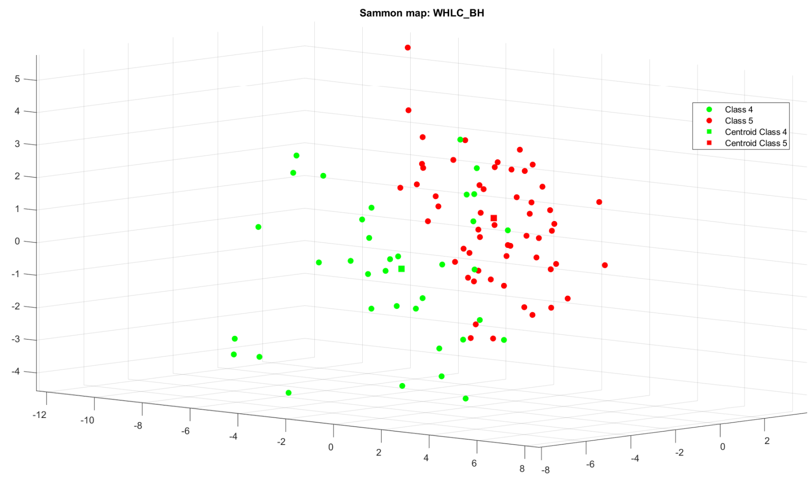

Figure 3.28: Sammon Map for Wave Hands Like Clouds.

In Fig.3.28 and Fig. 3.29 represents other two examples of how classes with a small number of subjects were handled. In Fig.3.28, representing exercise Wave Hands Like Clouds, it is possible to observe the pattern between classes even if, as it was for raising the power example, it is difficult to identify the separation between class 4 and 5. For what concerns classes 1, 2 and 3, all of them were populated by a single subject, however, since the data points presented similar features, they were merged in a single class to represents the global low proficiency level. In Fig.3.28 exercise Golden Rooster is shown, here classes 2 and 3 were deleted since differences between data points were too big to be merged in a single class. Differently from the previous cases for golden rooster it is easy to see that clusters of class 4 and 5 are well separated.

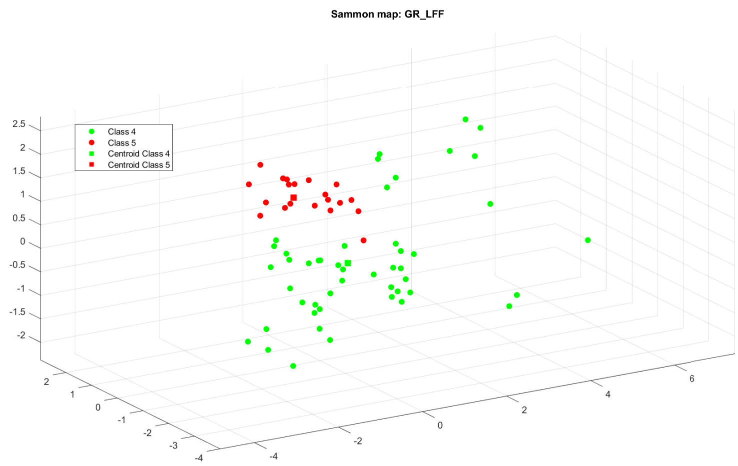

Figure 3.29: Sammon Map for Golden Rooster with left foot forward.

3.3.7 Predictive Model

Random forests has been used used as algorithm to build the regression model used for the analysis. Random forests is an ensemble method specifically designed for decision trees classifiers. As it is shown in Figure 3.30, it uses a multitude of regression trees each of which works by choosing at each node the variable that provides the best split, choosing from a random subset of features (in order for the trees not to become correlated).
To ensure diversity among the component trees, no pruning is employed as would be normal in building decision trees. When a new input is entered into the system, it is run down all of the trees and the output is calculated as the average of the predictions from all the individual regression trees or determined by the majority vote in the case of decision trees.

Regression was chosen instead of classification, since it allowed to evaluate differently the predictive mistakes between classes. Infact, in regression models the mismatch between two very different classes such as class 2 and class 5 is considered a very bad mistake compared to the mismatch of a class 2 with a class 3. This assumption is also verified in reality since, it would not be good at all confusing an excellent execution with a poor one. Random Forests algorithm was used since it is:

- Flexible with both classification and regression problems;
- Able to handle high dimensionality data;
- Robust to outliers and non-linear data;

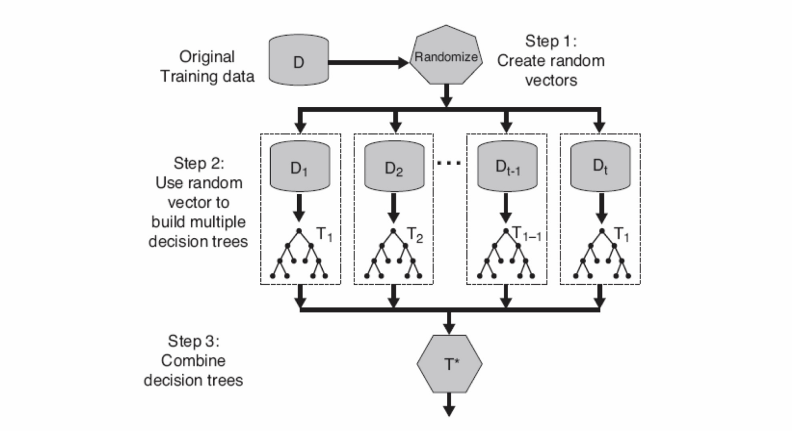

Figure 3.30: Random forests workflow.

- Able to provide competitive performances compared to other supervise algorithms.

Before moving on with the analysis, the hyperparmaters of the model such as the number of trees, the size of the leaf and the number of splits needed to be determined not only to optimize the final result but also to avoid the overfitting phenomena on data.
The tuning of the hyperparameters has been made using the Bayesian optimization, an algorithm already implemented in Matlab as the random forests. As any other optimization process this algorithm tries to locate a point that minimizes a real-valued function called the objective function.In this case represented by the Out-of-bag ensemble error.
To tune the parameters of random forests, Bayesian Optimization and Out-of-bag ensemble error are both widely used in literature, as an alternative to the cross-validation implementation. The obtained results showed a common results among all the exercises for size of the leaf and the number of splits parameters while very small differences were present for what concern the number of trees. In the following Figure 3.31 and Figure 3.32, represents the application of the Bayesian optimization applied to the data from exercise Wave Hands Like Clouds (WHLC), is shown.

Figure 3.32 represents the estimation of the minimum of the objective function according to the number of observations, set equal to 50, for exercise Wave Hands Like Clouds. The blue line represents the minimum value observed during the process while the green line the estimated minimum value of the objective function. For what concerns the Figure 3.31, the red shape represents the average behavior of the objective function, whereas the blue points represents the observed points . The number of observations was set equal to 50 and the final results of the tuning phase were: Number of trees=100; Minimum Leaf Size=1; Number of splits=100.

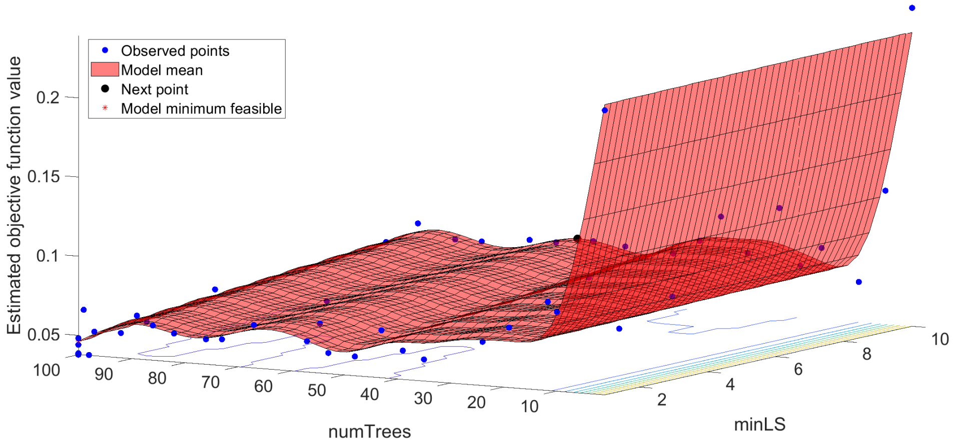

Figure 3.31: Out of Bag objective function model for exercise Wave Hands Like Clouds.

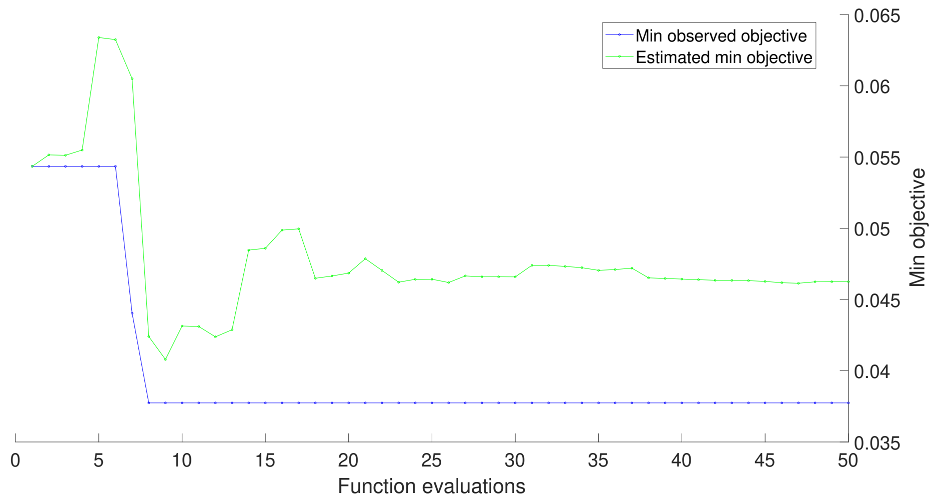

Figure 3.32: Estimation of the minimum of the objective function according to the number of observations.

Observing Fig 3.33, it is possible to see that, the the number of trees necessary for the out-of-the-bag (OOB) error to be stable, had to be larger than 80 trees. This assumption was confirmed by the output of the Bayesian optimization, shown in Fig.3.31 and Fig.3.32 equal to 100 for the number of trees and equal to 1 for the

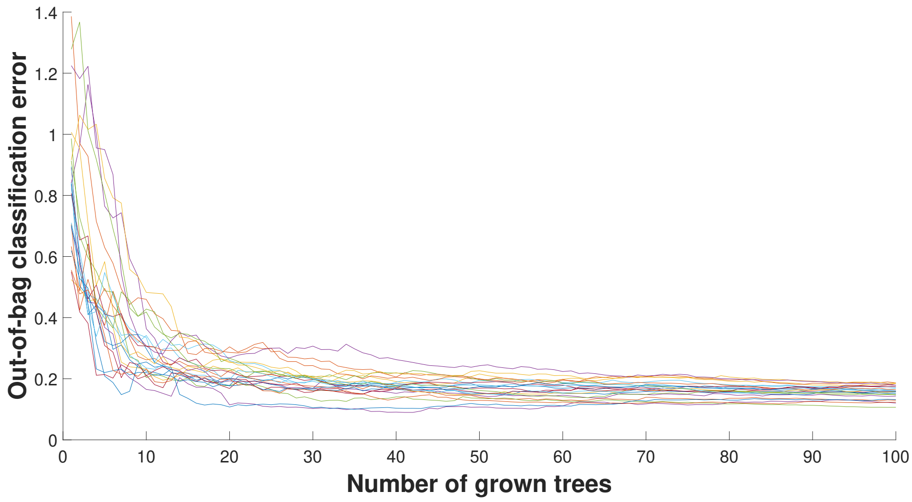

Figure 3.33: Out-of-bag error and number of trees for exercise Wave Hands Like Clouds .

minimum size of the leaf. As a further output of the optimization, the maximum number of split was found to be equal to 100 while the number of split has been set equal to 100 and the leaf size equal to 1.

3.3.8 Tuning of the Parameters

Once the hyper-parameters of the predictive model were defined it was necessary to to do the same for some others parameters such as the number of features, which type of filtered signal and the sequence of body segments to use for the analysis. As mentioned in one of the previous section, the detection of the appropriate number and sequence of body segments is very important in order to reduce the number of sensors and avoid the use of redundant data. For what concern the number of features, Minimum Redundancy Maximum Relevancy feature selection algorithm provided a list of feature sorted according to their relevancy and redundancy. Identify the correct number to use is very important in order to be able to have a good separations of clusters and then evaluate properly the proficiency level of the subjects. The possible number of features tested went from a minimum value of 10 features up to 100.

Furthermore it was also required the evaluation of which kind of data to use since, as described in the feature extraction section, features were extracted from low pass and band pass filtered signals recorded by accelerometer and gyroscope of each Shimmer unit.

Every combination of different filtered data, sensors, number of features and

sequence of body segments was used as setup of the predictive model for a number of iterations set equal to 10. This has been made in order to have an idea of the consistency of the results given that particular setup. The performances in terms of accuracy and root mean squared error have been evaluated across the ten iterations through the mean value and standard deviation.
The combination which reported the best performances was selected as set up for the relative exercise. All the configurations tested are reported in Table 3.5.
Although this was a time consuming approach, this method allowed to explore properly all the possible combinations of parameters ,of the algorithm used for the analysis, and consequently to choose the best configuration in order to optimize the results of the analysis. The results obtained will be presented in the next chapter.

Table 3.5: Possible combinations of parameters tested to identify the best configuration to optimize the results.

BODY SEGMENTS	FILTERED DATA	SENSOR	NUMBER OF FEATURES
Chest Upper-limbs Lower-limbs	Low Pass	Accelerometer	$n_{feat} = 10, .., i, ..,100$
		Accelerometer; Gyroscope	
		Accelerometer; Gyroscope; Orientation	
	Low Pass; Band Pass	Accelerometer	$n_{feat} = 10, .., i, ..,100$
		Accelerometer; Gyroscope	
		Accelerometer; Gyroscope; Orientation	

Chapter 4

Results

As result of the tuning operations previously described, a specific configuration of parameters for each exercise was obtained and used to perform the prediction of the proficiency level.
The outcomes of the analysis have been achieved through the application of the Leave-One-Subject-Out validation technique by which all the repetitions related to one subject per time was used as test set and the remaining subjects as training set. This validation technique since it avoids the bias of the model related to the presence of the subject testing the ability of the model to predict new data that was not used in estimating it as it happen using the K-fold cross validation. Moreover it allows to comprehend the level of generalization when it is applied to a new data-set reducing the problem of overfitting.
For every repetition included in the test set, a non-integer score describing the proficiency level was assigned according the predictive model evaluation. All the scores collected were rounded to the nearest integer in order to male possible the comparison between the predicted value and the actual one. The scores that had a fractional part bigger or equal to 0.5 were rounded to the next integer value otherwise to the previous one. The resulting performances are summarized in Table 4.21. Moving forward in the chapter the more detailed results for each exercise will be presented, in particular, will be reported a:

- Table to summarize the configuration used to get the results;
- Confusion matrix to show the differences between the predicted and the actual level of proficiency. An additional row-normalized row summary displays the number of correctly and incorrectly classified observations for each true class as percentages of the number of observations of the corresponding true class;
- A table with information about the number of subjects per class and the sensitivity score for each level of proficiency.

4.1 Brush Knee and Twist Step

The following tables and confusion matrices were obtained for the two sides of the exercise named Brush Knee and Twist Step.

Table 4.1: Brush Knee and Twist Step with left foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	25
Body Segments	Chest, AnkleR, AnkleL, WristL, WristR
Filtered Signals	Low pass, Band pass
Sensors	Accelerometer and Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

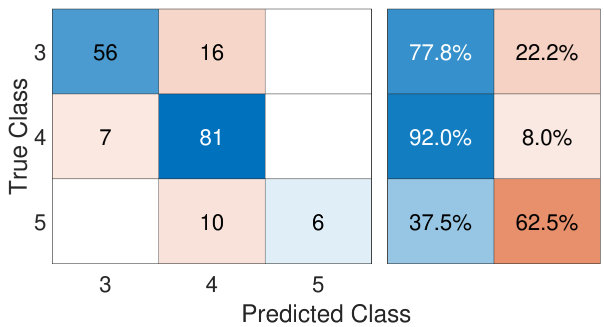

Figure 4.1: Confusion matrix of exercise Brush Knee Twist Step performed with left foot forward.

Table 4.2: Distribution of subjects into classes for the exercise Brush Knee Twist Step performed with left foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	0	0
3	10	72
4	11	88
5	2	16

Table 4.3: Brush Knee and Twist Step with right foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	18
Body Segments	Chest, AnkleR, AnkleL, WristL, WristR
Filtered Signals	Low pass, Band pass
Sensors	Accelerometer and Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

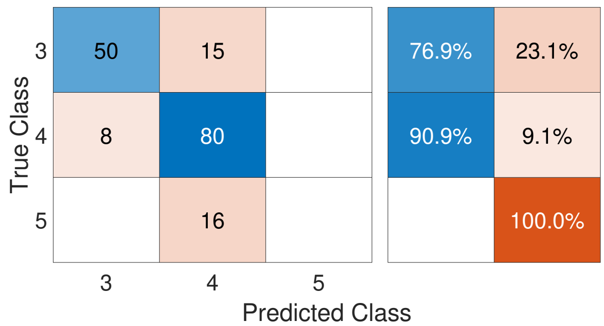

Figure 4.2: Confusion matrix of exercise Brush Knee Twist Step performed with right foot forward.

Table 4.4: Distribution of subjects into classes for the exercise Brush Knee Twist Step performed with right foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	0	0
3	9	65
4	11	88
5	2	16

4.2 Golden Rooster

The following tables and confusion matrices were obtained for the two sides of the exercise named Golden Rooster.

Table 4.5: Golden Rooster with left foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	10
Body Segments	Ankle-L,Shank-L,Thigh-L,Wrist-L,Chest
Filtered Signals	Low pass
Sensors	Accelerometer and Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

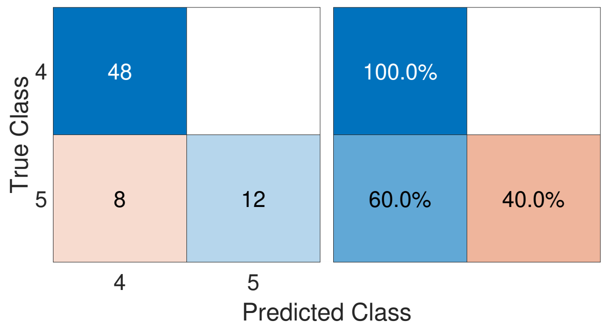

Figure 4.3: Confusion matrix of exercise Golden Rooster performed with left foot forward.

Table 4.6: Distribution of subjects into classes for the exercise Golden Rooster performed with left foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	2	8
3	1	4
4	12	48
5	5	20

Table 4.7: Golden Rooster with right foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	20
Body Segments	Ankle-R,Shank-R,Thigh-R,Wrist-R,Chest
Filtered Signals	Low pass
Sensors	Accelerometer and Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

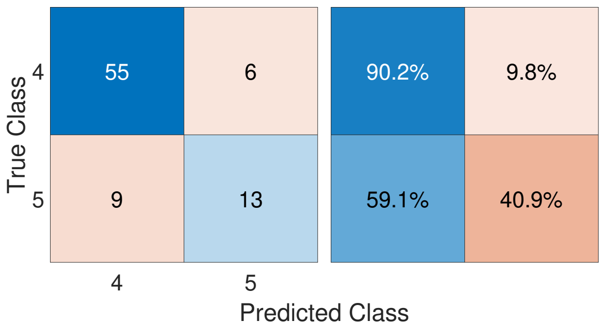

Figure 4.4: Confusion matrix of exercise Golden Rooster performed with right foot forward.

Table 4.8: Distribution of subjects into classes for the exercise Golden Rooster performed with right foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	2	8
3	1	4
4	16	16
5	5	5

4.3 Grasp the Sparrow's Tail

The following tables and confusion matrices were obtained for the two sides of the exercise named Grasp the Sparrow's Tail .

Table 4.9: GST with left foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	30
Body Segments	Ankle L-R, Thigh L-R, Arm L-R, Wrist L-R, Chest
Filtered Signals	Low pass and Band pass
Sensors	Accelerometer, Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

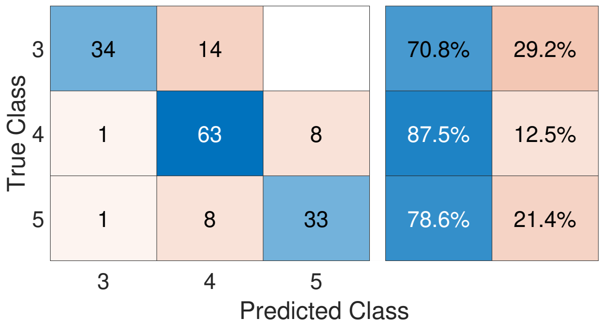

Figure 4.5: Confusion matrix of exercise Grasp the Sparrow's Tail performed with left foot forward.

Table 4.10: Distribution of subjects into classes for the exercise Grasp the Sparrow's Tail performed with left foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	2	15
3	5	33
4	10	72
5	6	42

Table 4.11: GST with right foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	20
Body Segments	Ankle L-R, Thigh L-R, Arm L-R, Wrist L-R, Chest
Filtered Signals	Low pass and Band pass
Sensors	Accelerometer, Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

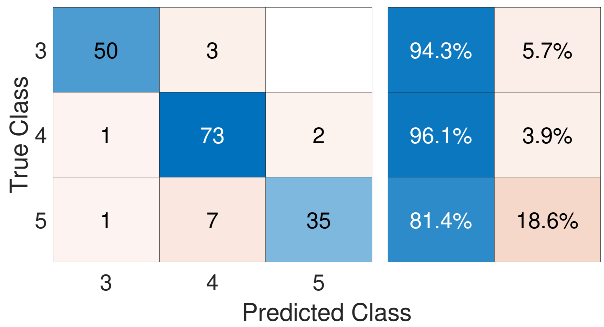

Figure 4.6: Confusion matrix of exercise Grasp the Sparrow's Tail performed with right foot forward.

Table 4.12: Distribution of subjects into classes for the exercise Grasp the Sparrow's Tail performed with right foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	2	13
3	5	40
4	10	76
5	6	42

4.4 Push

The following tables and confusion matrices were obtained for the two sides of the exercise named Push.

Table 4.13: PUSH with left foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	70
Body Segments	Chest, Shank L-R, Wrist L-R
Filtered Signals	Low pass
Sensors	Accelerometer, Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

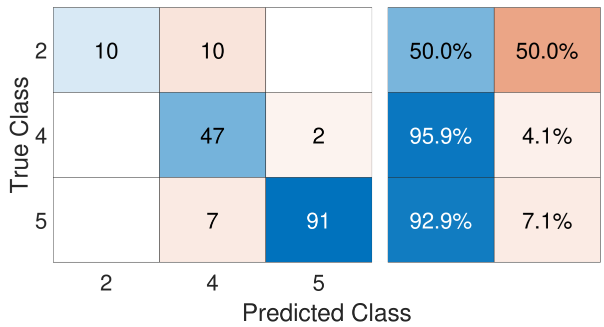

Figure 4.7: Confusion matrix of exercise Push performed with left foot forward.

Table 4.14: Distribution of subjects into classes for the exercise PUSH performed with left foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	3	20
3	0	0
4	7	49
5	14	98

Table 4.15: PUSH with right foot forward configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	55
Body Segments	Chest, Shank L-R, Wrist L-R
Filtered Signals	Low pass
Sensors	Accelerometer, Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

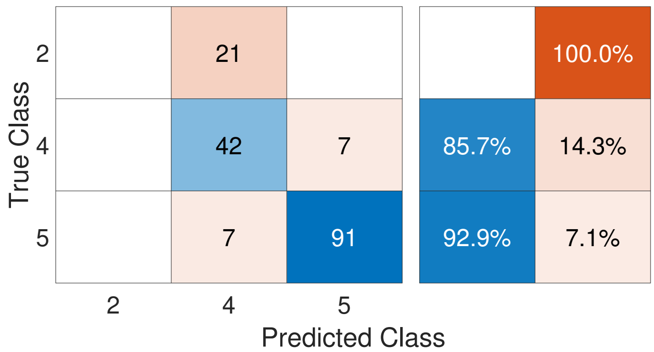

Figure 4.8: Confusion matrix of exercise Push performed with right foot forward.

Table 4.16: Distribution of subjects into classes for the exercise PUSH performed with right foot forward

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	0	0
2	3	21
3	0	0
4	7	49
5	14	98

4.5 Raising the Power

The following tables and confusion matrices were obtained for the exercise named Raising the Power.

Table 4.17: Raising the Power configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	20
Body Segments	Chest, Thigh L-R, Wrist L-R
Filtered Signals	Low pass
Sensors	Accelerometer, Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

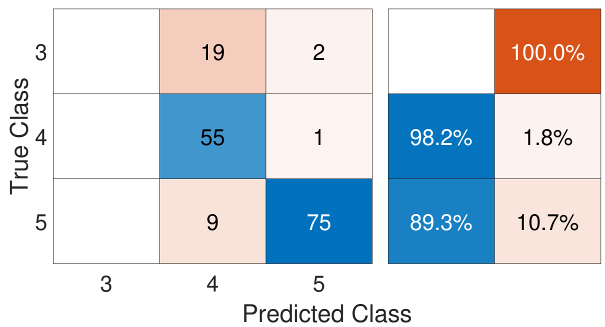

Figure 4.9: Confusion matrix of exercise Raising the Power.

Table 4.18: Distribution of subjects into classes for the exercise Raising the Power.

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	1	7
2	1	7
3	3	21
4	8	56
5	12	84

4.6 Wave Hands Like Clouds

The following tables and confusion matrices were obtained for the exercise named Wave Hands Like Clouds.

Table 4.19: WHLC configuration

PARAMETER	VALUES/ COMBINATIONS
Number of Features	15
Body Segments	Chest, Wrist L-R
Filtered Signals	Low pass, Band pass
Sensors	Accelerometer, Gyroscope
Number of Trees	100
Leaf Size	1
Number of Splits	100

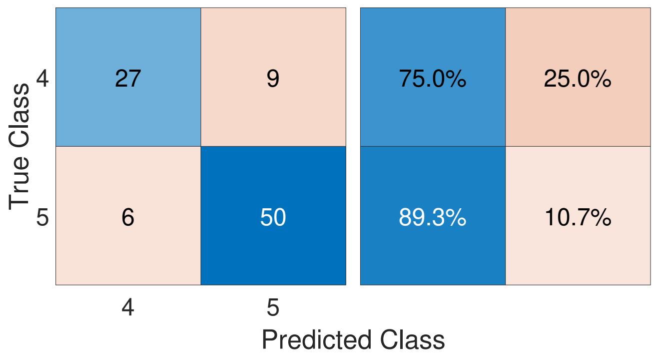

Figure 4.10: Confusion matrix of exercise Wave Hands Like Clouds.

Table 4.20: Distribution of subjects into classes for the exercise Wave Hands Like Clouds

PROFICIENCY LEVEL	NUMBER OF SUBJECTS	NUMBER OF REPETITIONS
1	1	4
2	1	4
3	2	8
4	9	36
5	14	56

To conclude this chapter, the resulting performances are summarized in Table 4.21. The performances have been evaluated in terms of accuracy, defined as the number of correctly classified instances divided by the total amount of the observations, and root mean squared error defined as the squared root of the averaged squared difference between the estimated value and the actual value.

Table 4.21: Results of accuracy and root mean squared error for all the different exercises

EXERCISE	ACCURACY (%)	RMSE
BKTS LFF	81.2	0.47
BKTS RFF	77	0.46
GR LFF	88.7	0.29
GR RFF	82	0.36
GST LFF	80.2	0.35
GST RFF	91.8	0.32
PUSH LFF	88.6	0.39
PUSH RFF	79.6	0.49
RTP	80.7	0.5
WHLC	83.7	0.36

Chapter 5

Discussion

These outcomes show that some exercises gave better results compared to others, however the number of corrected classified instances is generally positive on the majority of the exercises, infact, an accuracy value bigger than 80% was achieved in almost every task. As mentioned in Table 4.21, the best result has been obtained for the exercise grasp the sparrow's tail performed with the right foot forward which showed an accuracy score of 91.8% whereas the worst case has been represented by the brush knee twist step performed with the right foot forward.

Brush knee and twist step performed with the right foot forward represents the worst result obtained in the entire set of the exercises. Generally, brush Knee and twist step was recognized as the most difficult exercise to perform in the the protocol. This is confirmed by the fact that it is the only task characterized by the greatest number of subjects in classes 3 and 4 and the lowest number in class 5, as reported in Table 4.2 and Table 4.4 .
Looking at the confusion matrices, shown in Figure 4.1 and Figure 4.2, it is possible to see that the predicted outcomes are quite the same for classes 3 and 4 while the biggest difference regards the misclassification of class 5 between the left and the right side. The poor result achieved in the recognition of this class is probably related to the limited number of repetitions available while, the difference between the two sides due to the same score used to evaluate the two executions.

Due to its highly asymmetric execution, golden rooster was the only exercise in the protocol that required a specific subset of different body segments, as reported in Table 4.5 and Table 4.7, to correctly predict left and right side.
The features selected for the two sides were obviously different due to the fact that the subset of body segments was different too. However, the top ranked features were still comparable infact in both cases,the most used features belonged to the chest and to the leg lifted during the movement rather than the active wrist . According to the operations on data-set described in the "data-set description" section, classes 2 and 3 were discarded from the analysis since they were composed

only by a single subject each, as shown in Table 4.6 and Table 4.8 . The performance on the two sides, shown in the confusion matrices Figure 4.3 and Figure 4.4, are comparable with a better outcome for the left side where the misclassification error is equal to zero.
A further observation about some outlier data points between class 4 and 5. This issue can be related to the rounding process applied on the half points values provided by the Tai Chi masters. In this way all the non-integer scores have been rounded to the next value casing a potential error in the distinction between these two classes and then providing an incorrect evaluation of the entire set of repetitions executed by the subject.

Grasp the sparrow's tail was the exercise which gave the best results reaching almost the 92% of accuracy for the right side and the 80,2% on the left one. As it was in case of the Brush knee and twist step, the difference on the two sides can be the consequence of assessing the same average score to evaluate both the left side and the right side.
Classes 2 and 3 have been merged together in order to increase the number of subjects in a single class. This decision has been taken since the prediction performed on a set of four classes shown very poor performances due to the misclassification of instances in class 2.
So, after taking into account the distance between centroids and the distribution of data points, according to the features selected, the two classes were merged together.
This exercise is the only one that required a number of sensors bigger than five, Table 4.9 and Table 4.11, on the two sides. This fact is probably related to the choreography of the exercise which involves the movement of a bigger number of body segments.

As previously mentioned for exercise brush knee twist step, also for the exercise named push the highest misclassification error is associated to class 2 which is also the class with lowest number of subjects respect to the other classes, Table 4.14 and Table 4.16.
Moreover as reported in the confusion matrices Figure 4.7 and Figure 4.8, there is still one of the two sides that is performing better compared to the other. This allowed a partial correct classification only on the left side where ten instance out of twenty have been recognized while, on the other side, the number of correct classified instances is equal to zero. As described in the "description of the exercises" in chapter 3, this task is characterized by the symmetry of movements between the wrists and the weight shifting from the forward leg to the backward one. For both sides, from the features point of view it is important to notice that, coherently with the feature selection algorithm, the the top ranked features belonged to the upper limbs and from the leg placed forward respect to the body. The horizontal movement of the body has been captured by the acceleration of the chest and

the wrists while the symmetry of the movement has been evaluated through the correlation between the wrists and the correlation between each wrist with the lower limbs.

For what concerns the tasks raising the power and wave hands like clouds, for both exercises classes with few subjects have been discarded according to the approach previously mentioned, achieving an accuracy score value of 80.7% for raising the power and 83.7% for wave hands like clouds.
For what concerns the exercise raising the power, the most relevant features used by the model were the features belonging to the units major involved in the movement such as the wrists and the chest. The correlation between the wrists and the vertical shift recorded by the chest unit have been widely used to in the prediction of the different levels of proficiency. However, regarding the vertical shift, also the features from gyroscope and accelerometer, related to the units placed on the thigh have been used to evaluate this movement.

The results obtained, which are overall considered satisfactory, make it possible to determine, as a first approximation, the level of proficiency of an individual practicing Tai Chi, starting from the data obtained from the accelerometer and the gyroscope. Nevertheless, it is crucial to mention that some limitations which have been detected during the drafting of the thesis have reduced the significance of the results achieved.
As previously mentioned in chapter 3 and 4, the limited number of individuals compared to the number od the classes and the method of validation (Leave One Subject Out), has determined the employment of a series of operations on dataset which had the purpose of limiting the imbalance phenomenon regarding the number of the individuals in the various classes.
A fundamental aspect linked to the dimension of the dataset is connected with the non-assignment of scores to a section of the last individuals who have joined this study, therefore reducing the number of available individuals from 32 to 28. This condition has been further accentuated by the non-performance of the entire set of exercises included in the protocol. Exercises such as BKTS and GR have indeed recorded a number of performances which is lower than the total number of individuals. This aspect has predominantly affected the individuals who were familiar with the first exercise and had a precarious stability during the second exercise.
For this purpose it would be useful to further increase the dimension of the dataset, to have a population of individuals for each class in order to effectively recognise the different levels of proficiency. Furthermore, it is pivotal to analyse another aspect that is deeply connected to the evaluation method and which has been used with the purpose of assigning scores to the performances. The criterion which has been taken as a reference in this analysis is known as the Gross Competency. This choice has been possible because of its correlation with the other indicators and the

hypothesis that a first feedback should relate to the correct, or incorrect, execution of a certain choreography.
The latter assumption is derived from the opinion of the Tai Chi masters which have taken part in the project. However, their contribution to the project has showed that the evaluation of an exercise is not exclusively centered on the correct execution of its choreography, since the attitude and the emotional state of the practitioner are equally important.

One critical issue concerning the score system used in the project, which has been underlined in the results indicated in chapter 4, relates to the assignment of an average score for the exercises that included an execution with both sides of the body. Exercises such as BKTS, GR, GST and PUSH have showed a better performance on one of the two sides of the body with an average difference equal to 8%; the exceptional case of the GST exercise has recorded a success rate of 92% on the right side and 80.7% on the left side.

Chapter 6

Conclusions

This thesis has focused on the development of an algorithm for the evaluation of the level of proficiency in a group of individuals who have different background in the practice of Tai Chi.
The outocomes reported in Table 4.21, presented in chapter 4 and discussed in chapter 5 shown that it is possible to determine, the level of proficiency of an individual practicing Tai Chi starting from the data obtained from the accelerometer and the gyroscope. Results demonstrated that five inertial unit are enough to get a good comprehension of the quality of the corehography achieving outcomes ranging from 77% ,for brush knee twist step, to 91.8% for the exercise named grasp the sparrow's tail.
However, starting from the description of the study and the limitations discussed in the previous chapters, it is possible to define the main opportunities to improve the system, thereby enhancing its accuracy and effectiveness.
For this purpose it would be useful to further increase the dimension of the dataset, to have a population of individuals for each class in order to effectively recognise the different levels of proficiency and evaluate the performance of the model on a bigger number of classes achieving a more robust analysis.
A second aspect which could be optimised is the selection process of the body segments which represent a first step into the feature selection process. As indicated in chapter 4, it is evident that the sensor subset is generally different for every exercise. This aspect provides some basis for the assertion that it is possible to reduce the number of sensors so as to estimate the level of proficiency. Nevertheless, the variability between the possible sensor sequences should be reduced in order to define a single configuration that results to be practical and easy to use.
As far as the analysis of the scoring system is concerned, it would definitely improve its solidity and significance if the assessment made by the Tai Chi masters had differentiated the two sides of the body, furthermore assigning a single score for every repetition, rather than assigning a single evaluation for the entire set of

repetitions. Moreover, it would be advisable to identify an ensemble of features able to estimate the single subscores which constitute the scoring system and capable of providing a complete evaluation of the level achieved by the individual.
For what concerns, the data processing future step consists in the realization of an algorithm capable to detect automatically when the subject is actually practicing. In this study this purpose has been avoided since the activity has been identified through the application of the event markers during the data collection. A further possible improvement might also regard the development of an automatic algorithm, capable of identifying and segmenting autonomously the single repetitions of the various exercises from the protocol. During the development of the algorithm, it has been necessary to include the intervention of the technician for the qualitative evaluation of the recognition of the repetitions and, occasionally, the manual correction of the result which had been obtained.
In the light of the development of a wearable system which is able to provide a real-time feedback, the recognition of the exercise and the recognition of the singles repetitions plays a pivotal role which does not depend on the external intervention of the user. Taking into account the outcome of the project and the aforementioned observations, the development of a wearable system, which is also practical and easy to use, is deemed to be possible. The possibility of having a feedback from the system and a continuous monitoring of the progress by the Tai Chi masters, might encourage its use and lead to the consequent improvement of one's own abilities. In so doing, the individuals who will make use of this device would fully enjoy the physical and psychological benefits ensured by the practice of Tai Chi.

Appendix A

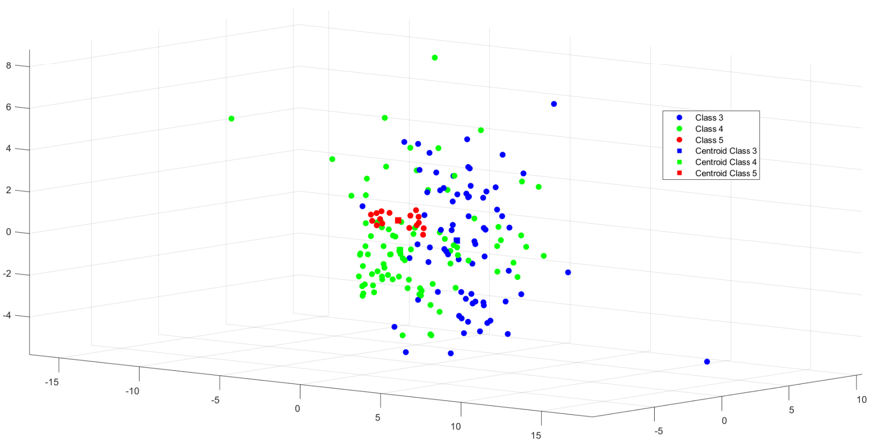

Figure A.1: Sammon Map for exercise Brush Knee and Twist Step performed with left foot forward.

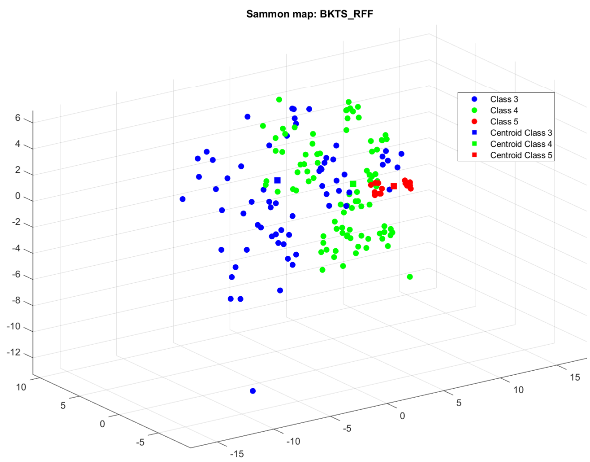

Figure A.2: Sammon Map for exercise Brush Knee and Twist Step performed with right foot forward.

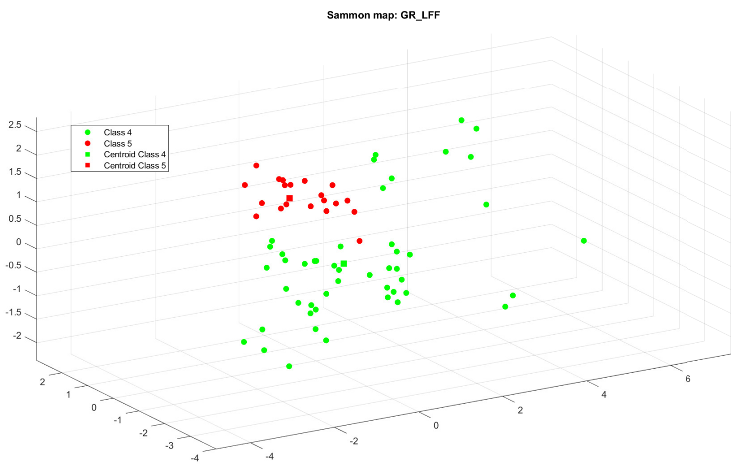

Figure A.3: Sammon Map for exercise Golden Rooster performed with left foot forward.

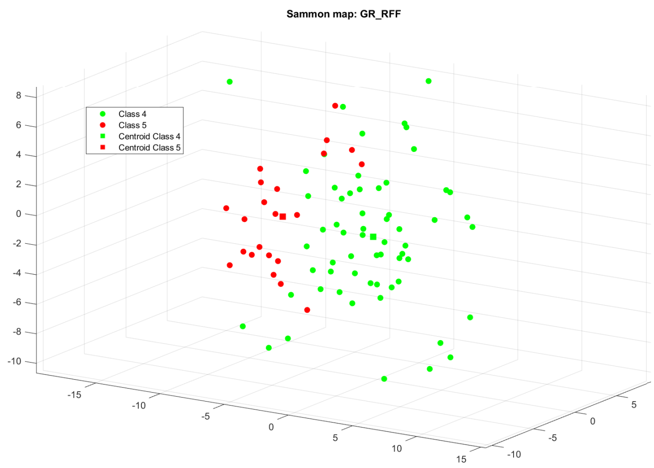

Figure A.4: Sammon Map for exercise Golden Rooster performed with left foot forward.

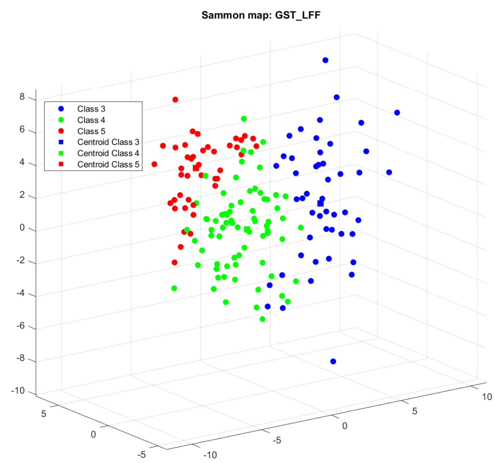

Figure A.5: Sammon Map for exercise Grasp the Sparrow's Tail performed with left foot forward.

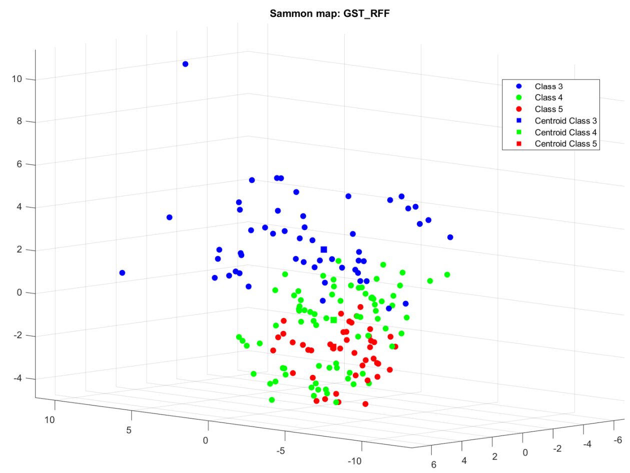

Figure A.6: Sammon Map for exercise Grasp the Sparrow's Tail performed with right foot forward.

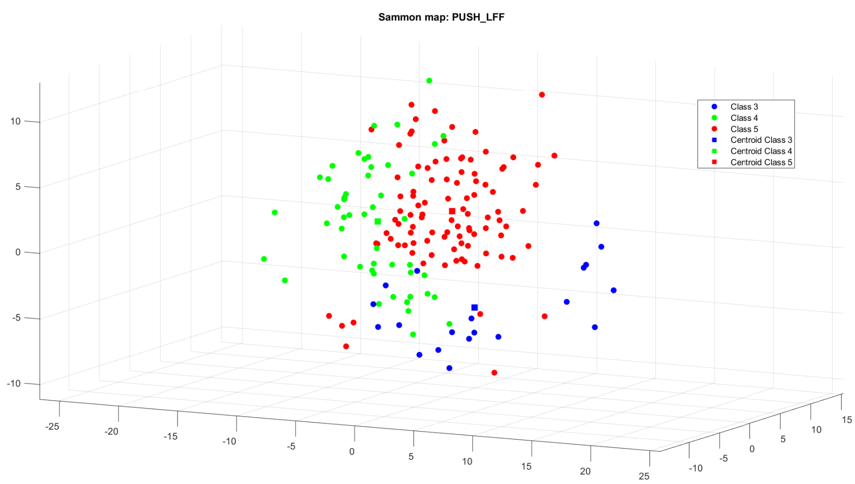

Figure A.7: Sammon Map for exercise Push performed with left foot forward.

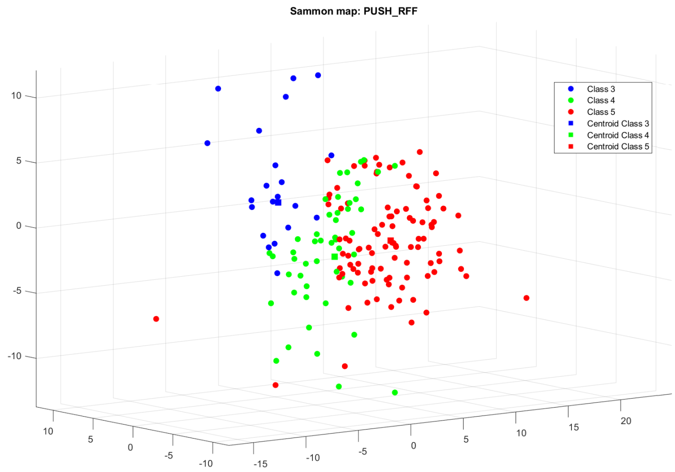

Figure A.8: Sammon Map for exercise Push performed with left foot forward.

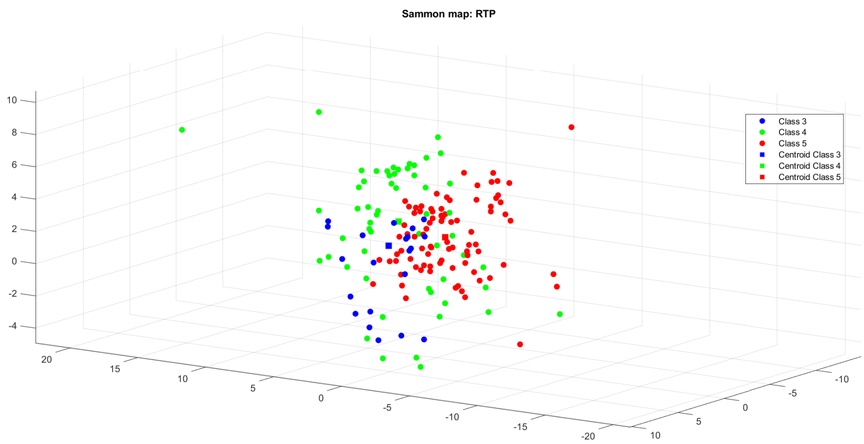

Figure A.9: Sammon Map for exercise Raising the Power.

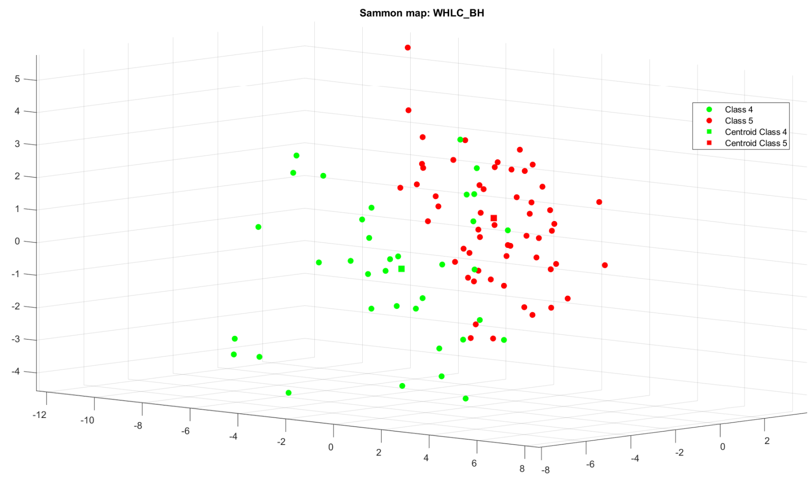

Figure A.10: Sammon Map for exercise Wave Hands Like Clouds.

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