POLITECNICO DI MILANO

Scuola di Ingegneria Industriale e dell'Informazione

Corso di Laurea Magistrale in Ingegneria Biomedica

USE OF WEARABLE SENSORS TO MONITOR TAI CHI PRACTICE

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Anno Accademico 2016 – 2017

Abstract

Tai Chi, a meditative/mind-body exercise, is one discipline growing in popularity in the U.S. and in general in the Western countries as a complementary and alternative medicine (CAM) therapy, especially for its beneficial impacts on balance and posture.

In research regarding Tai Chi a specific challenge is objectively quantifying measures of adherence and functional dosage, which require quantitative measures of practice proficiency.

In this study, a system of wearable sensors is used to monitor Tai Chi practice and specifically to discriminate which exercise is being performed and to determine the proficiency level of it.

Fifteen Tai Chi practitioners have been enrolled and they had to perform twelve different Tai Chi exercises. Nine Shimmer sensors composed by 3-axes accelerometers were put on the upper and lower limbs and on the trunk to capture the movements of the different body parts.

Data recorded has been used to train linear discriminant analysis, a machine learning technique able to predict both the exercise carried out and the proficiency level of the subject analyzed; this has been done basing on features that has been extracted from the accelerometer data and then analyzed and selected for their importance in achieving the goals of the study.

The analysis of recorded data and the results allowed us to draw conclusions concerning the position and the minimization of the number of wearable sensors needed to gather the most significant information.

The obtained predicted performance is satisfactory for both the purposes of the project; the results are good in terms of accuracy, and they can be further improved by carrying out a series of additional steps in the analysis.

Abstract

L'arte marziale Tai Chi è una delle discipline che sta divenendo sempre più popolare negli Stati Uniti d'America e nei paesi occidentali in generale, posti in cui questa attività è praticata come terapia medica complementare e alternativa (CAM), in particolar modo grazie ai benefici che comporta all'equilibrio e alla postura.

Nell'ambito della ricerca che riguarda il Tai Chi, un obiettivo è quello di quantificare oggettivamente l'utilità di quest'arte marziale, e ciò richiede misure quantitative riguardanti il livello di competenza e abilità con cui essa viene praticata.

In questo studio è stato utilizzato un sistema composto da sensori wearable per monitorare la pratica del Tai Chi; in particolare gli scopi sono quelli di riconoscere che tipo di esercizio viene eseguito e determinare l'abilità del professionista in questione.

Sono stati reclutati quindici professionisti di Tai Chi, ed è stato chiesto loro di eseguire dodici esercizi diversi. Sono stati utilizzati nove sensori Shimmer composti da accelerometri; essi sono stati posizionati sugli arti superiori e inferiori, così come sul tronco, con l'obiettivo di acquisire dati riguardanti i movimenti dei diversi segmenti corporei.

I dati registrati sono stati usati per alimentare il metodo di classificazione Linear Discriminant Analysis, che in questo progetto è stata capace di predire sia l'esercizio praticato che il livello di competenza del soggetto in questione; ciò è stato eseguito basandosi su features estratte dai dati degli accelerometri, che sono poi state analizzate e selezionate per la loro importanza nel raggiungere gli obiettivi del lavoro.

L'analisi dei dati registrati e i risultati ottenuti hanno permesso di trarre conclusioni che riguardano la miglior posizione e la minimizzazione del numero di sensori necessari per cogliere esclusivamente informazioni significative.

Per quanto riguarda entrambi gli obiettivi del progetto, le performance ottenute sono soddisfacenti; i risultati sono buoni in termini di accuratezza, e possono essere ulteriormente migliorati eseguendo step successivi sull'analisi dei dati.

Sommario

Il Tai Chi è un'arte marziale cinese praticata da più di 1200 anni e che si è diffusa negli ultimi anni come terapia di medicina alternativa e complementare (CAM).

Il Tai Chi prevede movimenti lenti, meditazione e controllo del respiro con l'effetto di indurre miglioramenti nella postura e nell'equilibrio, flessibilità e coordinamento a livello neuro-muscolare, soprattutto in adulti in età avanzata.

Dal momento che gli esercizi di Tai Chi si sono sviluppati nel corso delle ultime decadi specialmente nel campo riabilitativo, è sorta l'esigenza di misurare gli effetti di questa pratica per verificare quantitativamente i miglioramenti in termini di cammino e postura.

Gli studi condotti riguardanti l'uso clinico del Tai Chi per esplorare i suoi benefici sono numerosi, in particolare in pazienti affetti da malattie neurodegenerative.

Tra le diverse tecnologie presenti per monitorare la pratica del Tai Chi, il sistema optoelettronico per l'analisi del movimento si è stabilito come golden standard dal momento che fornisce come output misure accurate concernenti le posizioni dei diversi segmenti corporei del soggetto nello spazio, le forze scambiate durante i movimenti di Tai Chi, e ciò permette un'analisi quantitativa degli effetti di tale arte marziale.

Una promettente alternativa al sistema optoelettronico è fornita dai sensori wearable, i quali hanno un ampio range di applicazioni e vantaggi, come ad esempio la possibilità di effettuare misure e raccolte dati in un ambito diverso dal laboratorio. In questo modo, i pazienti o in generale le persone che si cimentano in esercizi diTai Chi possono essere monitorate in qualsiasi momento e in qualsiasi luogo, con lo scopo di fornire un feedback real-time.

Il progetto di tesi proposto si colloca in quest'ottica, ponendosi quindi come obiettivo primario il monitoraggio di persone che sono solite praticare Tai Chi tramite l'uso di sensori inerziali (Shimmer) per poter restituir loro un feedback riguardante la qualità dei movimenti svolti e i miglioramenti che devono essere fatti per ottenere benefici a livello di salute.

Per poter soddisfare questo scopo, il lavoro è stato diviso in due parti principali.

Il primo step è rappresentato dalla discriminazione dei diversi esercizi di Tai Chi; in particolare, gli esercizi analizzati sono dodici e sono di seguito elencati: Raising The Power (RTP), Push, Grasp the Sparrow's Tail (GST), Wave Hands Like Clouds (WHLC), Brush Knee Twist Step

(BKTS) e Golden Rooster (GR). Push, GST, BKTS e GR presentano due differenti versioni, una svolta con il piede destro posto anteriormente e l'altra con il piede sinistro posizionato anteriormente. WHLC, invece, presenta tre versioni, due delle quali sono svolte o solo con il braccio destro o solo con il braccio sinistro, mentre la terza versione è svolta utilizzando entrambi gli arti superiori.

La seconda parte del progetto invece è costituita dalla verifica del livello di esperienza dei soggetti praticanti Tai Chi, ai quali è stato attribuito un punteggio (che varia da 1 a 5) da un maestro di Tai Chi.

Più precisamente, i punteggi sono stati assegnati ad ognuno dei sei esercizi di Tai Chi, senza considerare quindi le diverse versioni che un esercizio può avere, e pertanto l'analisi in questa fase del lavoro è stata svolta esercizio specifica.

Entrambi gli step sono stati eseguiti posizionando nove sensori inerziali costituiti da un accelerometro in diverse parti del corpo di quindici persone che sono solite seguire classi di Tai Chi.

In particolare, i sensori sono stati posti sul polso destro e sinistro, sul braccio destro e sinistro, sulla vita, sulla coscia destra e sinistra e infine sulla caviglia destra e sinistra.

I quindici soggetti hanno ripetuto i dodici esercizi con un numero di ripetizioni da loro scelto ma nella nostra analisi abbiamo ritenuto opportuno considerare le prime quattro ripetizioni per ogni esercizio e per ogni soggetto.

Oltre ai nove sensori inerziali, durante la raccolta dati è stato utilizzato anche il sistema optoelettronico Vicon, posizionando sui soggetti 35 marker riflettenti seguendo il modello Plug-in-Gate full body.

I dati provenienti dal sistema optoelettronico non sono stati analizzati ma soltanto utilizzati durante la segmentazione nei dodici diversi esercizi dei dati ottenuti dai sensori inerziali.

La prima parte del progetto, la discriminazione dei dodici esercizi di Tai Chi, è stata divisa in diversi step di seguito riportati: processamento dei dati forniti dagli accelerometri, segmentazione dei dati nei dodici esercizi e nelle diverse ripetizioni, estrazione di features significative con lo scopo di catturare aspetti specifici riguardanti i diversi esercizi, selezione delle features più importanti per la separazione degli esercizi sulla base dell'algoritmo ReliefF e dell'indice di Davies-Bouldin, visualizzazione grafica dei dati tramite l'uso di Sammon map e classificazione dei dati attraverso una tecnica di machine learning nota come Linear Discriminant

Analysis (LDA) in modo tale da poter stimare la classe di ogni feature presente nel nostro dataset.
Per verificare le performance del classificatore implementato sono stati applicati due diversi metodi di validazione: il primo è noto come Leave-One-Trial-Out mentre il secondo è rappresentato dal Leave-One-Subject-Out. Entrambi dividono il dataset in due parti, il training set e il test set, in modo iterativo fornendo come risultato finale l'errore di classificazione.
I risultati ottenuti in termini di accuratezza in questa prima fase sono stati soddisfacenti; in particolar modo, attraverso una più approfondita analisi, è stato possibile osservare che accuratezze più elevate sono state fornite da soggetti con un alto livello di esperienza, mentre le accuratezze peggiori provengono da soggetti con un basso livello.
In generale, le accuratezze ottenute si collocano intorno al 90%, permettondoci di concludere che è possibile una discriminazione di diversi esercizi di Tai Chi tramite l'utilizzo dei soli sensori inerziali.
La seconda fase del lavoro, la verifica del livello di esperienza dei quindici soggetti, è stata condotta applicando due diverse tecniche: la prima consiste nell'utilizzo del template matching mentre la seconda è rappresentata dall'uso della Linear Discriminant Analysis, tecnica utilizzata anche nella prima parte del progetto.
La tecnica del template matching si basa sul confronto dei segnali provenienti dai sensori inerziali, estraendo un segnale di riferimento (template) da misurare con gli altri segnali per ottenere una misura di errore. In particolar modo, nella nostra analisi è stata utilizzata l'implementazione dell'algoritmo noto come Dynamic Time Warping (DTW), che ci ha permesso di ottenere come output le distanze tra template e segnali, verificando la prossimità dei diversi segnali rspetto a un determinato template.
Questa prima tecnica non ci ha fornito risultati positivi in termini di accuratezza, probabilmente a causa del tipo di template scelto; pertanto è stata applicata la seconda tecnica che prevede gli stessi step che sono stati condotti per la discriminazione degli esercizi e di seguito riportati: processamento dei dati, segmentazione dei dati, estrazione di features in grado di descrivere i diversi livelli di esperienza, selezione delle features più significative tramite implementazione dell'algoritmo chiamato ReliefF e dell'indice di Davies-Bouldin, visualizzazione dei dati attraverso Sammon map e classificazione tramite Linear Discriminant Analysis per assegnare ogni feature a un determinato livello di esperienza.

Per avere una misura dell'errore di classificazione commesso, sono stati applicati due metodi di validazione: il Leave-One-Trial-Out, già implementato nella prima parte del progetto, e la 10-fold cross-validation.
Tramite l'applicazione di questa seconda tecnica è stato possibile ottenere risultati molto più soddisfacenti per la verifica dei diversi livelli di esperienza dei soggetti praticanti Tai Chi; infatti le accuratezze per i diversi esercizi si aggirano intorno al 95%.
I risultati ottenuti sia per la discriminazione dei dodici esercizi di Tai Chi sia per la verifica del livello di esperienza dei quindici soggetti analizzati, ci permettono di concludere che tramite l'utilizzo di sensori inerziali è possibile il monitoraggio quantitativo di questa arte marziale.
Inoltre, i risultati ottenuti in entrambe le fasi del lavoro, ci hanno dato modo di valutare quali sensori inerziali hanno fornito dati più significativi per il raggiungimento dei nostri scopi.
Pertanto è stato possible minimizzare il numero di sensori da utilizzare nell'analisi, mantenendo così solo quelli che acquisiscono informazioni utili per raggiungere gli obiettivi prefissati.
In conclusione si può affermare che è così stata aperta la possibilità a numerosi sviluppi futuri concernenti il monitoraggio real-time della pratica del Tai Chi, utile sia per chi lo pratica che per chi necessita di tenere sotto controllo colui che si esercita.

Acknowledgements

We would like to thank first Dr. Paolo Bonato that accepted us in the Motion Analysis Laboratory at Spaulding Rehabilitation Hospital in Boston, giving us the opportunity to learn a lot from this experience, both from a working and personal point of view, providing us support and advices.

Living this experience would not have been possible without the collaboration of Prof. Manuela Galli that encouraged us to find a project abroad; thus sincere thanks to her also for being present as much as possible with her suggestions during the months spent in Boston.

We would like to thank Dr. Peter Wayne for following us in our project, making us understand the importance of Tai Chi practice in the rehabilitation field and for all the useful advices he gave us.

Another person that has to be thanked is Ing. Stefano Sapienza for all his suggestions, guidelines and support he provided us during our experience, our gratitude to him to have been always available for our several questions and to have been such a great person.

Big thanks also for all the members of the Motion Analysis Laboratory to have made our experience unforgettable and to have contributed to our thesis with their helps.

The last persons, not for importance, that we would like to sincere thank are our families and friends that supported our decision of working on the thesis abroad, allowing us to live a wonderful experience that made us grow. Thanks for having been and being present with help and support during our lives, especially with several kilometers dividing us, and for encouraging us to become better persons.

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Chapter 1: Introduction

1.1 Motivations

Tai Chi is a traditional Chinese exercise that has been practiced for over 1200 years. It is a Chinese traditional multi-component mind-body exercise that has become, in the last few years, a popular form of complementary and alternative medicine with similarities to aerobic exercise, especially in older adults.

Tai Chi combines physical movement, meditation and breathing to induce relaxation and tranquility of the mind.

This kind of martial art integrates training in balance, flexibility, and neuromuscular coordination which together may result in benefits to gait health and postural control. In fact, there is medical evidence that Tai Chi movements have strong rehabilitation implication towards improving balance and posture, improving cardiovascular and circulatory, strengthening hip muscles and developing strategies to avoid falls in healthy elderly, frail individuals and neurologically impaired older adults.

Furthermore, Tai Chi is a safe exercise for the elderly because it is characterized by slow and graceful movements that can be conducted by anyone without complications.

Since Tai chi exercises are widely performed, the need of measuring their impact has arisen in research field in order to quantitatively assess and verify their efficacy to improve postural and gait aspects.

In fact, in the past decade, a several number of studies has been conducted in the field of the clinical use of Tai Chi to explore its health-enhancing qualities for neurologically impaired patients.

The quantitative information coming from research could be useful for both the people in charge of monitoring the patient and the practitioners, allowing them to understand how and in what measure they need to improve.

Among the different technologies to achieve this goal, the optoelectronic system for motion capture is established as gold standard. It is able to provide outputs concerning positions of the subject in space, forces exchanged while the Tai Chi movements are performed, to quantify the progress of the testing subject.

A cheap alternative to obtain this aim is represented by the use of wearable sensors, an improving technology with wide range of applications and advantages, such as their usage outside the environment of laboratory allowing the recording of useful signals at any time anywhere, being easy and quick to set up. In this way, the practitioners could apply by themselves wearable sensors at home and perform the exercises while data are recorded to obtain a real-time feedback.

1.2 Aims of the study

The main goal of the proposed study is the use of Shimmer platform to monitor the practice of Tai Chi in subjects that are used to perform this martial art to give them a feedback. Thus they can understand how well they are performing and in which way they can improve their training to obtain better results for their health.

To achieve this purpose, it is necessary to pass through two different stages; both of them required the use of Shimmer sensors positioned on different part of the body.

The first step is represented by the identification of the performed exercise and the second one consists in the assessment of the proficiency level of the practitioners.

The process is repeated for fifteen subjects while they are executing twelve different Tai Chi exercises.

In the first stage, the attention is focused on the analysis of the specific features so that it could be possible to obtain the discrimination and the recognition of each different Tai Chi exercise.

Once this first purpose is achieved, practitioners could receive a feedback to adjust movements that characterize a specific exercise.

The second stage is the development of proficiency measures focused on identifying objective quantitative biomarkers of proficiency.

To assure that the Tai Chi proficiency parameters have robust validity, at least one Tai Chi expert is required to develop a set of proficiency criteria, using a visual scoring system similar to other competitive sports.

The analysis of recorded data and the results in term of the possibility to determine which kind of exercise is performed and with which proficiency level could allow us to draw conclusions concerning the type, the location and the minimization of the number of Shimmer sensors are needed in order to gather the most significant information.
In this way, it could be feasible to generate a feedback specific for each subject and for each exercise, taking into account the proficiency level to weight the adjustment response.

1.3 Thesis outline

In the following chapter, a literature review will be presented, first regarding the use of Tai Chi as alternative medicine especially for rehabilitation purposes and studies conducted in this field with the aim of assessing the benefits of this martial art will be shown.
After that, the attention will be focused on the employment of wearable sensors for medicine and rehabilitation, following their division in different classes.
Special attention will be given to a particular type of wearable sensors, the motion sensors; they are able to detect movements and for this reason they have become a cheap alternative to the gold standard (optoelectronic system).
In the third chapter, the aims of this research project will be presented in detail, starting from the data collection procedure and afterwards data analysis will be described.
Forth chapter will present the results of the data analysis carried out and the fifth chapter will focus on the future development discussion, underlining the achievements and the limits of our work.

Chapter 2: State of Art

2.1 Wearable sensors for health monitoring

2.1.1 Introduction to wearable sensors

Wearable sensors have become very popular in many applications such as entertainment, security, commercial and medical fields. They could be very useful in providing accurate and reliable information on people's activities and behaviors.

In the past few years, there has been a growing usage of wearable sensors, especially in the medical field, because there are a lot of different applications in monitoring physiological activities.

In fact, it is feasible to monitor patients, body temperature, heart rate, brain activity, muscle activity and other physiological data: they have diagnostic as well as monitoring applications.

The main requirement that wearable sensors must have is the lightness so that they could be worn on the body without impeding movements of the patients, in order to gather useful data to be monitored.

Since wearable sensors are small devices and they are easy to set up, it is possible to avoid hospitalization for recording data from subjects because the same treatment could be performed at home.

Indeed, patients after an operation usually undergo recovery/rehabilitation process where they follow a strict routine and their physiological signals must be monitored to assess their health status.

Wearable sensors, during rehabilitation, may also provide audio feedback, virtual reality images and other rehabilitative services. [1].

Whichever the parameters recorded by the system, the obtained measurements are sent (via a wireless or a wires link) to a central node (a PDA, a smart-phone, a pocket PC or a custom designed microcontroller-based device) that can display the information on a user interface or send it to a medical center.

The development of microelectronics, micromechanics, integrated optics and other related technologies has allowed the development of different kind of sensors to record data more efficiently and faster.

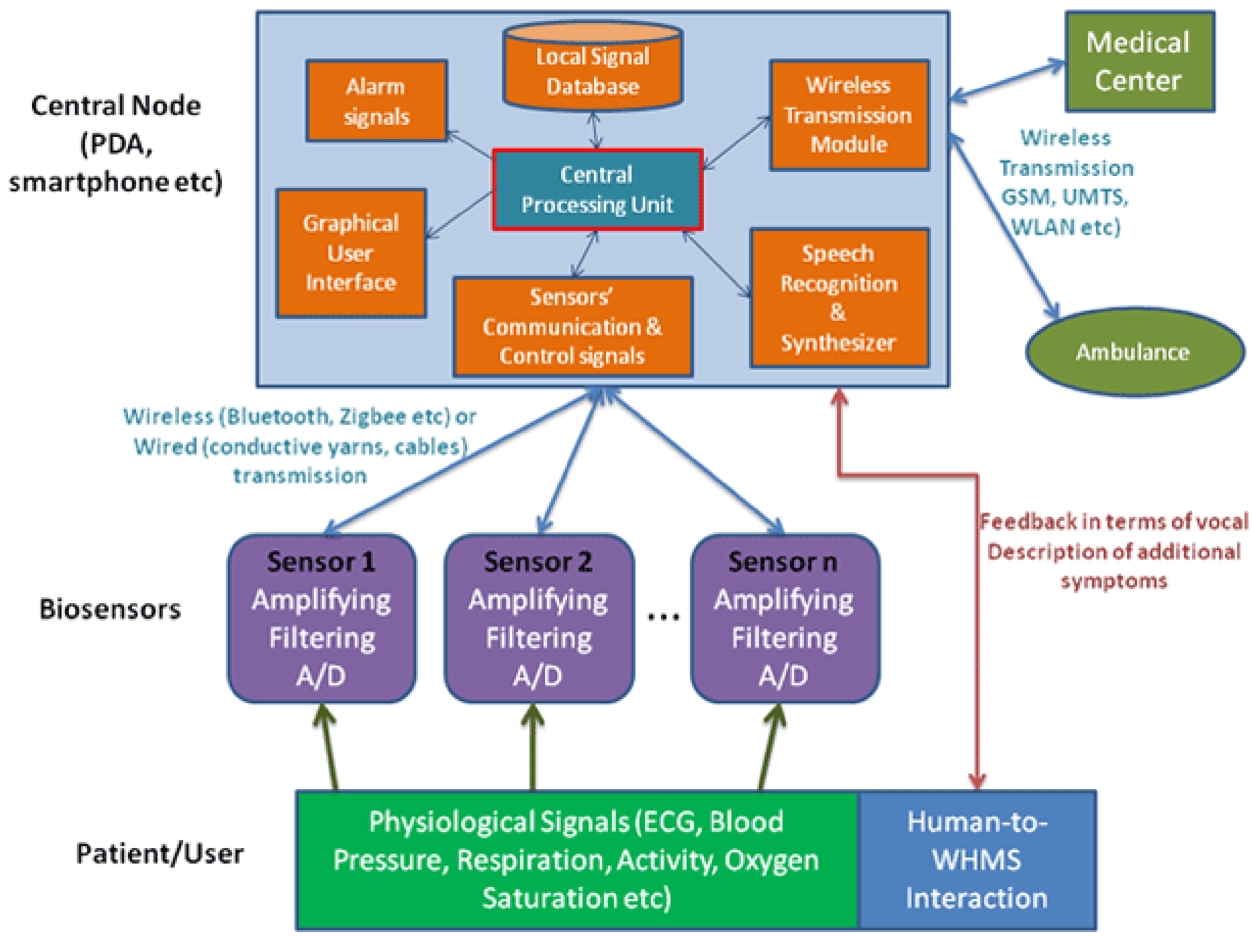


Figure 2.1: Architecture of wearable sensors for human health monitoring

Wearable systems for patients' remote monitoring consist of three main building blocks:

1. The sensing and data collection hardware to collect physiological and movement data
2. The communication hardware and software to relay data to a remote center

3. The data analysis techniques to extract clinically-relevant information from physiological and movement data

The design of this kind of system represents a challenging task, since several constraining and often conflicting requirements have to be taken into account. In fact, certain strict medical criteria need to be satisfied, but at the same time ergonomic constraints and hardware resource limitations represent issues that have to be considered.

In particular, the attention must be focused on the wearability of the device, for this reason its weight and size have to be controlled in detail, so that it doesn’t become cumbersome for the user.

Other important features are related to the security and privacy of the collected data, power consumption and the price (it has to be affordable in order to be available to a wide public) [2].

Wearable sensors used to monitor human health can be classify in three main categories:

1. Physiological sensors
2. Biochemical sensors
3. Motion sensors

A partial list of the most common wearable sensors used in medical field is provided in Table 2.1.

Type of Bio-signal	Type of sensor	Description of measured data
Electrocardiogram (ECG)	Skin/Chest electrodes	Electrical activity of the heart
Blood pressure(systolic & diastolic)	Arm cuff-based monitor	Pressure exerted by circulating blood on the walls of blood vessels
Body and/or skin temperature	Temperature probe or skin patch	Measure of body's ability to generate and get rid of heat
Respiration rate	Piezoelectric/Piezoresistive sensor	Measure of the expansion (inspiration) and contraction (expiration) of the chest
Oxygen saturation	Pulse Oximeter	Measure of the oxygenation of the blood
Heart rate	Pulse Oximeter/skin electrodes	Number of cardiac cycles per unit time
Sweating or skin conductivity	Galvanic Skin Response	Measure of the electrical conductance of skin due to activity of sweat glands
Heart sounds	Phonocardiograph	Measure of sounds and murmurs made by heart
Blood glucose	Strip-base glucose meters	Measure of the amount of glucose in the blood
Electromyogram (EEG)	Skin electrodes	Measure of electrical activity produced by skeletal muscles
Electroencephalogram (EEG)	Scalp-placed electrodes	Measure of electrical activity of the brain
Body Movements	Accelerometer	Measure of linear acceleration/angular velocity of body segment

Table 2.1: Types of wearable body sensors [2]

Health monitoring applications of wearable systems most often employ multiple sensors that are typically integrated into a sensor network either limited to body-worn sensors or integrating body-worn sensors and ambient sensors [3].

2.1.2 Physiological sensors

Physiological sensors are responsible for the measurement of parameters such as heart rate, blood pressure, blood oxygen saturation, respiration and muscle activation.

Values of these parameters are indicators of health status and have a remarkable importance from a diagnostic point of view [3].

This kind of sensor, able to detect vital signs, could be deployed, for instance, when monitoring patients with congestive heart failure or patients with chronic obstructive pulmonary disease undergoing clinical intervention.

Body temperature is one of the most common physiological parameter measured by wearable sensors. The variation in temperature measured on the skin can be used to detect the symptoms of medical stress that may lead to various health conditions, including stroke, heart attack and shock [1].

The next most common physiological parameter is the heart rate of subject under monitoring. Heart rate is a precisely regulated variable, which plays a critical role in health and disease of human. There are several methods available to measure heart rate of a person: Photoplethysmography (PPG) based technology, [4], sound based, [5], based on changes on brightness of person's face.

Wearable ElectroCardiogram (ECG) sensors are also used for short-time assessment of cardiovascular diseases, especially for subjects with chronic heart problems.

A low power high resolution Thoracic Impedance Variance and ECG monitoring has been developed and incorporated in a compact sensor for wearable low cost cardiac healthcare [6].

An asynchronous analog-to-information conversion system has been introduced for measuring the RR intervals of the ECG signals. This system is characterized by a modified level-crossing analog-to-digital converter and a novel algorithm for detecting the R-peaks from the level-crossing sampled data in a compressed volume of data [7].

Heart-To-Go, instead, is a system developed by Jin et al. and it consists in a standalone cell phone-based ECG platform able to collect, record, display and transmit data in real-time, as well as analyze the acquired data, automatically detect cardiac abnormalities and match these last with particular cardiovascular diseases (CVD) conditions by means of both personalized medical information and an established ECG database.

The signal is acquired with the Alive Technology's wireless ECG and heart monitor equipped with Bluetooth, able to send data to cell phones or other wireless devices.

An ECG processing module extracts features from the recorded signals (i.e. heart rate, RR interval, QRS duration) used to classify each heart beat as normal or not, first with a rule-based checker, then with a Hybrid Fuzzy Network based neural classifier [8].

A pilot study combining the use of wearable ECG and GSR (Galvanic Skin Response) sensors was developed by Crefaci et al. to determine the feasibility of a system for a cardiovascular and stress monitoring of adolescents with Anorexia Nervosa (AN).

Patients with eating disorders show, in fact, a very high cardiovascular mortality rate and monitoring heart rate variability (HRV) may provide an important help for intervention to avoid occurrence of major or even fatal arrhythmias.

Furthermore, the possibility to detect stressful events through changes in GSR signals could allow analyzing the different forms of reaction of the subject to emotional stress.

The device was tested on 27 girls with AN and 15 healthy girls and the obtained results prove to be promising and they have a great importance for further studies on this system that could make a huge difference for clinicians, who may benefit from the data gathered both in home setting, as well as in a clinical, controlled setting [9].

The device implemented by Oliver and Flores-Mangas, called HealthGear, [10] address another type of pathological condition: sleep apnea, an under-diagnosed but common sleep condition that could affect both children and adults, characterized by periods of interrupted breathing (apnea) and periods of reduced breathing (hypoapnea). The immediate effects are represented by increased heart rate and blood pressure, while long-term symptoms consist in extreme fatigue, slow reaction time and cardio/cerebrovascular problems.

HealthGear consists of a set of non-invasive physiological sensors wirelessly connected via Bluetooth to a cell phone which stores, transmits and analyzes physiological data and presents it to the user in an intelligible way.

The three main hardware components of HealthGear's current implementation are an oximetry sensor, a data transmission module and a cell phone (central processing unit).

Figure2.2: HealthGear's Hardware

Pulse oxymetry is a non-invasive method for determining the percentage of hemoglobin (Hb) saturated with oxygen (an example of oxymetry sensor is shown in figure 2.3) and it constantly monitors and analyzes the user's blood oxygen level (Sp02), heart rate and plethysmographic signal.

Figure2.3: Example of pulse oxymetry

Once the data is sent to the cell phone, the analysis could start in order to determine if an episode of sleep apnea is occurring. Two different algorithms were tested: the first one consider that desaturation begins as soon as the oxygen level falls below a baseline by a specified amount, while the second one evaluates the peaks in the periodogram of the oxymetry signal.

The device was tested on 20 volunteers and was found to be easy to use, comfortable and performing very well (100% accuracy of the detection algorithm).

Another example of physiological sensor is the system developed by Corbishley et al. [11] to measure respiratory rate using a miniaturized wearable acoustic sensor. The microphone was placed on the neck in order to record acoustic signals associated with breathing. By developing techniques to filter out environmental noise and other artifacts, the authors manage to achieve an accuracy greater than 90% in the measurement of breathing rate.

Furthermore, another promising project is the one that QUASAR is currently developing: an integrated Physiological Sensor Suite (PSS) with the aim of monitoring physiological and cognitive states in operational settings [12]. The PSS has been designed to be wearable, with particular attention on the capability of long-term monitoring of physiological signals.

The PSS is based on two non-invasive bioelectric sensor technologies pioneered by QUASAR: a capacitive bioelectrode capable of through-clothing measurements of electrocardiograms (ECG) [13] and measurements of electromyograms (EMG) and electrooculograms (EOG); an hybrid bioelectrode capable of measurements of through-hair electroencephalograms (EEG) [14].

These sensors are combined with miniature, ultra low-power microprocessor-controlled multichannel data acquisition (DAQ) units and miniaturized wireless transceiver (WT) units that will allow data acquisition to be done close to the locations of electrodes.

Each physiological measurement is performed by a single module (comprising sensors, DAQ and WT units) that communicates wirelessly to a data logger worn by the subject.

Figure 2.4: QUASAR hybrid EEG biosensor [12]

Figure 2.5: QUASAR capacitive biosensor with 10c coins for scale [12]

2.1.3 Biochemical sensors

Biochemical sensors have recently gained a big amount of interest among researchers in the field of wearable technology. These types of sensors can be used to monitor the bio-chemistry as well as levels of chemical compounds in the atmosphere.

From a design point of view, biochemical sensors may be the most complex since they often require collection, analysis and disposal of body fluids.

An example of biochemical sensor is given by Dudde et al. [15] who developed a minimally-invasive wearable closed-loop quasi-continuous drug infusion system that is able to measure blood glucose levels and to infuse insulin automatically.

The glucose monitor consists of a silicon sensor that continuously measures glucose levels using a microperfusion technique and infusion of insulin is achieved by a modified insulin pump.

This system has integrated Bluetooth communication capability for displaying and logging data and receiving commands from a personal digital assistant (PDA) device.

Another promising technology is the one represented by an array of biochemical sensors developed as part of the BIOTEX project, supported by the European Commission.

The BIOTEX project consists in the integration of biochemical sensors into textiles for monitoring body fluids. This system allows in-vitro and in-vivo testing of pH, sodium and conductivity from body sweat [16].

By in-vitro and in-vivo testing of the wearable system, researchers have shown that the system can be used for real-time analysis of sweat during physical activity.

Recently, growing interest has been shown in the implementation of self-contained lab-on-chip systems that have the potential to change the world of medical testing and diagnosis by making it fast, cheap and easily accessible.

An example is given by Want et al. [17] who developed a fully specified and functional biomedical sensor interface system-on-chip in order to acquire, process and communicate sensor data wirelessly which integrates a pH and temperature sensor.

Similarly, Ahn et al. [18] carried out a low cost disposable plastic lab-on-chip device for biochemical detection of parameters such as blood gas concentration and glucose.

In the biochip, two elements are present: an integrated biosensor for the detection of different parameters and a passive microfluid manipulation system.

2.1.4 Motion sensors

The last category of wearable sensors is represented by motion sensors that are largely used for movement detection and tracking.

They have become very popular since they are inexpensive, small and require very little power, making them attractive for patient monitoring applications.

Motion sensors include accelerometers and gyroscopes, sometimes used together with magnetometers.

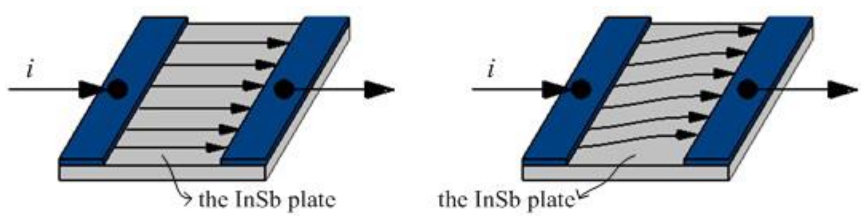
An accelerometer is a type of inertial sensor that can measure acceleration along its sensitive axis. The operation principle of accelerometers is based on a mechanical sensing element that comprises a proof mass attached to a mechanical suspension system, with respect to a reference frame. Based on Newton's second Law (force = mass × acceleration), the acceleration can be measured electrically using the physical changes in the displacement of the proof mass.

Nowadays, three common types of accelerometers are available: piezoelectric, piezoresistive and capacitive. Piezoresistive and capacitive accelerometers can provide dual acceleration components and have higher stability, so they are suitable for measuring the motion status in human gait [19].

A gyroscope is an angular velocity sensor; the micromachined gyroscope is based on the measurement of the Coriolis force, which is an apparent force proportional to the angular rate of rotation, in a rotating reference frame.

By detecting the linear motion from the Coriolis force and performing an integration of the gyroscopic signal, the angular rate can be obtained [20].

A magnetometer is a device that measures magnetic field. Nowadays there are different types of magnetometers, one of them is represented by the magnetoresistive sensor based on the magnetoresistive effect. It refers to the change in resistivity of a current carrying ferromagnetic material resulting from a magnetic field, with the resistance change proportional to the tilt angle in relation to the magnetic field direction.



(a) (b)

Figure 2.6: The model of the magnetoresistive effect. (a) Current mode under non-magnetic field, (b) Current mode under magnetic field [20]

Based on the magnetoresistive effect, the device can estimate changes in the orientation of a body segment in relation to the magnetic North or the vertical axis in gait analysis [21].

Furthermore, magnetometers can provide a reference measure for body orientation, in addition to the earth gravity field.

Inertial sensors have been used for several years to study gait and other human movements, or for the measurement of tremor and motor activity in neurological patients.

An example is given by the study developed by Patel et al. [22] that presents the results of a pilot study where the use of accelerometer data to estimate the severity of symptoms and motor complications in patients with Parkinson's disease is proposed.

Uniaxial accelerometer sensors positioned on the upper and lower limbs (Figure 2.7) were employed in order to gather movement data during performance of standardized series of motor tasks. Accelerometer data was filtered, segmented and meaningful features were extracted and then used to build a classifier to estimate the severity of Parkinsonian symptoms and motor complications, by using Support Vector Machine (SVM).

In the proposed study, promising results in term of accuracy were achieved, allowing the assessment of longitudinal changes in patients' status in an objective way.

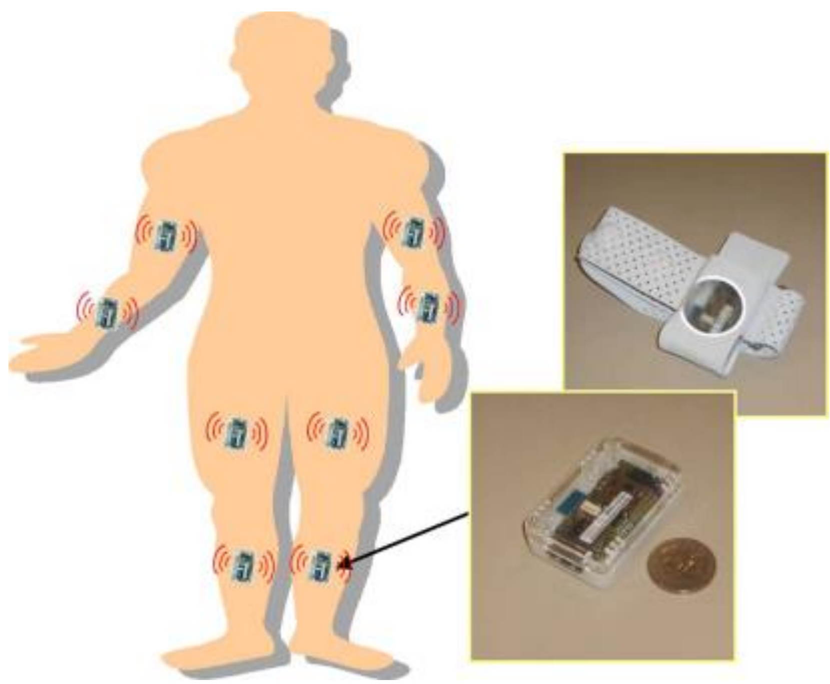


Figure 2.7: Schematic representation of the position of sensors on the body employed in Patel study [22]

The quantitative assessment of motor abilities in stroke survivors is the aim of another study developed by Patel et al. [23] in which accelerometer data are recorded during performance of fifteen motor tasks in order to estimate clinical scores for each individual task.

The procedure is similar to the one described before, but this time only three accelerometers were employed and, instead of SVM to implement the classifier, random forests was chosen.

The obtained results were promising: the estimates of six motor task scores of the total Function Ability Scale (FAS, a clinical scale used to assess levels of impairment and functional limitation) were marked by a bias of only 0.04 points of the scale and a standard deviation of 2.43 points.

Furthermore, other types of pathologies can be monitored by inertial sensors, such as chronic pulmonary diseases characterized by disabling breathlessness and impairment of functional exercise capacity.

These symptoms can lead to a reduced physical activity and can produce losses in global functioning and life quality.

Pulmonary rehabilitation, which includes graded exercises, strength and flexibility training, is necessary for improving health and life quality and the use of motion wearable sensors allow collecting data, adding precision to the measurement of free-living daily activity.

The study carried out by Belza et al. [24] involves the use of the StayHealthy RT3 triaxial accelerometer (Figure 2.8).

By means of the accelerometer, activity over one minute epochs are measured, so that it is feasible to capture brief bouts of activity over longer periods of time (up to 21 days). Data collected allow examining different levels of activity during daily living as well as during exercises.

The main limitation that characterizes this device is represented by the inability to measure static exercises, where the employment of body movements is not involved.

Additionally, the motion sensor described may not be able to accurately monitor frail older adults with slow gaits.

Figure 2.8: RT3 accelerometer from StayHealthy

From a wider point of view in health monitoring, wearable motion sensors can also be used to monitor physical activity in subjects without pathologies and several numbers of researches as well as commercially available products have been developed with this purpose.

The work of Maurer et al. [25] was carried out with the same aim described before; in this case the monitored activities are represented by walking, standing, sitting, ascending and descending stairs.

The study was developed using the eWatch (Figure 2.9), a multi-sensor platform worn on different parts of the body. This system contains four parts: a dual axes accelerometer, light, temperature sensor and microphone, in order to identify the user's activity in real-time and record the classification results during a day.

In particular, Maurer et al. investigated the dependency of the eWatch classification accuracy on given different body positions: the belt, shirt pocket, trouser pocket, backpack and necklace.

They employed and compared several classification methods (Decision Trees, k-Nearest Neighbor, Naïve-Bayes and Bayes Net classifier) and the best results in term of recognition accuracy were obtained with the use of Decision Trees and Naïve-Bayes.

Furthermore, the results showed that any of the six positions are good for detecting walking, standing, sitting and running. Instead, ascending and descending stairs were difficult to distinguish from walking in all positions, since the classifier was trained for multiple persons.

Figure 2.9: eWatch sensing platform

2.2 Tai Chi Chuan: interest and related technologies

2.2.1 Complementary and alternative medicine

Complementary and alternative medicine (CAM) is the term used to define medical products and practices that are not part of standard care, as there is insufficient proof that they are safe and effective. Standard care is what medical doctors, doctors of osteopathy, and allied health professionals, such as nurses and physical therapists, practice [26].

While complementary interventions are used together with conventional treatment (an example is the use of acupuncture to help with side effects of cancer treatment), alternative interventions are used in place of conventional treatment (like treating heart disease with chelation therapy instead of using a standard approach) [27].

The reasons to approach such different solutions can vary. People might be looking for ways to improve their health, wellbeing, to relieve symptoms caused by chronic, even terminal, diseases, as well as side effects of conventional treatments. Other reasons could be related to having a holistic health philosophy, or to the need to have a better control on one's own health.

Many types of CAM practitioners try to treat not only the physical and biochemical manifestations of illness, but also the nutritional, emotional, social, and spiritual context in which the illness arises.

The National Institutes of Health's National Center for Complementary and Alternative Medicine (NCCAM) classifies CAM therapies into five major domains: alternative medical systems (which includes traditional Chinese medicine, ayurveda, homeopathy, and naturopathy); mind-body interventions (including meditation, hypnosis, dance music, and art therapy); biologically based treatments (such as vitamins, minerals, herbs, and vegetarianism); manipulative and body-based methods (including chiropractic and massage therapies); and energy therapies—with some overlap across categories [28].

According to [28], commonly used CAM therapies in the US include nonvitamin, nonmineral, natural products; deep breathing exercises; meditation; chiropractic care; yoga; massage; and diet-based therapies. CAM was most often used to treat back pain or back problems, head or chest colds, neck pain or neck problems, joint pain or stiffness, and anxiety or depression. Even if less common, another application included treating or providing symptom relief for cancer, cardiovascular diseases, and lung diseases. CAM use was found to be more prevalent among women, among adults with higher level of education or who engaged in leisure-time physical activity, who had one or more existing health conditions or who made frequent medical visits in the prior year.

In a context in which CAM practices are becoming more and more popular, the need emerges to understand them more, to verify their effects and to test their possible applications with a scientific approach.

Biomedical engineering will play a pivotal role in the process of facilitating the integration of conventional medicine and CAM therapies (or integrative medicine, IM).

IM can be defined as practicing medicine in a way that selectively incorporates elements of complementary and alternative medicine into comprehensive treatment plans alongside solidly orthodox methods of diagnosis and treatment [28].

According to the article by Atsumi and Kamohara, biomedical engineering has two major roles: of developing essential methods and instruments to evaluate safety and efficacy of CAM therapies, as well as new methodologies to apply holistic approaches of IM.

2.2.2 Tai Chi: an introduction

“Tai Chi Chuan”, casually referred to as “Tai Chi”, is a deep, meditative, internal Chinese practice. At its original core, it is a martial art used for self-defense, but it is nowadays commonly practiced and taught in a manner that strengthens and promotes the mind/body health of dedicated practitioners.

The term can be translated as “Supreme Ultimate Boxing” or “Grand Ultimate Fist”. It describes a form of boxing or exercise that is based on the principles of yin and yang, dynamic change and transformation, integrating the body and mind, and the internal and the external [29].

Figure 2.10: A man performing a Tai Chi exercise

Indeed, Tai Chi incorporates the Chinese concept of Yin and Yang, also known as the Tai Chi symbol. This concept is fundamental in all Chinese culture, philosophy, medicine and science. Yin and Yang symbol depicts two complementary polar opposites that together come to create a dynamic, balanced, integrated and inter-dependent whole.

The practice of Tai Chi embodies this idea at different levels. At a physical level, it aims at integrating different parts of the body (upper and lower, left and right, extremities with inside…); at the same time though, it also has the purpose of integrating body and mind [29].

Another Chinese concept fundamental in this martial art is Qi, a vital energy or life force - the intrinsic energy in the body that travels along pathways in the body called meridians. Practicing Tai Chi is said to support a healthy balance of Yin and Yang, thereby aiding the flow of Qi. Accounts of the history of Tai Chi vary. A popular legend credits its origins to a Taoist monk who lived in the 12th century, Chang San-Feng, who developed a set of 13 exercises that imitate the movements of animals. He also emphasized meditation and the concept of internal force (in contrast to the external force emphasized in other martial arts, such as kung fu and taekwon do) [30].

Many varieties of Tai Chi have evolved during the centuries, sharing many basic principles, but emphasizing slightly different characteristics (the most popular are Chen, Yang, Wu, Hao and Sun, all named after the founder's family name). Some, because of the positions they include, are more demanding, while others are ideals for beginners, but they all involve a series of slow, meditative body movements with each movement flowing seamlessly into the next without hesitation (a certain number of postures composes a choreographed routine called form) [31]. All the movements, furthermore, are integrated with breathing and cognitive skills (such as mindfulness and imagery).

2.2.3 The health benefits of Tai Chi

In the last 50 years, 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. Tai Chi classes have become popular not only in sports centers, but also in hospitals, clinics, community and senior centers.

Since the first Western, randomized, controlled trial evaluating the effects of Tai Chi for balance and range of movement in older adults (in 1987), more than 700 peer-review papers studying the health benefits of this form of exercise have been published, with this number growing exponentially [29].

In 2006, Yeh et al. indicated that performing 12-week Tai Chi exercise program could enhance functional mobility, and further increase T cell mediators transforming growth factor and interleukin 10 [32]. In 2012, a research article was published in New England Journal of Medicine by Dr. Fu-Zhong Li [33], which randomly assigned 195 patients with Parkinson's disease into three groups. Each group performed 60 minutes of an exercise program twice a week and lasted for 24 weeks. The group of patients who performed Tai Chi as their exercises were better than those who performed resistance-training or stretch-training in the tests of balance.

These were just two examples, but in the last few years, Tai Chi has been shown to improve aspects of strength, balance, cardiovascular health, the immune system, sleep, psychological disorders, well being, fall prevention, bone health [34][35].

The applications include pathologic conditions as Parkinson's, multiple sclerosis, arthritis, osteoporosis, fibromyalgia, and depression [36].

As far as improved balance is concerned, this is the most studied application of Tai Chi.
Many researchers already proved that it does really reduce the risk of falling in older adults. This aspect is particularly important if we consider that falls in this population can lead to serious injuries and fractures (statistics show that 1 out of 5 older adults with fall related fractures die within one year because of the complications associated with it) as well as to high economic costs for society [37].
Today, three millions Americans practice Tai Chi specifically for health.
The main reason is that this martial art is able to provide a form of therapy in prevention and rehabilitation that involves not only the body, but also the mind and spirit (a form of biopsychological approach).
Also, the fact that it does not require the use of special equipment, expensive outfits or specific athletic conditioning is a key factor in its diffusion, also as a cost-effective intervention. Other advantages in choosing Tai Chi as a part of health programs are its flexibility in terms of practice time and place as well as the fact that people of all ages can participate [38].
For health related 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.

2.2.4 Technologies to monitor the performance of Tai Chi exercises

Video analysis and motion capturing are standard tools in professional sports, used to monitor and improve athletic performances by fine-tuning the quality of movement.
However, cutting-edge systems with high-quality sensors hardly suffice to fulfill these needs, and trainers and other experts still find themselves analyzing the recorded data by hand. The limits connected to this practice are not only related to the large amount of time needed, but also to the low effectiveness of the analysis, error-prone since it depends on the humans doing it. Hence, the large-scale use of similar analyses for the masses (not professionals) requires a different approach [39].

Lee et al. [40] designed a physical rehabilitation system based on Kinect sensor to assist patients with movement disorders to perform Tai Chi exercises at home.

The idea in this case is to provide an alternative solution for people for whom going to the hospital every time to follow rehabilitation programs might be inconvenient, for example if they live in the suburbs (having to spend additional time and money on the transportation). In this case, hiring a home therapist can be a solution, but often not an economically viable one.

Tele-rehabilitation, on the other hand, could allow people to attend rehabilitation sessions by following instructions given by therapists or messages from the system.

In the application proposed in the paper, the Kinect Sensor is used, which is now a very popular device in many computer vision researches. The Kinect Sensor, originally designed for video games, features an RGB camera, depth sensor and multi-array microphone, which provide full-body 3D motion capture, facial recognition and voice recognition capabilities.

Although its main use in video games, there are also some applications in developing health-care, rehabilitation or in-home activity monitoring of elders. For example, Stone and Skubic presented a system based on Kinect sensor, for in-home activity monitoring of elderly adults fall risk assessment [41]. Metcalf et al. developed a system which can capture and measure hand kinematics, and can be used for home-based upper limb rehabilitation [42]. Kitsunezaki et al. [43] reported four types of Kinect-based physical applications. These applications measure parameters such as walking time or joint angle ranges, to determine training effectiveness.

In Figure 2.11, a flowchart of the system designed by Lee et al. The first element on the right, the database, was obtained by asking Tai Chi instructors to perform an exercise, while Kinect sensor was recording movements information. These movements performed by the coaches are considered as standard movement, and the skeletons of these movements are then extracted for comparison. When a patient uses this system for rehabilitation, first standard movements are shown on the screen. The patient follows the information on screen to perform Tai Chi, and their movements are then compared to the movements of instructors through a comparison between the skeletons. The results are then shown on screen to inform the user. In this process, a fundamental step is the normalization of the skeletons.

Once the head-body-arm ratio is consistent among different skeletons, the comparison can be carried out by calculating the mean distance between the skeleton of standard movement and the skeleton of patient’s movement as well as the mean difference of angles between the two.

Finally, fuzzy logic is used to give a score for each key movement (the possible outcomes are "try it again", "good work", "excellent" and "perfect"). In the study, a female 60-year-old patient was invited to test the system. A baseline (A) / intervention (B) strategy was used to assess its effectiveness, with an ABAB sequence.

According to experimental results, the patient has significantly improved in performing Tai Chi with the aid of the system [40].

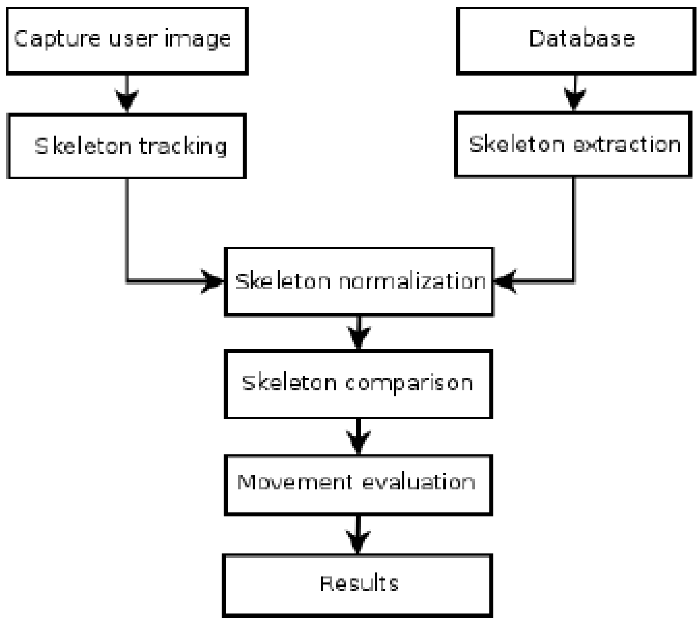


Figure 2.11: A flowchart of the system in [40]

Another system with the purpose of helping Tai Chi practitioners in correctly performing exercises was developed by Sasaki et al [44]. The idea comes, in this case, from the fact that most novices encounter a number of difficulties in learning how to practice Tai Chi, due to the complexity of the movements involved. It can be hard for them to imitate movements performed by teachers, even if they observe them carefully, and the instructions received might be confusing or ambiguous.

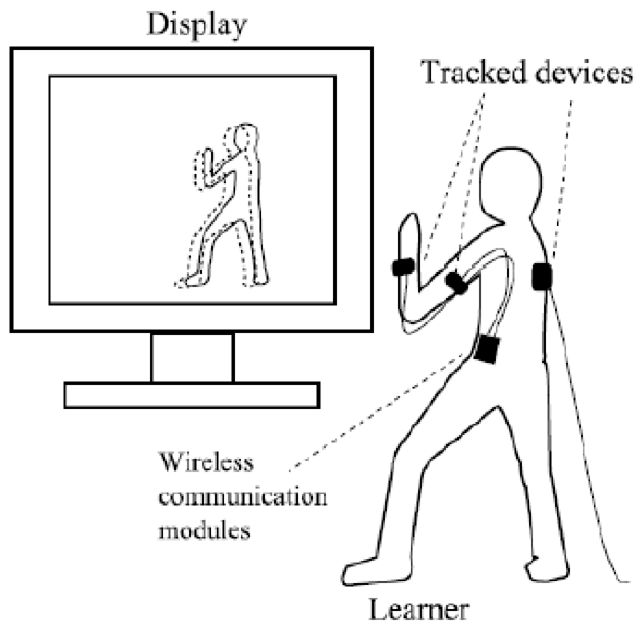


Figure 2.12: Learning with the instruction display in [44]

The systems chosen to record the movements of the different body segments in time were the IS-900 Motion Tracker (InterSense Inc., USA) and HiBall-3000 Wide-Area Tracker (3rdTech Inc., USA). Both systems consist of an array of emitters (either ultrasonic or LED) mounted on the ceiling and tracked devices with receivers and accelerometers. The dimensions of the tracking space covered with the emitters on the ceiling are 6 m in width, 6 m in depth, and 2.3 m in height. This kind of tracking systems shows some advantages compared to traditional stereophotogrammetry (the fact for example that it does not require a careful arrangement of the cameras in order not to have covered markers during the movement). The tracked devices are fixed on the body segments involved in the movements characterizing the exercise. In this case the exercise (Parting wild horse's mane) made it sufficient to put the devices on the trunk and left upper limb (upper arm, forearm and hand).

As in the study described before, learner's movements are compared to the ones of an expert (previously recorded). In order to do so, the expert's motion data is scaled so as to fit to the lengths of the learner's body segments.

At the beginning of the measurement, the involved subject is requested to keep specified posture for recording positions of tracked devices and anatomical landmarks. The nominal joint positions in any posture and time frame are, thus, estimated from the relative positions recorded at the beginning, and the positions and orientation of the tracked device in the global coordinate system at that time frame.

Information about the motion is shown on the display while the subject is performing the exercise (Figure 2.13). The instruction display shows indeed 3-dimensional computer graphics (3D CG) models of the learner, the expert and the trajectories traced by the different body segments in the preliminary experiment with the expert.

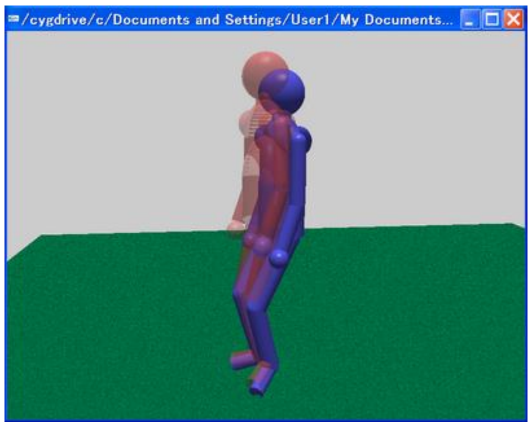


Figure 2.13: Contents of the instruction display in [44]

Moreover, the skill level index gives quantitative information about the quality of the exercise. It is calculated from the motion data of the learner and expert based on a technique used in automatic speech recognition, expressing the degrees of similarity of the two time series aligned in order to cancel the difference of the learner and expert in speed.

Chua et al. developed a game to allow a better training in Tai Chi [45]. This is one of the few articles found in literature about this application where a motion capture system is used. In this case, in fact, the training environment uses the Vicon motion capture system (equipped with 12 cameras) to record motions of the student, who wears a head mounted display (HMD) during the session, through which they see a rendered virtual environment (quiet and peaceful, as it should be for practicing this martial art) containing animated representations of both the student and the teacher.

Figure 2.14 Left: a student in the Tai Chi trainer, Right: the virtual world, student is in light, teacher in dark clothes [45]

The student wears a Spandex unitard (skin-tight one-piece garment with long legs) with reflective markers (41 in total, with a diameter of 14 mm each) applied to the clothing and skin, as well as a belt that holds batteries and the receiver for the HMD. With the Vicon system, it is possible to compute a 17-bone skeleton. The difference between the positions of these bones for the teacher (previously recorded, then normalized) and the student is used to define the error. Furthermore, different types of training environments were tested, in which the relative position of teacher and student would change (side by side, superimposed, etc.). However, the participants in the study expressed no significant preference among them.

Two major sources of error were found: the first is related to the orientation, because if the student was not oriented in precisely the same way as the teacher, additional error would be added to all bones in the student's body; the second is a consequence of the tendency of the students to lag behind the master. In order to minimize these errors an offset angle for the orientation and a time shift were applied.

A research with a similar objective, carried out by W. O. de Morais and N. Wickstrom [46], intended to develop a serious computer game (where serious means not only with the purpose of entertaining, but to achieve a major goal as well) to assist Tai Chi training for the elderly, but in this case by using wearable sensors and a camera. The specific aim of the project comes from the fact that older adults are particularly exposed to health issues resulting from falls and the associated costs for the Health System are high. As said before, Tai Chi is a good option when it comes to reducing these risks.

The system designed in the study is decomposed in two modules (Figure 2.14). The first is the game design, consisting in recording the gestures of a Tai Chi instructor while he is performing a sequence of movements. In order to do this, a camera was used (recording grey scale images), as well as a Shimmer wireless sensor platform, worn by the instructor on the wrist. Acquired data are then processed to create gestures and a virtual instructor.

The second module consists in the game play, during which the player tries to imitate the movements of the virtual instructor. To assess the quality of the performance, only data from the wireless wearable inertial measurement units is used, by comparing it with a prerecorded template (of the instructor). The comparison was done by using a specific technique, the Longest Common Subsequence (LCSS), which enables the system to match two sequences by allowing some elements of them to be unmatched, in space, time or both. By changing the fundamental parameters for this algorithm, it could also be possible to set different levels for the game.

Conclusions drawn from the study include the need to add more Shimmer units (not only positioned on the arms), to provide online feedback to the user and to better investigate the usability of the system.

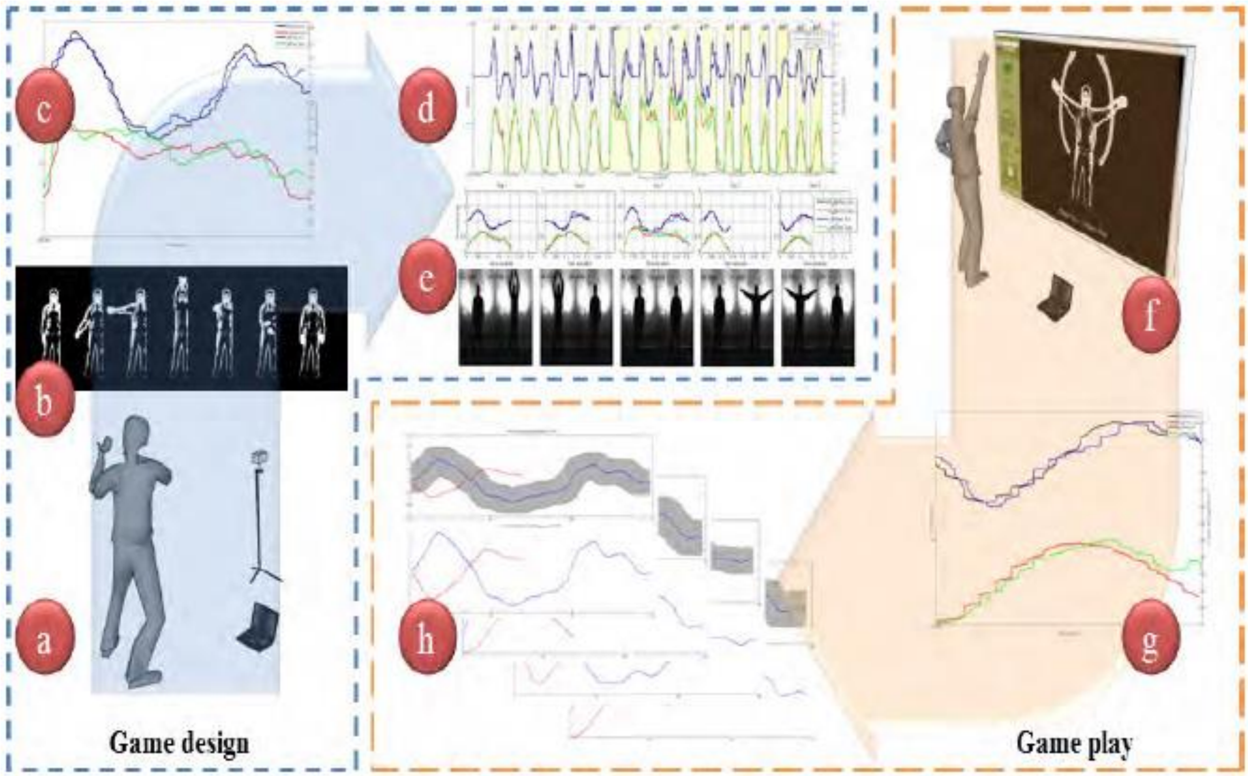


Figure 2.15: The complete system in [46] consists of a) the Tai Chi instructor training being recorded using a camera and wearable inertial measurement units; b) extracted movement silhouettes, used to create a virtual instructor; c) measured kinematic data; d) image analysis, used to decompose the training into segments; e) a gesture template; f) the player interacting with the game; g) the player's gestures are measured; h) computed similarity between the measured gesture and a stored gesture template

In a paper by Kwon and Gross, a system is developed for Tai Chi training combining body and visual sensors, consisting in a camera, a wireless sensor network and a display device (a projector or a monitor) [47]. During the acquisition, signals are collected from both the body sensor and the visual sensor. The input motion is then analyzed (segmented first, then motion detection is performed) and assigned a score by comparing it with reference data. Visual data is processed in real-time to track the body position (time stamps allow to synchronize it with sensors data). Visual feedback is then generated in the images incorporating the body sensor data. The choice was to display a moving circle along the path of the sensor, changing its size according to the magnitude of the acceleration (Figure 2.16).

Usually, similar systems are developed specifically for trainees, and not for trainers.

However, trainers could use such technologies to create instructive material, which the trainees can then refer to. This is allowed by the system of this study, permitting to generate motion-training videos very easily, a process that usually takes a lot of time. In fact, as soon as the input motion is detected, both the relevant video frames and the body sensor data are saved. Then a video is generated, displaying body sensor data along the tracked sensor positions.

Figure 2.16: Example video frames for visual feedback with the mean power of acceleration signal [52]

In [48], the idea is to use low cost wearable sensors to enhance mobile interactions with learning and games multimedia, developing a system suited to anytime anywhere use. Since 10 sensors are worn (on the arms, legs, waist and torso), it is possible to recognize what the user is doing. Tai Chi was chosen in this particular study, as it presents a large number of sub movements, each of which requires classification. For this purpose HMM (Hidden Markov Models) technique was used, proven to work sufficiently well for the purpose of multimedia interaction. Furthermore, in order to calculate each limb's Cartesian position in 3D space (shown on a screen as an avatar bone model), the sensor data is processed within a forward kinematics algorithm. As there is no relationship between the avatar and the actual size of the user, the movements of different users can be directly compared. The technique used allows calculating the mesh for any number of avatars and rendering their animation in real time. Also, it is possible to compare the models of teacher and student, and to help the latter improving their performances, by giving a text message with instructions for example, or by changing the colors of the limbs involved in the error.

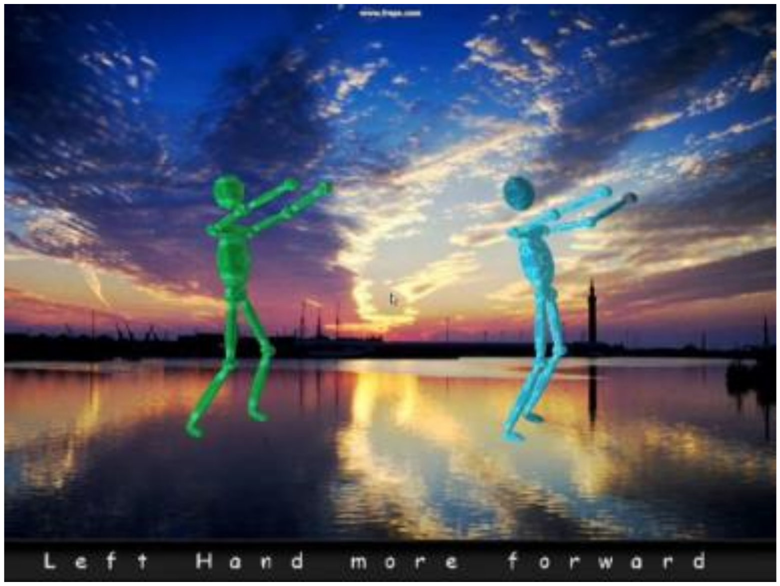


Figure 2.17: Comparison of a teacher's avatar and a student's avatar in real time [48]

Kunze et al. carried out a particularly interesting study, with the aim of recognizing different Tai Chi movements by using inexpensive wearable sensors [49]. In fact, tiny gyroscopes and accelerometers represent a cheap alternative for motion capture, as they let people move and roam about freely independent of any additional infrastructure (a set up that, as we saw before, opens up a wide range of potential application, including rehabilitation). However, the problem for this type of use, is that the algorithms used should be able to compensate for inaccuracies inherent to inexpensive wearable sensors systems, coming from limited resolution and sampling rate of the sensors, variations in sensor placement, dynamic sensor displacement during user motion, and other sources of noise (e.g. environmental magnetic fields or temperature-related sensor drift). In the design of these algorithms, the challenge is to find features that are sensitive to the relevant motion characteristics and at the same time insensitive to the inaccuracies mentioned before. As far as Tai Chi is concerned, because of its clinical value, it would be important to be able to assess the quality of exercises as we said before, but even experts find it hard to quantify and judge the quality of Tai Chi performances.

The study features four different people (two experts and two amateurs with limited experience) as test subjects and three kinds of basic Tai Chi movements (each performed five times). The sensors used were eight in total, placed on the subjects' arms, legs, feet, hip and neck. Each sensor used houses a 3-axis accelerometer, a 3-axis gyroscope and a 2-axis magnetometer.

By looking at accelerometer and gyroscope data, some differences between experts and amateurs were evident. The signals corresponding to experts were smoother and more periodical, and the number of events where the absolute sum of the foot gyroscopes is smaller than 0.1 was much less with them (this could mean that pauses and choppy movements are more present in amateurs). A total of 20 features were extracted, including the squared angular velocity, as indication for the rotational energy. This latter is particularly meaningful if we consider that one key principle in Tai Chi is that the total consumed energy is supposed to be as small as possible.

Different sets of features were then used to train a K-nearest-neighbor (KNN) clustering algorithm, giving promising results in classification (with two features, the 75% percentiles and the frequency range power, 76% of the instances were correctly classified, see Figure 2.18). This gave evidence that an automated evaluation of Tai Chi is, in fact, possible.

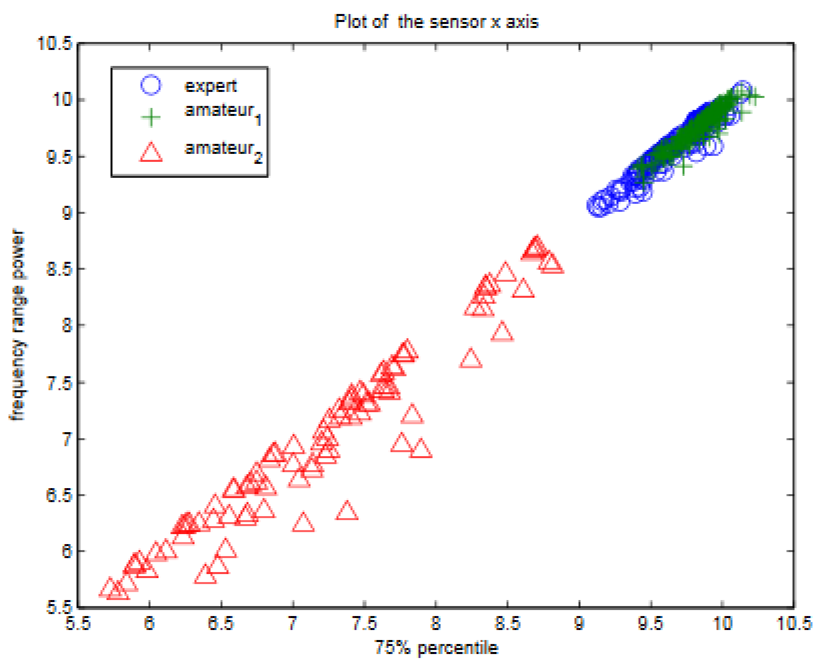


Figure 2.18: 75% percentile plotted against the frequency range power from the neck accelerometer [49]

A recent commercial device aims working as a fitness trainer, but also at helping in a task that is a fundamental element in Tai Chi practice: meditation. Lumafit Zen App guides the user through in meditative breathing and gives a visual representation of the reduction of stress. This is mainly achieved by analyzing the hearth's response to meditative breathing, as the device includes an ECG sensor, but also by tracking the head movement, thanks to the presence of an accelerometer sensor [50].

Furthermore, unlike the majority of the commercially available health gadgets worn on the wrist, the Lumafit is an earpiece that clips onto the earlobe. The interesting aspect of this device is that, as far as the fitness trainer functionality is concerned, it is supposed not only to track the amount of physical activity carried out by the user, but also to evaluate whether or not the exercises are done correctly. In the future, a further advance in the device and a wise choice in the placement of the motion sensors could allow transferring the technology to the evaluation of Tai Chi practice.

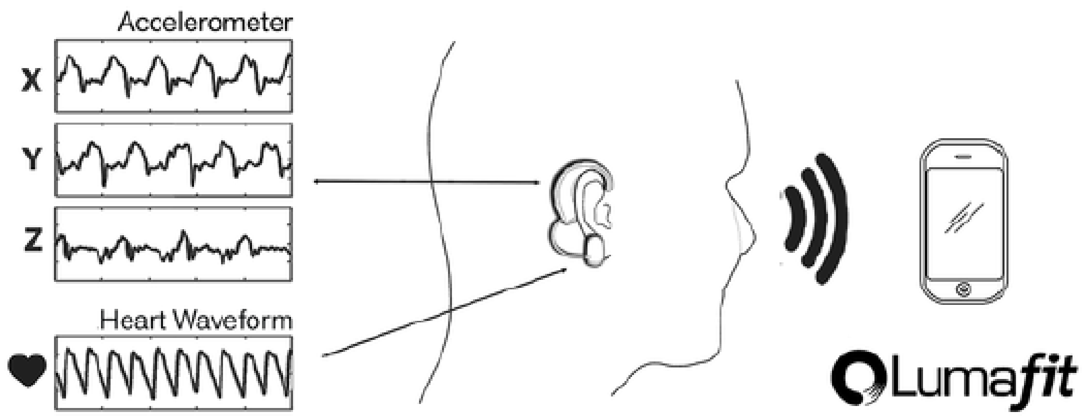


Figure 2.19: Schematization of the Lumafit Trainer

This kind of devices are becoming popular and interesting on the market, since the future of digital health combines two big trends, one is behavioral, making user experiences that make being healthy more fun, the other is about data, giving people tighter feedback on their overall health and insight into how to make this data meaningful [51].

Wu et al developed another system for Tai Chi training, very different from the ones presented before [52]. The prototype they describe in their article aims at facilitating group Tai Chi exercises, and is characterized by less physical constraints compared to conventional camera-based motion capture systems, so that users can practice exercises almost anytime anywhere.

The system architecture (shown in Figure2.20) allows a Tai Chi master to create a Tai Chi class on a social network and invite friends to join. While all of them are performing the exercises, users motions are collected by remote BSNs and rendered on the social network. In fact, a user who wants to exercise Tai Chi with this system has to carry a BSN, which is composed by 9 sensor nodes (two on the arms, two on the legs and one on the trunk, each composed by a 3-axes accelerometer, a digital compass, an event controller and a wireless module) and one sink node (running a polling protocol to collect sensory data from the sensor nodes, reporting the data to the Tai Chi engine through Wi-Fi).

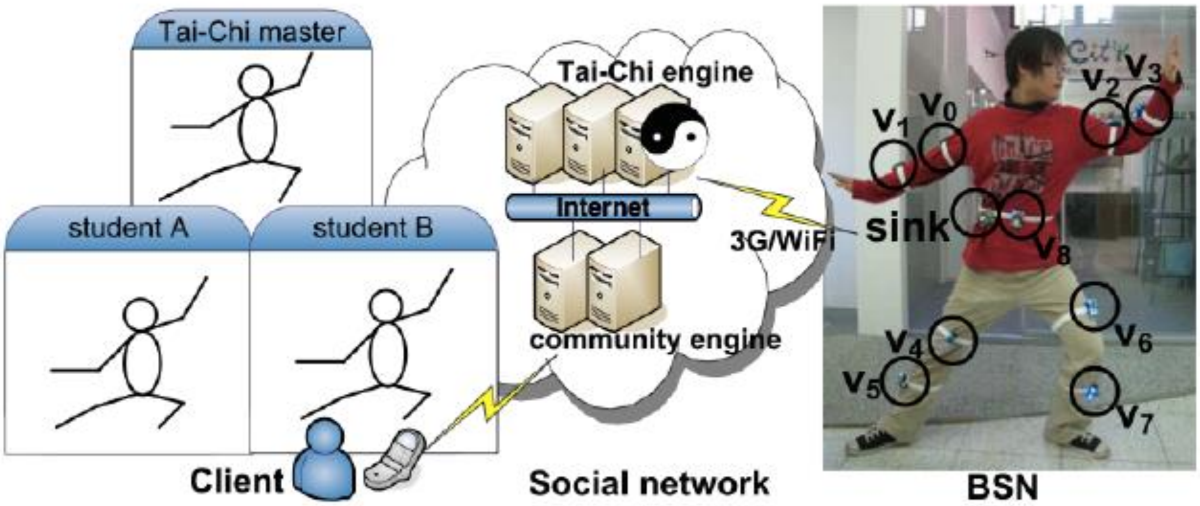


Figure 2.20: Architecture of the virtual / physical Tai Chi social network [53]

The Tai Chi engine is responsible for computing and rendering user's motions, while the other component of the social network, the community engine, allows the users to interact with each other.

Such a system presents great potential, especially if we think about its possibilities in telerehabilitation, allowing following a physical therapy program consisting in Tai Chi from home.

2.3 Basic concepts of Machine Learning

Machine learning is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed, a subject that studies how to use computers to simulate human learning activities, and to study self-improvement methods of computers to obtain new knowledge and new skills, identify existing knowledge, and continuously improve the performance and achievement [53].

Machine learning focuses on the development of computer programs that can change when exposed to new data; so in general, it is about learning to do better in the future based on what was experienced in the past.

Tom Mitchell defines a well-posed learning problem as a problem where a computer program is set to learn from an experience E with respect to some task T and some performance measure P if its performance on T as measured by P improves with experience E [54].

Although a subarea of AI, machine learning also intersects broadly with other fields, especially statistics, but also mathematics, physics, theoretical computer science and more.

There are many examples of machine learning problems. Here are a few:

– Optical character recognition: categorize images of handwritten characters by the letters represented

– Spam filtering: identify email messages as spam or non-spam

– Topic spotting: categorize news articles (say) as to whether they are about politics, sports, entertainment, etc.

– Medical diagnosis: diagnose a patient as a sufferer or non-sufferer of some disease

– Customer segmentation: predict, for instance, which customers will respond to a particular promotion

– Fraud detection: identify credit card transactions (for instance) which may be fraudulent in nature [55]

The different problems we can encounter in machine learning can be solved in a variety of ways, but a first distinction breaks machine learning into two broad regimes: supervised learning and unsupervised learning.

In order to understand them, though, some basic definitions are fundamental. First, an example (sometimes also called an instance) is the object that is being classified.

Usually, an example is described by a set of attributes, also known as features or variables.
The label is the category that we are trying to predict. During training, the learning algorithm is supplied with labeled examples, while during testing only unlabeled examples are provided.
In Supervised Learning, we have a dataset consisting of both features and labels (to take the spam example from before, we would have both emails and their related classification as spam or non spam). The process entails learning a mapping between a set of input variables X (features) and an output variable Y (label) and applying this mapping to predict the outputs for unseen data. Supervised learning is further broken down into two categories, classification and regression. In classification, the label is discrete, while in regression the label is continuous. Whether we are trying to solve a classification or a regression problem, the aim will be of inferring a function from labeled training data, trying to minimize a cost function that expresses the error committed when predicting labels from an input example.
Unsupervised Learning addresses a different sort of problem. Here the data has no labels, so the aim is to find hidden structure in unlabeled data [56].
In order for learning to succeed, different conditions must be met. For example, it is fundamental to have enough data. Moreover, a rule has to be found that makes a low number of mistakes on the training data. Also, this rule has to be as simple as possible.
The last two requirements are typically in conflict with one another, so it is always necessary to find a good balance between the two.
From what was said before, it is clear that the first step when applying machine learning is to extract features able to capture the information needed for the prediction to be possible.
However, the number of features can rapidly become very big and data visualization, useful to evaluate their efficacy, as a consequence has to be carried out using dimensionality reduction. This is the task of deriving a set of new artificial features that is smaller than the original feature set while retaining most of the variance of the original data. The technique is not only useful for visualization of high dimensional datasets, but it can also be used as a preprocessing step to help speed up supervised machine learning methods that are not computationally efficient with high number of features [57].
For this purpose, in Chapter 3, Sammon mapping will be used, an example of non-linear approach for dimensionality reduction. In fact, when operating a form of dimensionality

reduction, it is useful to preserve structure as much as possible, which means that the geometric relations between the original data points should be left intact to the greatest extent feasible.

More specifically, the measure used by the Sammon mapping is designed to minimize the differences between corresponding inter-point distances in the two spaces and a transformation is regarded as preferable if it conserves the distance between each pair of points as much as possible. In addition, it attempts to ensure that the mapping does not affect the topology, so the importance of preserving relations between nearby points is emphasized [58].

Since the number of features can be very high, another step that can be taken before building the predictive model is the one of feature selection.

This is the process of reducing the number of total features by eliminating the ones that are redundant (they do not provide any additional information to the one obtained with all the other features extracted) or irrelevant (they do not capture any relevant information).

In this work, feature selection is performed in two steps. First, the ReliefF [59] algorithm has been used; this algorithm ranks the features in decreasing order of importance.

The ReliefF feature selection algorithm is an extension of the original Relief algorithm proposed by Kira et al. [60]. The ReliefF algorithm iterates through every instance updating the weights assigned to a feature at each iteration.

The second step of the feature selection procedure consisted of selecting an appropriate number of top ranked features provided by the ReliefF algorithm in step 1.

In this specific case, the aim is the selection of the top N ranked features that provided the maximum class separation among classes associated with different clinical scores defined in the reduced feature space; this purpose is achieved by calculating the Davies-Bouldin (DB) cluster validity index [61].

The DB index measures how well-separated data samples belonging to different classes are and how similar samples in the same class are. It is a function of the ratio of the sum of within-class scatter to between-class separation.

Thus, smaller values of the DB index indicate better class separation and vice versa. The DB index is calculated by incrementally adding, one at a time, features ranked according to the ReliefF algorithm.

The effect of the process of feature selection will consist in a model that is easier to interpret, shorter time needed to train it and better generalization capabilities, thereby reducing overfitting.

When a good set of features is extracted, the following steps consist in choosing and building a model.

A number of different algorithm can be used, but for the purpose of better explaining the techniques used in this project, only the one that was chosen will be presented: Linear Discriminant Analysis.

Linear Discriminant Analysis (LDA) is a well-known scheme for feature extraction and dimension reduction. It has been used widely in many applications involving high-dimensional data, such as face recognition and image retrieval [62].

This classification method has been originally developed in 1936 by R. A. Fisher. It is simple, mathematically robust and often produces models whose accuracy is as good as more complex methods.

The idea of LDA is to find a linear transformation of feature vectors X from an n-dimensional space to vectors Y in an m-dimensional space ($m < n$) such as the ratio of the between-class distance to the within-class distance is maximal, thus achieving maximum discrimination [63].

LDA is based upon the concept of searching for a linear combination of variables (predictors) that best separates two classes (targets). To capture the notion of separability, Fisher defined the following score function.

$$Z = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_d x_d$$

$$S(\beta) = \frac{\beta^T \mu_1 - \beta^T \mu_2}{\beta^T C \beta} \qquad \text{Score function}$$

$$S(\beta) = \frac{\bar{Z}_1 - \bar{Z}_2}{\text{Variance of Z within groups}}$$

Given the score function, the problem is to estimate the linear coefficients that maximize the score which can be solved by the following equations.

$$\beta = C^{-1}(\mu_1 - \mu_2)$$ *Model coefficients*

$$C = \frac{1}{n_1 + n_2}(n_1 C_1 + n_2 C_2)$$ *Pooled covariance matrix*

Where:

β : *Linear model coefficients*

C_1, C_2 : *Covariance matrices*

μ_1, μ_2 : *Mean vectors*

A simple linear correlation between the model scores and predictors can be used to test which predictors contribute significantly to the discriminant function. Correlation varies from -1 to 1, with -1 and 1 meaning the highest contribution but in different directions and 0 means no contribution at all.

Chapter 3: Materials and Methods

3.1 Experimental setup

In this session, the fundamental devices used for the data collections will be briefly presented, as well as a detailed description of the data collection procedure.

3.1.1 Vicon motion capture system

The Vicon optoelectronic system (Oxford Metrics, UK) is an example of motion capture system available on the market today.

Motion capture is the recording of movement by an array of video cameras in order to reproduce it in a digital environment. The Vicon system includes hardware and software applications for the complete control and analysis of motion capture [64].

The two fundamental elements necessary to explain how the system works are the cameras and the reflective markers.

A typical motion capture space comprises an area, the capture volume, surrounded by a variable number of high-resolution cameras.

Each camera, which operates between 50 and 240 Hz, presents a ring of infrared light emitting diodes fixed around the lens. When collecting data with the system, light from the strobe is reflected back through the markers into the camera lens and strikes a light sensitive plate creating a video signal. A filter ensures that only light the color of the strobe (red or infra-red) is allowed to strike the light sensitive plate behind the lens.

Markers have the shape of small spheres covered with a retro reflective material and are placed on well-defined positions of the subject whose movement is going to be recorded.

The two-dimensional data from each camera are then combined with calibration data to reconstruct the equivalent digital motion in three dimensions. The above mentioned calibration is one of the most important steps in a data collection with the Vicon system, allowing it to define the capture volume and to measure each camera's position relative to the others (information that then make the reconstruction process possible).

At the same time, other kinds of signals can be recorder as well, as analogue signals from force plates, EMGs, etc.
The files generated from the system come in the C3D (Coordinate 3D) format, developed in the past to get a convenient and efficient format to store data collected during biomechanics experiments, and representing today the most common data file format for biomechanical 3D data. These files store 3D trajectories, as well as analog data and parameters of interest for the data analysis (force plates positions, data points labels, measurement units, but also subject's name, physical parameters…).

3.1.2 Shimmer sensors

Shimmer's wearable sensor platform and equipment (Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability), commercialized by Shimmer Research, a division of Realtime Technology Ltd. in Ireland, allows for simple and effective biophysical and kinematic data capture in real-time for a wide range of application areas [65].
Designed to be robust, flexible and configurable, Shimmer's wireless sensor technology provides high quality scientifically reliable data to support researchers and academics in their data collection.
Shimmer can also incorporate, through internal and external connectors, wireless ECG (Electrocardiogram), EMG (Electromyogram), GSR (Galvanic Skin Response) accelerometer, gyroscope, tilt and magnetic sensors and records and can transmit physiological and kinematic data in real-time [66].

Figure 3.1: Example of a Shimmer unit used during the data collection

The platform consists of a TI MSP430 microprocessor; a Chipcon CC2420 IEEE 802.15.4 2.4GHz radio; a MicroSD card slot; a triaxial MEMS accelerometer, the Freescale MMA7260Q, which can be configured with sensitivities of 1.5, 2, 4, or 6g; and optionally, a Bluetooth radio which allows streaming of sensor data at high rates.

The SHIMMER device is unique in that it combines computation, radio communication, multiple sensor modalities, and a large flash memory into a tiny, wearable rugged plastic enclosure. The device measures 4.45 x 2 x 1.3 cm and weighs approximately 10g.

It includes a re-chargeable lithium polymer battery for easy maintenance.

The above-mentioned MMA7361L is a low-power, low profile capacitive, 3-axis micromachined accelerometer. Some typical features are signal conditioning, single-pole low pass filter, temperature compensation, self-test, 0g-detect that detects linear free-fall and g-select, which allows for the selection between sensitivities.

For this specific application, since an ECG Shimmer unit was included in the set up, a sampling frequency of 256 Hz was set for all of the sensors.

3.1.3 Data collection procedure

The data collections were carried out on 15 healthy subjects (all in the same age range: 40-70 years old) who came for one single session, lasting about two hours.

All of them were enrolled in a Tai Chi class in the Boston greater area, but presented heterogeneous experience in this martial art, ranging from some weeks to decades of practice.

They were all asked to wear comfortable clothing, consisting in shorts and a tank top ideally.

Every time, before starting preparing the subjects for the data collection, they were consented. After every aspect of the study was explained to them (including study procedures and equipment, risks of the testing, benefits, privacy…) and all of their questions were answered, they signed the informed consent and a copy of it was given to them.

The first part of the experiment consisted in the setup.

Thirty-five reflective markers were placed in specific points of the body using adhesive tape, following the Plug in Gait full body model of the Vicon system. Four of them were positioned on the head of the subjects, seven on the trunk and back, four on each arm, four on the pelvis, and six on each leg.

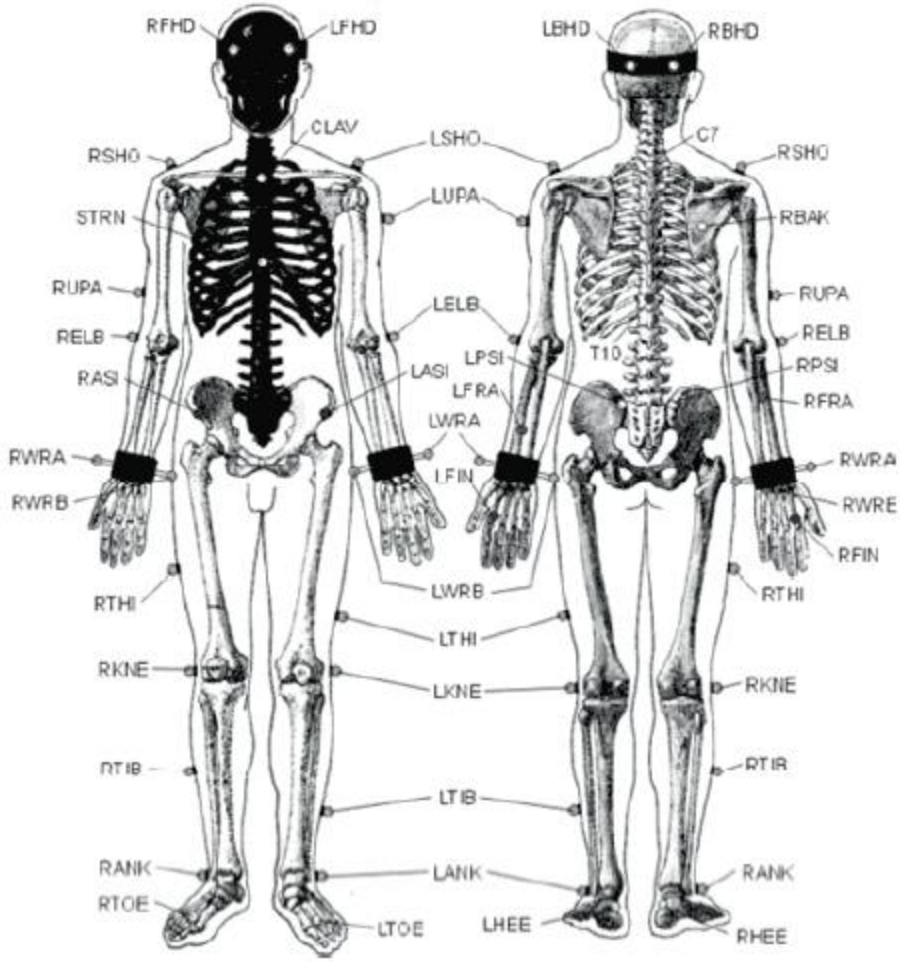


Figure 3.2: Vicon Plug-in-Gait model markers placement [66]

After turning them on, ten sensors were then placed on the body by using Coban (a self-adherent wrap used to secure dressings and other devices), in the following positions: upper arm, wrist, thigh, ankle (all on the right as well as left side of the body), plus waist and chest. Both of the sensors positioned on the ankles were connected to disposable insoles (previously prepared in order to match the subject's shoe size) inserted in the shoes of the subject, presenting pressure sensors underneath them (Figure 3.3).

Figure 3.3: Insole equipped with pressure sensors (heel and toe)

The sensor on the right wrist was also measuring the galvanic skin response (GSR), collecting the signal from electrodes attached to straps closed around the index and middle fingers (Figure 3.4).

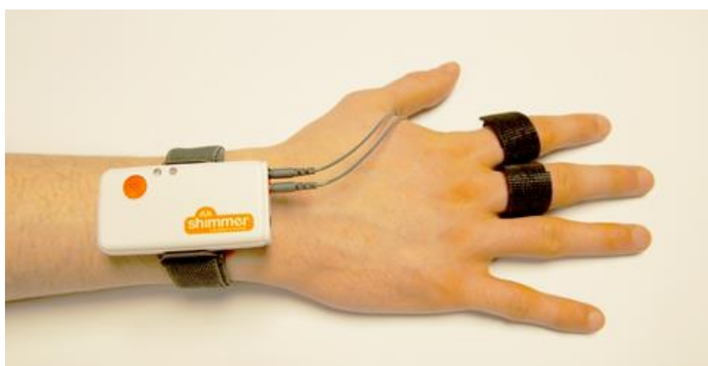


Figure 3.4: An example of Shimmer GSR sensor [65]

The sensor on the chest also recorded the ECG signal of the subject, being connected to three electrodes positioned to form a triangle (one on the right side of the chest, one on the left side of it, and the third below the latter on the left side of the belly).

The orientation of all the sensors was kept constant among the different subjects, and if changes were applied they were noted in the session trials sheets, so that appropriate corrections could be made.

For the sensors on the limbs, the x-axis of each Shimmer was oriented along the caudal axis of the body, the y-axis along the anteroposterior and the z-axis along the mediolateral. The only exception was represented by the sensors on the wrists, for which x and y-axes were reversed.

The eleventh sensor that was used was placed on the desk where the Vicon computer was, connected through a cable to a push button used with the Vicon system. The button was pushed three times at the beginning and at the end of each task the subject was asked to perform, to allow the segmentation and synchronization of the sensors data with the Vicon data.

After completing the setup (which took in average 30 minutes), some measurements were taken on the subject and saved on the Vicon software: ankles, knees, wrists and elbows widths, legs length, shoulder offsets and hands thickness, all required by the Vicon full body Plug in Gait model.

The subject was then asked to stand on a force plate. While recording with the Vicon system, first a static trial was captured. This involves the subjects standing in a stationary position for about three seconds and labeling the trial. It enables Plug-in-Gait to associate captured markers with known positions or labels and to calculate key parameters that are used later in the processing of the trials. During this stage, Nexus creates a Vicon Skeleton that is scaled to fit the particular subject and which will automatically label subsequent trials [68].

After that, two tasks were performed to test purely the balance of the subject: first standing with eyes closed for thirty seconds, then doing the same thing while counting backwards from a certain number aloud (to test the ability to maintain balance while also doing something else, in this case calculations). Each of them was repeated three times.

Once these trials were completed, the subject was shown videos of a Tai Chi master performing specific Tai Chi exercises. People were allowed to watch the videos as many times as they needed and to practice while watching them. Once ready, data was collected with the Vicon system while the subject kept performing the exercise without looking at the video, until an established number of repetitions (varying from 4 to 9) was reached.

This was repeated for six different Tai Chi exercises previously chosen by the Tai Chi master: Raising the Power (RTP), Push, Grasp the Sparrow's Tail (GST), Wave Hands Like Clouds (WHLC), Brush Knee Twist Step (BKTS) and the Golden Rooster (GR). Push, GST, BKTS and GR were performed in two versions, either with right or left foot forward. WHLC presented three variations, two in which only the right or left hand was moving, and the last in which both moved at the same time.

All the sessions were videotaped, so that videos could be segmented and sent to the Tai Chi masters in charge of giving scores to them.

When the data collection was completed, all the markers and sensors were removed from the body of the subjects and the sensors turned off.

3.2 Data analysis

3.2.1 Vicon data processing

This phase, as well as the data collection, was carried out by colleagues who previously worked with these data.

Data acquired by means of Vicon system was first reconstructed and after that, every trial was fixed so that all markers were correctly labeled and no gaps were present in their trajectories (due to markers not seen by the cameras for a certain amount of time).

Dynamic processing was then applied in order to obtain angles, moments and forces for the different body segments.

The following step that has been done is represented by the data segmentation in the 12 different exercises and then in the different repetitions for each exercise. A particular position (usually the starting position in the videos of Peter Wayne) was chosen as the starting point for each repetition.

Events were placed on the Nexus software at frames corresponding to those reference positions.

3.2.2 Shimmer data processing

After every session, data were downloaded from each Shimmer sensor on a computer and then imported into Matlab, saved in a structure.

Accelerometer data (ADC values) were converted to g's, and the data were low pass filtered, by means of Butterworth filter with a cut off frequency of 12 Hz, in order to remove the noise at high frequency from the useful signals.

The ECG signal was band pass filtered, using a Chebychev filter with 5 Hz and 40 Hz as cut off frequencies.

GSR data were fixed using factors, due to automatic changes in gain of the Shimmer sensors during the data collection.

Accelerometer signals from sensors on the left side of the body were flipped (on the x and z axis) in order to fix differences in their orientations compared to the ones on the right side.

As for the Vicon data, the segmentation of Shimmer data was carried out in order to divide them first in 12 different exercises, by means of the signal from the eleventh sensor connected to the push button of the Vicon system.

After that, a second segmentation was used to split the different repetitions of each exercise, this time using the events added on the C3D files, after synchronization of the sensors and the Vicon data.

3.2.3 Discrimination of Tai Chi exercises

In order to monitor Tai Chi performers, it is necessary to fulfill two main goals: the discrimination of the 12 Tai Chi exercises and the assessment of proficiency level of each practitioner; in this part, the attention will be focused on the first purpose, describing in details the workflow to reach the results.

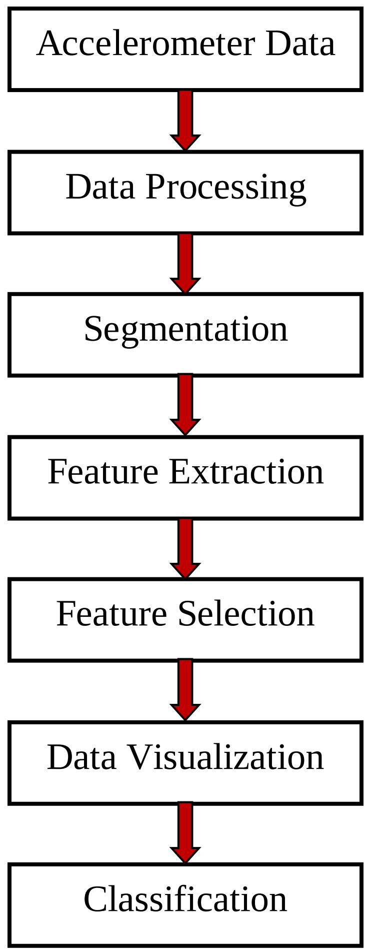


Figure 3.5: Workflow to analyze accelerometer data

In the figures below, signals of two different exercises are presented, the left version of GST and WHLC exercise, coming from the sensor put on the left wrist of one subject with high proficiency level, in order to understand how the signals of different exercises can vary and to decide which meaningful features can be extracted.

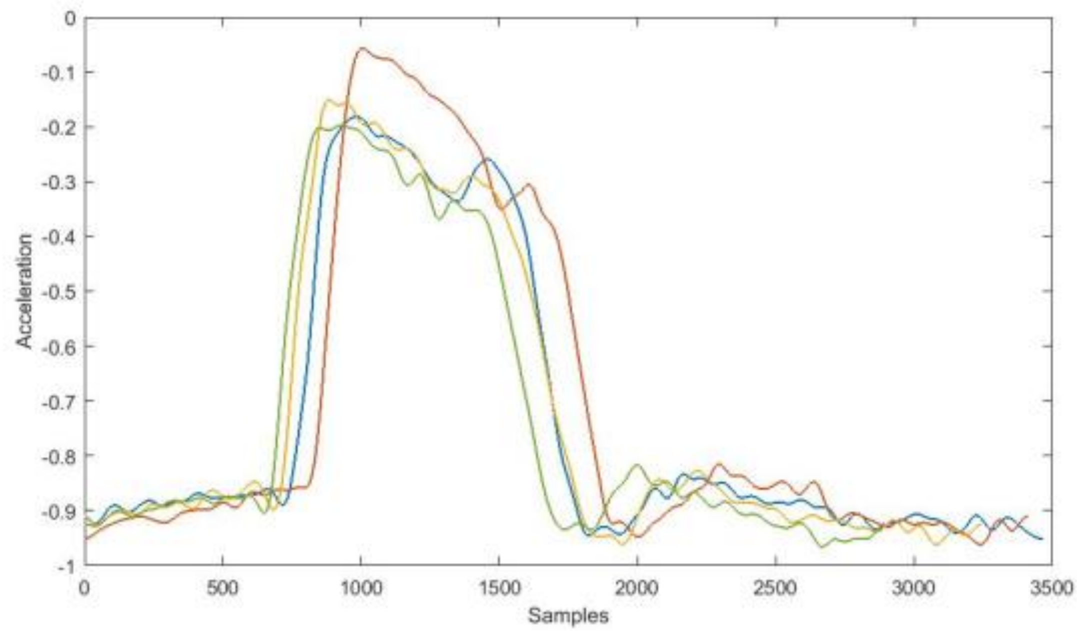


Figure 3.6: Acceleration on the x-axis of the sensor put on the left wrist for different repetitions of GST_L

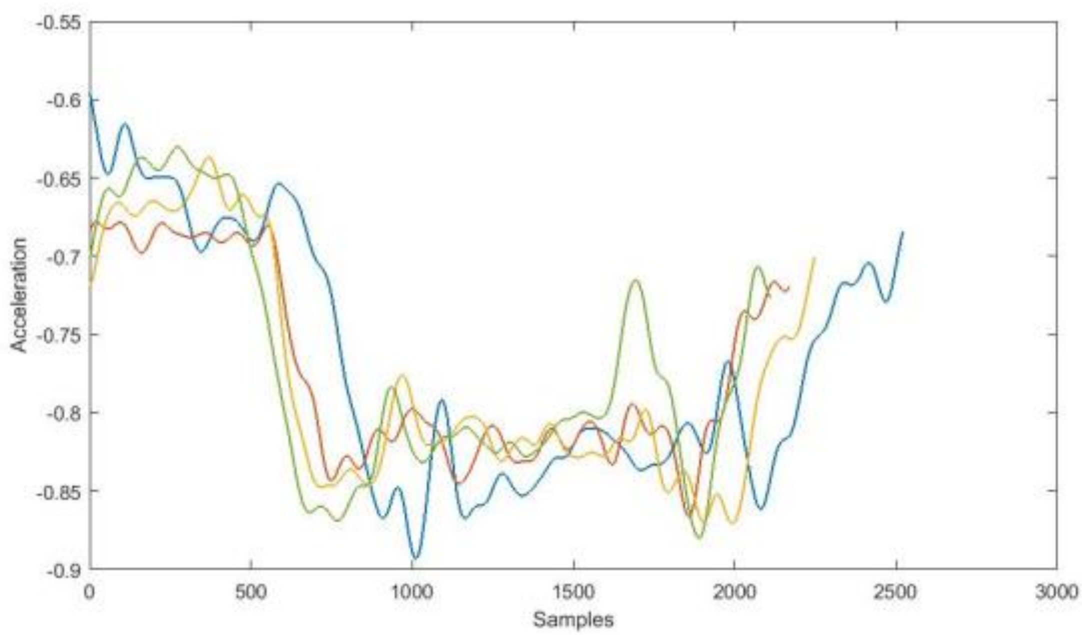


Figure 3.7: Acceleration on the x-axis of the sensor put on the left wrist for different repetitions of WHLC_L

The following figures, instead, could help to comprehend how the same sensor is more or less important to capture important features for different exercises.

The first figure shows the signals of one static exercise (RTP) coming from the sensor put on the left ankle of a subject with high proficiency level, while the second one shows the signals of one dynamic exercise (left version of BKTS) coming from the left ankle sensor of the same subject.

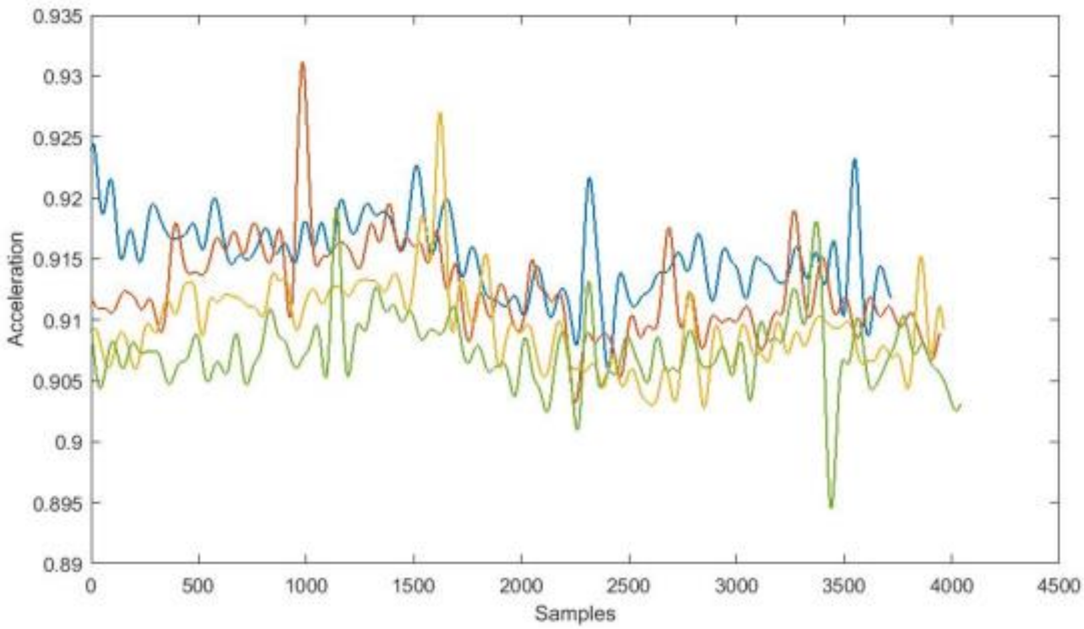


Figure 3.8: Acceleration on the x-axis of the sensor put on the left ankle for different repetitions of RTP

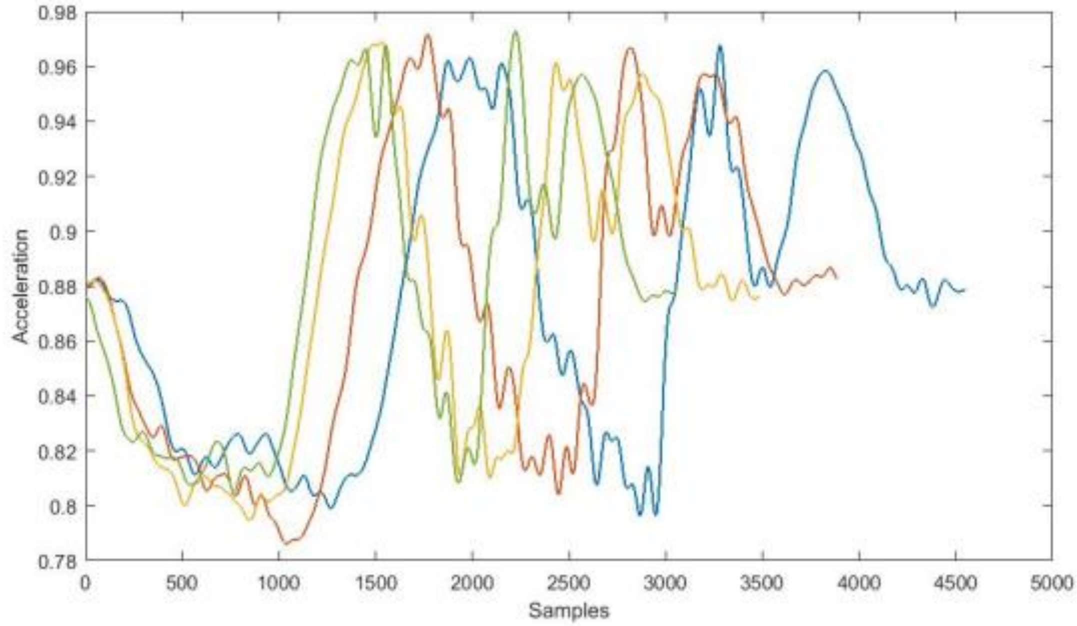


Figure 3.9: Acceleration on the x-axis of the sensor put on the left ankle for different repetitions of BKTS_L

3.2.3.1 Features extraction

This step is characterized by the search for the best features to use in order to obtain a good separation between the different exercises performed and to capture significant aspects of movement for each exercise, such as orientation and intensity of the signals.

Features were extracted from fifteen practitioners and from all accelerometers except for the one put on the chest because data were not completed for some subjects.

Since each practitioner performed the exercises in a different number of repetitions respect to the others, we decided to consider just the first repetitions for each of them, in order to obtain consistent results.

Specifically, the extracted features were represented by: range of acceleration, root mean square (RMS) of acceleration, standard deviation, frequency entropy, frequency range power and magnitude of the acceleration. The choice of these types of features was based on what has been done in literature in studies which had the goal to discriminate different exercises, and also based on the observation of the accelerometer signals, as well as the observation of movements that characterized each exercise.

For instance, the range of acceleration along the three axis provides us information about the orientation of the Shimmer sensors, while RMS of acceleration could tell us if a specific part of the body is moving or not. This last feature was calculated on the original signals, as well as on high pass filtered version of them (by using a cut off frequency of 0.8 Hz), so that the gravity component could be removed.

All the features were derived from the low pass filtered version of the data and considering separated the three axis of the nine sensors considered in the analysis, in order to keep the orientation of the wearable platforms during the exercises.

3.2.3.2 Features selection

This stage was developed in two different steps with the aim of finding the most relevant features to use in the discrimination of the 12 Tai Chi exercises.

First, the use of ReliefF algorithm allowed us to rank the features in a decreasing order of importance.

The ReliefF algorithm is an extension of the Relief algorithm proposed by Kira et al. [60] and it weights each feature according to its relevance to the class. Initially, all weights are set to zero and then updated iteratively. In each iteration, this non-deterministic algorithm chooses a random instance i in the dataset and estimates how well each feature value of this instance distinguishes between instances close to i. In this process two groups of instances are selected: some closest instances belonging to the same class and some belonging to a different class. With these instances, Relief will iteratively update the weight of each feature and it differentiates data points from different classes while, simultaneously, recognizing data points from the same class. At the end, a certain number of features with the highest weights is selected.

The second step of the features selection procedure consists then in the use of the Davies-Bouldin Index (DBI) which provides an appropriate number of top ranked features, based on the results of the ReliefF algorithm.

The Davies-Bouldin Index is defined as following:

$$\mathrm{DBI}\ (\mathrm{C}) = \frac{1}{K}\sum_{i=1}^{k} \max_{\mathrm{i}\neq \mathrm{j}} \left\{ \frac{\Delta(\mathrm{C_i}) + \Delta(\mathrm{C_j})}{\delta(\mathrm{C_i}, \mathrm{C_j})} \right\}$$

where $C = (C_1, \dots, C_K)$ is the clustering of the data set into K clusters, $\Delta(\mathrm{C_i})$ is the intra-cluster distance and $\delta(\mathrm{C_i}, \mathrm{C_j})$ is the inter-cluster distance.

Since the DBI is a function of the sum of within-class scatter to between-class separation, it measures how well-separated data samples belonging to different classes are and how similar samples in the same class are.

Thus, smaller values of the DB index indicate better class separation and vice versa.

At the end of the second step, the cardinality of the feature subset that produced the minimum DBI was selected.

3.2.3.3 Dimensionality reduction and data visualization

In order to evaluate if the features used were useful for the purpose of the project and to facilitate the visualization of the clusters corresponding to the different Tai Chi exercises, 3D Sammon mapping algorithm was used. This is a non-linear approach that provides a dimensionality reduction by trying to preserve the structure of the inter-point distances in the higher-dimension in the lower-dimension projection.

Sammon mapping is considered a non-linear technique since the mapping cannot be represented as a linear combination of the original variables, as in other approaches like PCA (Principal Component Analysis).

Sammon map is built by using the features extracted and ranked before in the previous steps in order to have the best separation of clusters.

The first separation that has been done is represented by the discrimination between the static and dynamic exercises, where static exercises are considered the ones in which the subjects do not move the legs, whereas dynamic exercises are the ones in which the subjects move the lower limbs as well as the upper limbs.

This first discrimination was carried out since it was the simplest one, thus it could show if the algorithm was working properly.

Other discriminations that have been done consist in the separation of the six exercises, without taking into account the left and right version of each of them.
The last mapping is given by the twelve different exercises, the first main goal to achieve, and some examples of each discrimination are shown below.

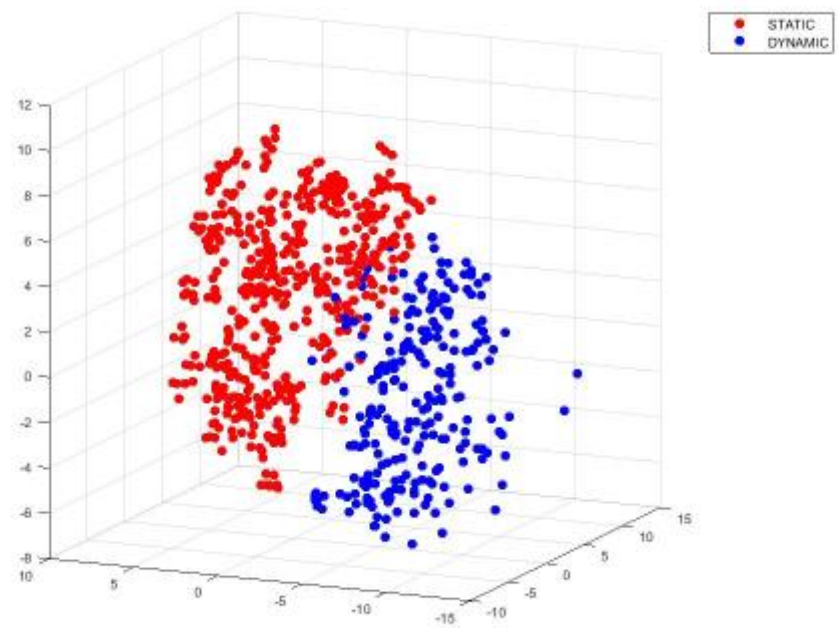


Figure 3.10: Sammon mapping to discriminate static and dynamic exercises by using all accelerometers

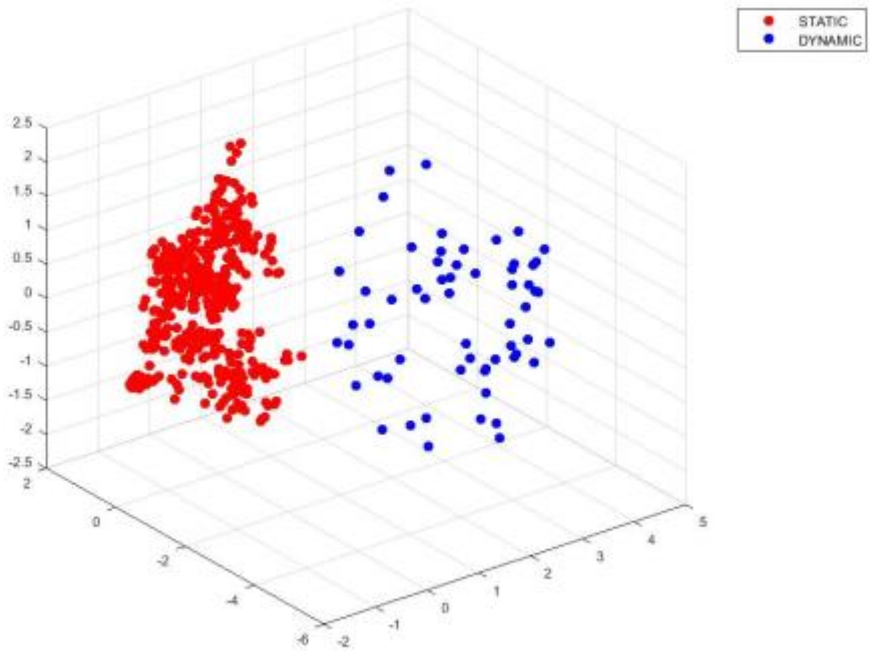


Figure 3.11: Sammon mapping to discriminate static and dynamic exercises using only ankles accelerometers

As shown in the figures, the 3D Sammon mapping used as technique to visualize data features in different clusters performs very well since it is possible to see clearly two distinct groups, both using all Shimmer sensors and only the sensors put on the ankles.

The same procedure was employed to visualize the data corresponding to the six exercises and the twelve exercises, by using both all sensors and, this time, the sensors put on the ankles and wrists.

The resulting mappings are not as clear as the previous ones since more clusters are involved in the analysis and the data comes from subjects with different proficiency levels, making more difficult obtaining twelve clusters well separated.

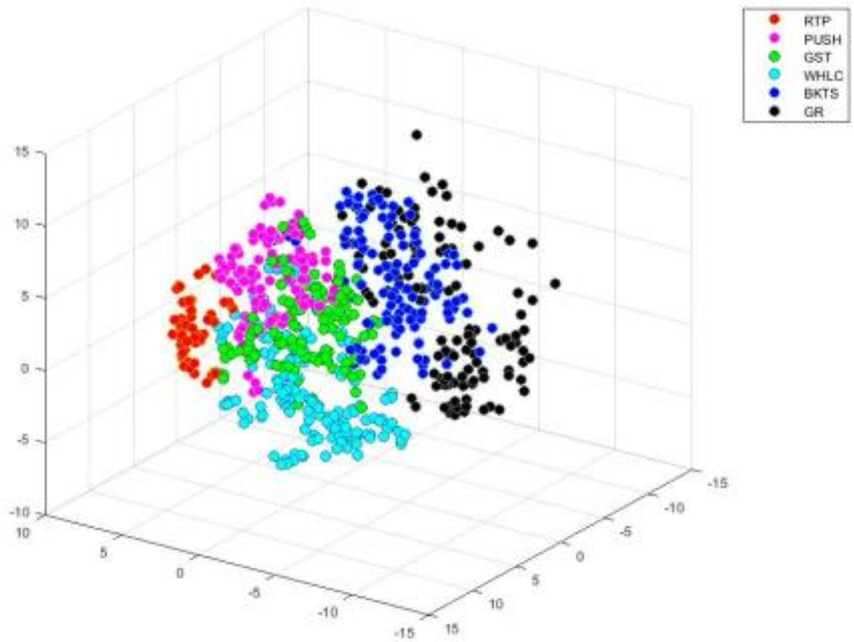


Figure 3.12: Sammon mapping to discriminate the 6 Tai Chi exercises using all accelerometers

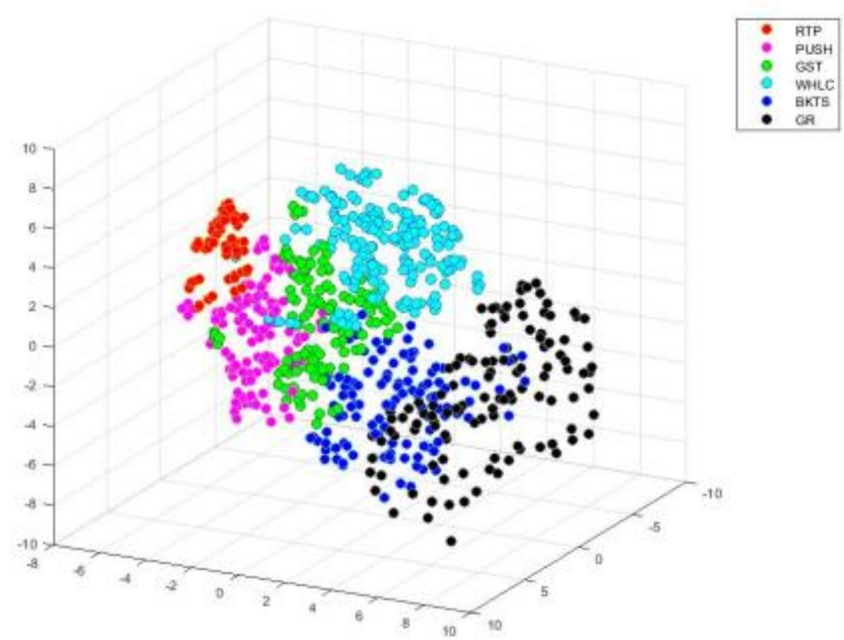


Figure 3.13: Sammon mapping to discriminate the 6 Tai Chi exercises using only ankles and wrists accelerometers

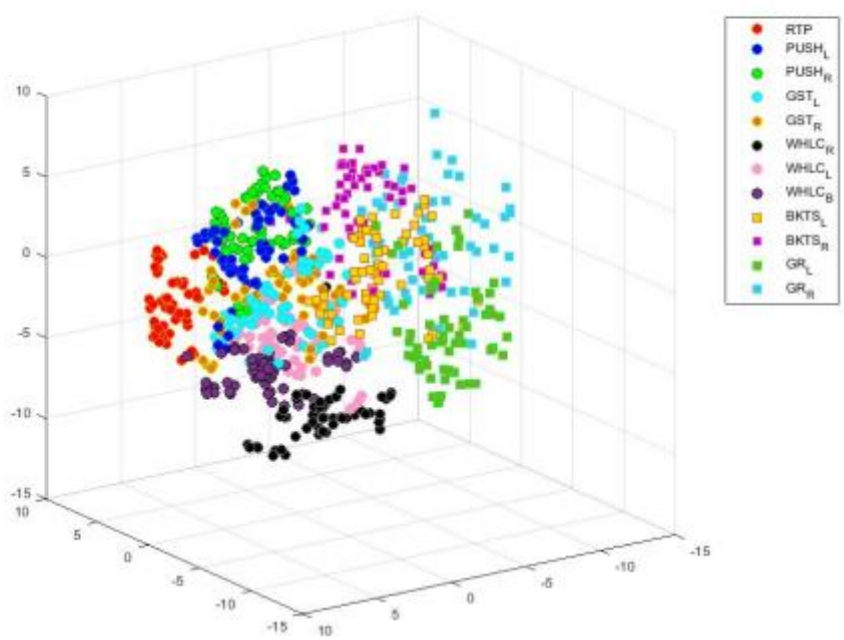


Figure 3.14: Sammon mapping to discriminate 12 Tai Chi exercises using all accelerometers

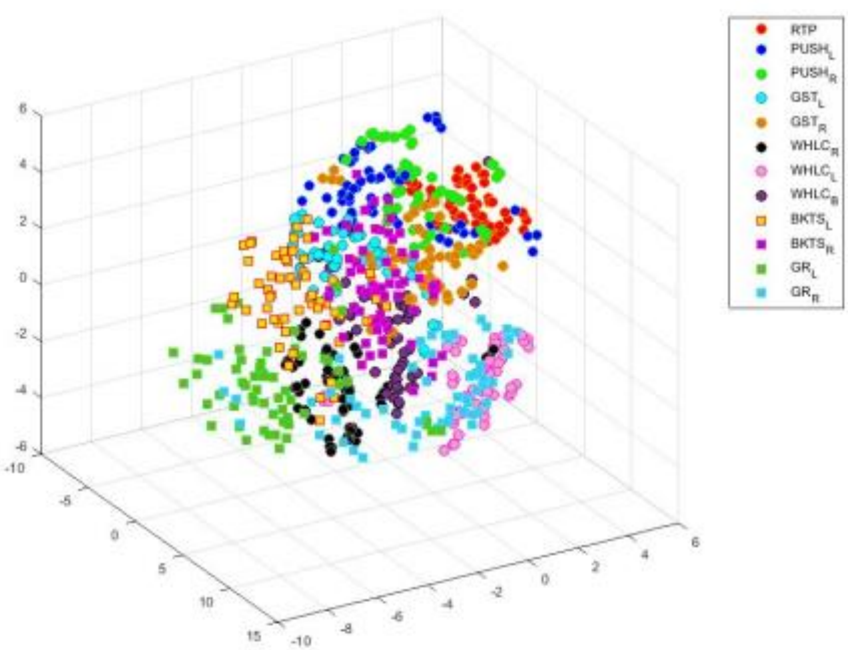


Figure 3.15: Sammon mapping to discriminate 12 Tai Chi exercises using ankles and wrists accelerometers

Furthermore, the discrimination between left and right version of the same exercise was performed to assess the chosen features.

In the figures below, two examples represented by Push and Wave Hands Like Clouds (WHLC) are shown.

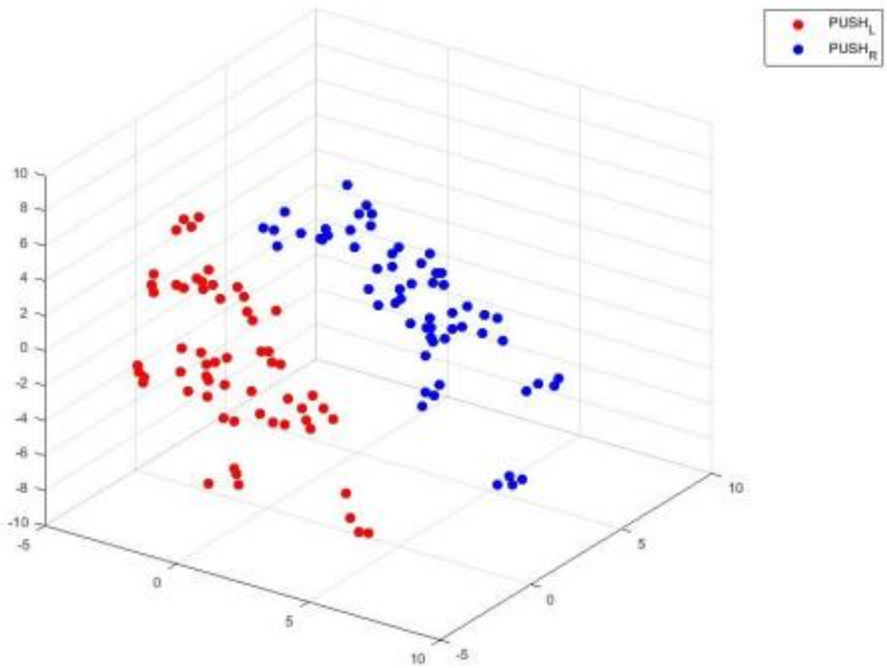


Figure 3.16: Sammon mapping for Push (left and right version) using a subset of sensors

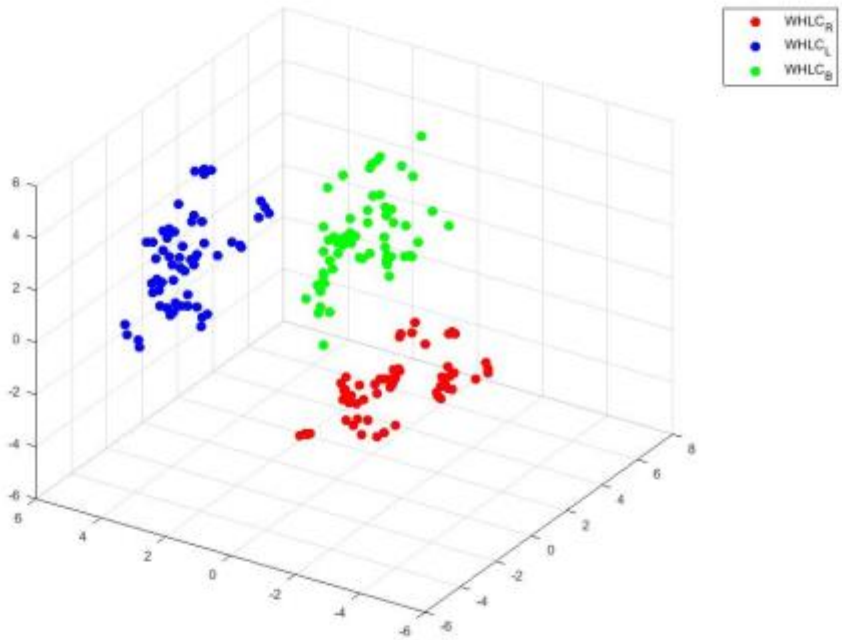


Figure 3.17: Sammon mapping for WHLC (three versions) using a subset of sensors

For the Push exercise, a subset of accelerometers was taken into account to build the Sammon mapping: the sensor put on the ankles, on the thighs and on the wrists respectively.
This choice is due to the results obtained by the use of the features selection performed before and the same subset was used for the discrimination of the three versions of WHLC exercise.
In both exercises, the clusters are clearly separated as a confirmation that the features and the sensors selected were appropriate.

3.2.3.4 Predictive model

To estimate the class corresponding to each features present in our dataset, a classification method was chosen: the Linear Discriminant Analysis (LDA).
This is a data mining algorithm that can be used for supervised or unsupervised learning proposed by R. Fischer in 1936.

The intuition behind the method is determining a subspace of lower dimension, compared to the original one, in which the data points of the original problem are separable in terms of statistical measures of mean value and variance. One advantage of this algorithm is represented by the possibility to obtain the solution by solving a generalized eigenvalue system.

The original algorithm was proposed for binary class problems but multi-class generalizations have been proposed, and this is the case of our analysis, in which twelve classes had to be discriminated.

The first classification that has been done is the one to predict the static and the dynamic exercises, thus a binary classification, in order to assess if the algorithm was working properly, since it is the simplest classification.

After that, the evaluation of the six exercises, without considering the left and right version, was carried out and the last classification is represented by the one to discriminate the twelve exercises.

All the classifications were built by using a subset of features and sensors, basing the decision on the outputs obtained by the features selection.

The selected features correspond to the range and the root mean square of the acceleration of the original signals, while the selected sensors are the ones put on the ankles and on the wrists.

In order to assess the performance of the classifier, two model validation techniques have been employed: the Leave-One-Trial-Out and Leave-One-Subject-Out cross-validation.

Both of them are special case of cross-validation, in particular, the Leave-One-Trial-Out is the case in which one instance is picked as test set, while all the remaining instances are used to build a predictive model and its error is evaluated on the single-point held out. A generalization error is obtained by repeating this procedure for each instance present in the features space, averaging the results.

The second technique, the Leave-One-Subject-Out algorithm, is another particular case of cross-validation, but this time the features concerning one subject are picked as test set, while the instances of all the other subjects are used to train the predictive model. The procedure is repeated for each subject present in the dataset, obtaining a general error of the classifier.

The reason why cross-validation has been used instead of using conventional validation (partition of the data in two sets of 70% for training and 30% for test) is that there was not enough data to partition into distinct training and test sets without losing significant modeling or testing capability.

3.2.4 Proficiency level estimation

With the intention of assessing the proficiency level of the exercises for each subject we conducted two different procedures in parallel, with the goal of comparing them and evaluate pros and cons of both and evaluate the best one.

The first method consisted in the implementation of the template matching technique, whereas the second one implemented is the same followed in the previous part of our project for the discrimination of the exercises.

3.2.4.1 Scoring criteria

In order to start thinking about which features to extract from the data, it was important to understand what the Tai Chi masters would be looking at when watching the videos.

One Tai Chi master provided us with a draft of the main criteria he considered meaningful in the process of evaluating the proficiency of the subjects in the study.

He designed the system in order for it to be simple, easy to administer in a short period of time, and with clear criteria so that it could be utilized and replicated in other Tai Chi studies.

Moreover, the chosen criteria were designed to specifically evaluate a Tai Chi protocol he previously developed.

To keep the visual scoring system simple, he also proposed to not make any assumptions about prior Tai Chi experience (i.e., no graded/scaling point system for being novice vs. intermediate vs. expert) and to only utilize a positive scoring system (i.e., no systematic point deduction system).

The proposed visual scoring system has five criteria. Each of them is equally weighted, with a range of possible scores for each item from 1 to 5 (5 being the most proficient).

Peter Wayne provided the scores examining together the versions performed with one side of the same exercises; in this way only 6 movements are evaluated. As a result the minimum total score a participant can receive is 30 (6 exercises x 5 criteria x 1 point), while the maximum is 150 (6 exercises x 5 criteria x 5 points).

Here is a list of the five criteria:

1. **Gross competency in choreography**: this simply evaluates the general familiarity and ability to perform the different Tai Chi forms in the protocol.

2. **Clear expression of Yin/Yang Tai Chi principle**: understanding and expressing Yin/Yang dynamics during performance of all movements is considered particularly important. This aspect can be visually assessed, for example, by looking at weight shifting (how fully does weight get transferred to active vs. passive legs during shifts in Push, Brush Knees, or Wave Hands Like Clouds) and opening and closing of joints (e.g. open vs. relaxed palm in Raising the Power; expanded vs. neutral positions of the spine during end of push or brush knee).

3. **Alignment and posture**: structural alignment and posture are a key criterion, with many sub-components. One alignment principle that informs most Tai Chi movements is verticality; that is, the head is centered over the torso, the torso rests over the hips, and the hips are centered over the base of support, the legs and feet.

Other alignment principles include: the centering of the knee joint over the central axis of the foot; proper foot orientation (e.g., feet parallel in raising power and wave hands like clouds, bow stance for push and brush knee twist step and grasp sparrows tail); the relaxed suspension of the elbows between the shoulders and wrists.

4. **Dynamic integration**: the emphasis on slow, coordinated, integrated movements. Changes from one alignment/posture to another should smoothly unfold through time (though sometimes they appear almost simultaneous. Maintenance of balance during transitions and single leg stances are also related to this principle.

5. **Range of motion**: focus on the lack of stiffness in the movements and on the range of motion of specific parts of the body, in particular the waist and the wrists.

For our analysis, the five sub-scores (Figure 3.18) as well as the medium scores and the general scores were taken into account; particularly, the steps consisting in data visualization by means of Sammon mapping algorithm and the classification have been carried out by using separately the three types of score for each exercise.

The five sub-scores are the five criteria described before; the general scores are represented by the sum of the five sub-scores (Figure 3.20) whereas the medium scores specific for the six Tai

Chi exercises have been obtained by summing the five sub-scores and assigning a score ranging from 1 to 5, based on the table shown in figure 3.19.

Subject Number/ID: 014				GRAND TOTAL SCORE		118
Evaluator: SC						
Date: 7/8/2015						
Scoring elements/notes (1 = Poor, 5 = Excellent)	Raising the Power	Withdraw and Push (L/R)	Grasp Sparrow's Tail (L/R)	Wave Hands Like Clouds	Brush Knee and Twist Step (L/R)	Golden Rooster (L/R)
Gross competency in choreography/accuracy in movements	5	4	4	5	2	2
• Obvious, Cheng Man-Ching/Peter Wayne protocol						
Clear expression of Yin and Yang	4	5	4	5	3	3
• Weight shifting						
• Yin and yang wrist, spine, etc.						
• Balance between effort and allowing						
Alignment and posture	3	4	4	3	4	3
• Verticality						
• Ankles and knees						
• Wrist and shoulders						
• Nose and navel						
• Anterior/posterior leaning minimal						
Flow/dynamic integration	4	5	5	5	5	4
• Silk reeling flow -- no stops and starts						
• Legs and arms temporally and biomechanically coordinated						
• No bobbing						
Range of motion	3	5	4	4	3	4
• Waist						
• Flexibility/use of kua						
• Wrist (lack of stiffness)						
INDIVIDUAL MOVEMENT SCORE	19	23	21	22	17	16

Figure 3.18: Example of sub-scores for one subject for each exercise

	PROFICIENCY LEVEL							
	RTP	PUSH	GST	WHLC	BKTS	GR		SCORES
TC001	5	5	5	5	5	5		1-5 : 1
TC002	4	4	3	4	3	4		6-10 : 2
TC004	4	3	3	3	2	3		11-15 : 3
TC005	4	4	3	4	3	4		16-20 : 4
TC006	5	5	3	4	3	3		21-25 : 5
TC008	5	4	5	5	5	4		
TC009	4	4	3	4	3	3		
TC010	5	4	3	4	3	3		
TC011	5	5	5	5	4	4		
TC012	5	4	4	4	3	4		
TC013	5	5	4	4	4	4		
TC014	4	5	5	5	4	4		
TC015	4	5	3	3	3	3		
TC018	4	3	4	4	3	4		
TC020	3	3	3	4	2	3		

Figure 3.19: Medium scores of the fifteen practitioners for each exercise

	PROFICIENCY LEVEL						
	RTP	PUSH	GST	WHLC	BKTS	GR	TOTAL SCORE
TC001	25	25	25	25	25	25	150
TC002	18	20	15	18	15	19	105
TC004	17	12	13	14	9	12	77
TC005	16	17	15	20	15	16	99
TC006	21	21	14	19	15	15	105
TC008	21	20	22	22	22	18	125
TC009	18	16	13	18	13	13	91
TC010	21	20	14	18	14	15	102
TC011	23	23	23	25	17	18	129
TC012	21	20	16	18	12	16	103
TC013	24	24	19	18	17	18	120
TC014	19	23	21	22	17	16	118
TC015	18	21	14	13	11	15	92
TC018	17	14	19	20	15	17	102
TC020	15	12	15	18	10	13	83

Figure 3.20: General scores of the fifteen practitioners for each exercise

3.2.4.2 First method: template matching technique

The first method applied in order to assess the proficiency level of each subject for each exercise is represented by the template matching.

This is a technique used to isolate certain features in an image, that can be single pixels, lines, edges or complete object.

In general, the template matching can be employed for different applications and it consists in the process of detecting an event buried in a signal by comparing it to a predefined template.

Thus, the technique relies on the use of a basis template that is compared to the signal, in order to create a measure of error (or of difference) against the input signal.

To clarify how template matching was used in the proposed study, the workflow followed during the analysis is shown below (Figure 3.21).

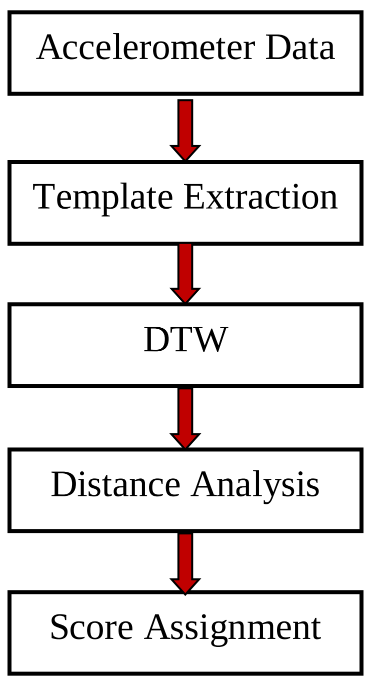


Figure 3.21: Workflow for template matching

As for the discrimination of the exercises, the raw data coming from the Shimmer sensors was low pass filtered to remove noise and only the accelerometer data was taken into account for the same reasons explained before for the discrimination of exercises, but this time the 3 axis of the accelerometer were combined to obtain the magnitude of acceleration.

3.2.4.2.1 Template extraction

Nine Shimmer sensors were considered in the analysis (the ones put on the ankles, thighs, upper arms, wrists and waist) and the first four repetitions for each exercise were picked to create a template.

The analysis has been developed considering one exercise at a time to assess the proficiency level of each subject for the specific exercise.

Considering one exercise at a time, the signals coming from subjects with the same score given by the Tai Chi master have been analyzed to create a template represented by the average of the signals taken into account. Then the same process has been followed for each score, sensor and exercise.

In particular, templates have been extracted from each of the nine sensors used in the analysis since signals corresponding to different Shimmer sensors have different shapes.

An example of template is shown in the figure below (Figure 3.22), considering the Push exercise. The figure shows the signals coming from subjects with proficiency score for Push equal to 3, and the sensor taken in consideration was the one put on left ankle.

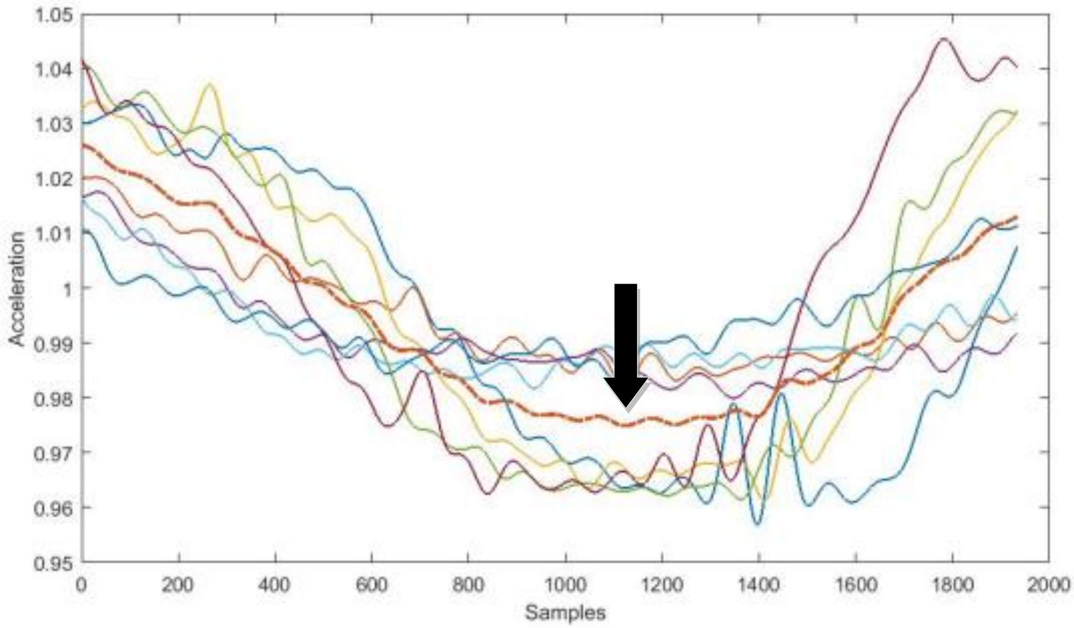


Figure 3.22: Extraction of template as average of signals

The main drawback of using as template the average of signals is that the shape of the template is attenuated compared to the others signals employed in the analysis.

3.2.4.2.2 Dynamic time warping (DTW)

In this phase, the Dynamic Time Warping algorithm has been carried out to compute the distances between the template and all the signals coming from a certain sensor.

Dynamic Time Warping is a well-known technique to find an optimal alignment between two given (time-dependent) sequences.

In particular, the algorithm aims at aligning two sequences of feature vectors by warping the time axis iteratively until an optimal match (according to a suitable metric) between the sequences is found. Originally, DTW has been used to compare different speech patterns in automatic speech recognition.

In fields such as data mining and information retrieval, the algorithm has been applied to automatically deal with time deformations and different speeds associated with time-dependent data.

In time series analysis, DTW is one of the algorithms employed to measure similarity between two temporal sequences which may vary in speed, and this is the reason why it has been chosen for our analysis.

In the following figure, an example of stretched signals is presented, by using the DTW technique.

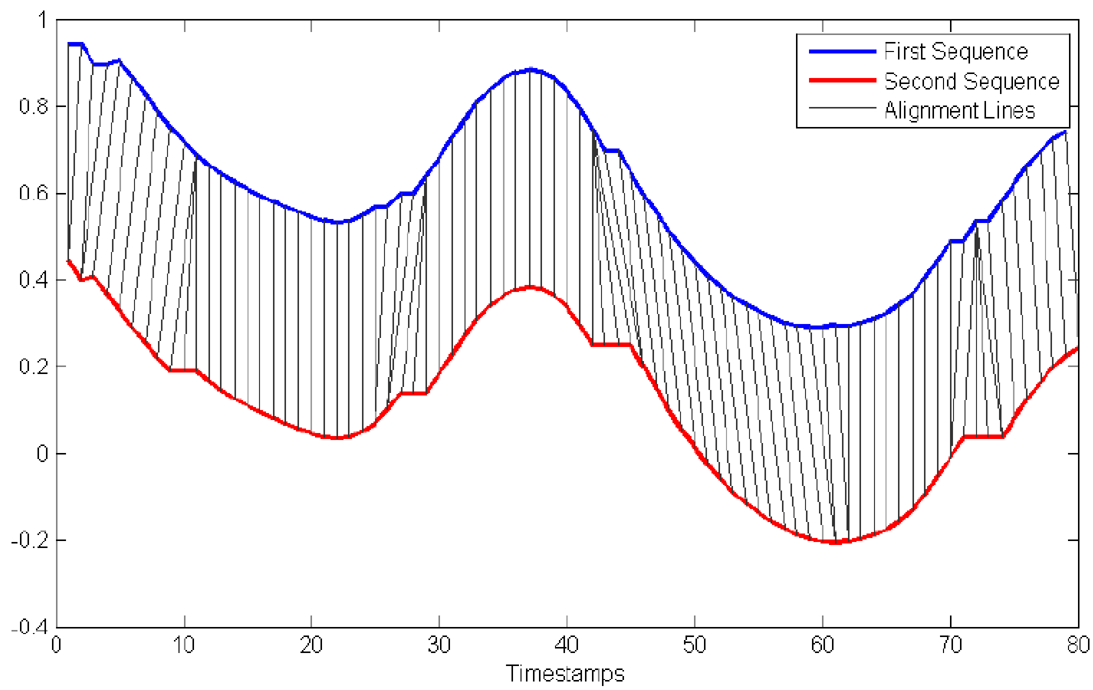


Figure 3.23: Time alignment of two time-dependent sequences using DTW

In the proposed work, the DTW implementation in Matlab has been used to stretch two signals (the template and the signal to compare) and get the minimum distance between them as output.

The algorithm has been repeated for each score of each exercise, considering one sensor at a time so that vectors of distances have been obtained as results.

In fact, considering one exercise at a time, each template has been compared with all the other signals coming from the fifteen subjects to obtain the corresponding distances.

3.2.4.2.3 Distance analysis and score assignment

In this part, the analysis of the distances obtained by the use of DTW algorithm has been developed to verify the similarity between template and the other signals.

To clarify how the analysis has been carried out, an example is given considering just one exercise (Raising The Power).

For this exercise, the Tai Chi master assigned three different scores to the fifteen practitioners, ranging from 3 to 5, so that three different templates have been extracted (one for each score) from each Shimmer platform.

After the extraction, the DTW algorithm has been applied to get the distances between each template and all the other signals. As result, three vectors of distances has been obtained for each sensor and then analyzed in order to pick the minimum distance between them.

In this way, it has been possible to know if a signal was closer to the template of score equal to 3, or to one of the other two templates, and the corresponding score has been given after the analysis of the minimum distance.

As last step, the obtained scores were compared with the ones given by the Tai Chi master to assess the accuracy of the technique applied.

3.2.4.3 Second method: linear discriminant analysis

As it has been done to reach the first aim of the project, here is the same workflow followed also in this part, in order to assess the proficiency level of the exercises performed.

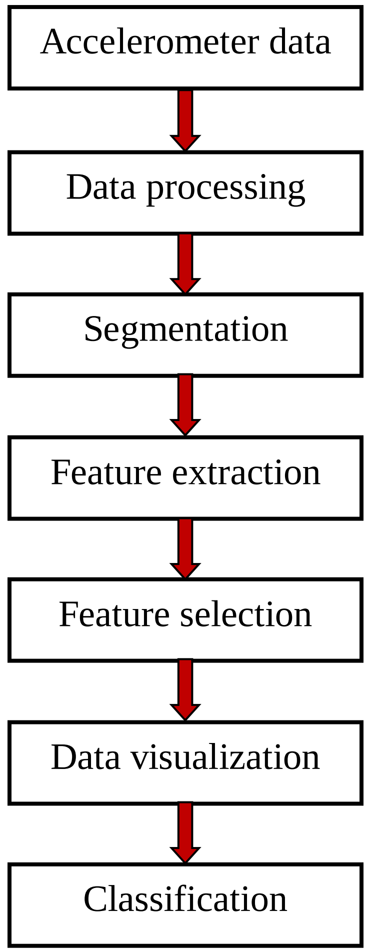


Figure 3.24: Workflow to analyze accelerometer data

In Figures 3.25 and 3.26 below, two examples of acceleration signals on the x-axis during a specific exercise, Brush Knee and Twist Step, in its version with the left foot forward (BKTS_L).

The first is a subject with a high proficiency level:

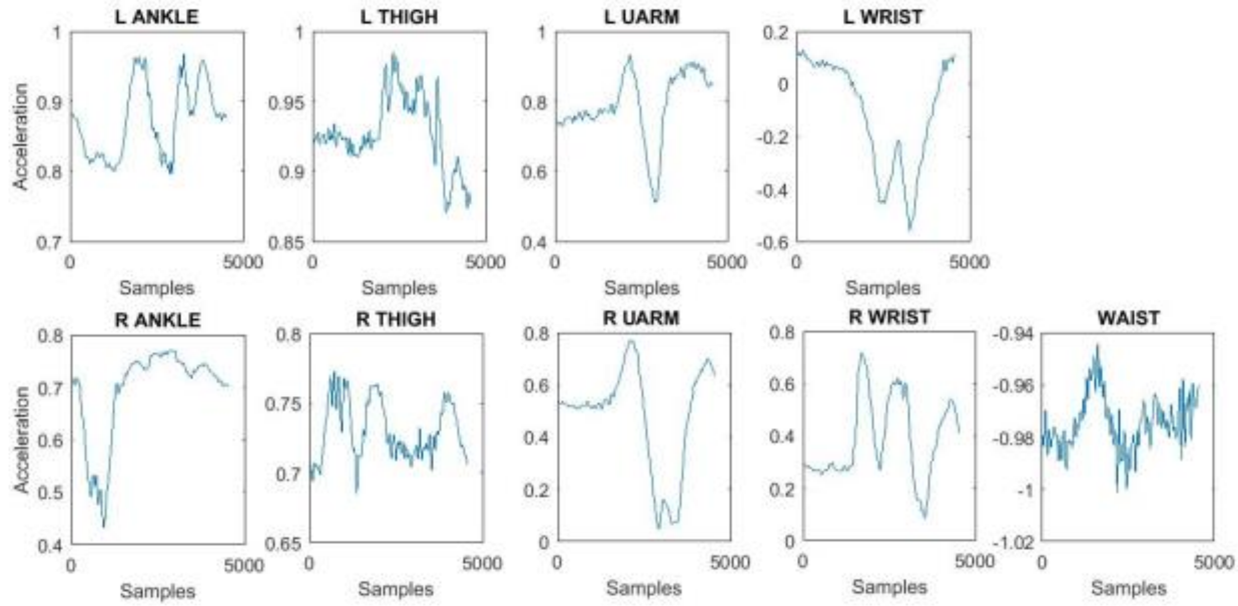


Figure 3.25: Acceleration on the x-axis in BKTS_L for a subject with high proficiency level

The second, on the other hand, is a subject characterized by a low level of proficiency:

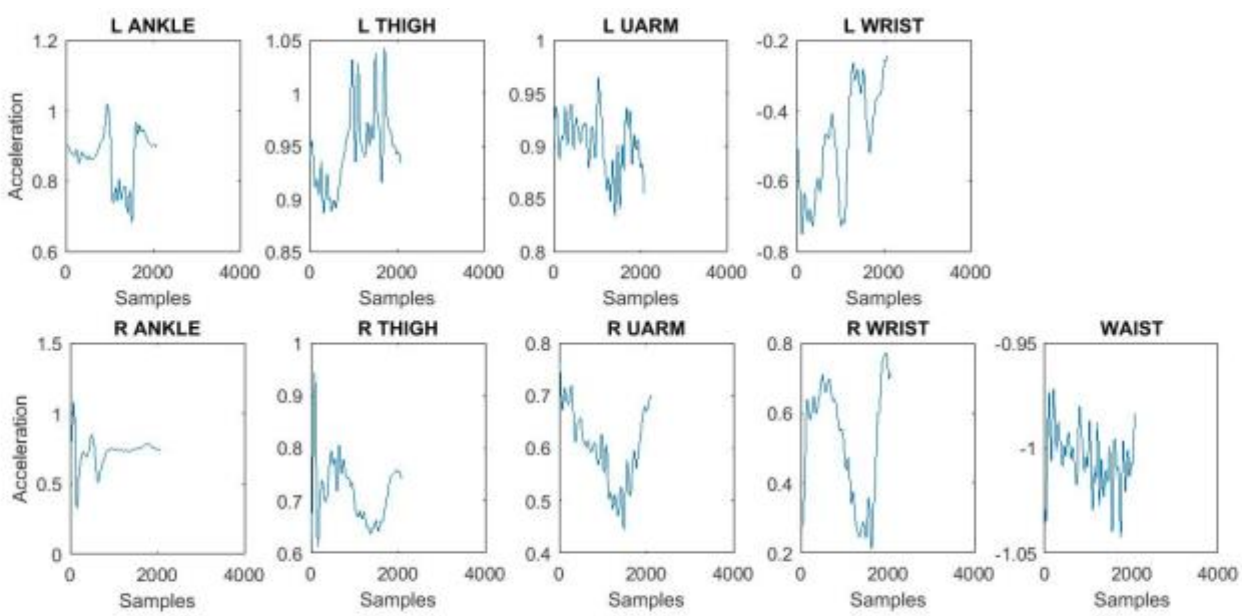


Figure 3.26: Acceleration on the x-axis in BKTS_L for a subject with low proficiency level

From a first look at the signals, differences can be found. Indeed, in the first series of graphs, the signal looks smoother, more regular and homogeneous among repetitions, as well as characterized by a higher range.

By observing these graphs for different subjects and exercises, it was possible to determine the sensors that were giving the most information about the movement and the ones that were not collecting meaningful data for the application. It will be validated using a feature selection algorithm.

3.2.4.3.1 Features extraction

A set of features was extracted from the data of the fifteen subjects, for whom the proficiency scores by Peter Wayne were available, as previously shown.

All the features were calculated considering both the three axis separated and using the magnitude value of them, and in the classification process a comparison was made between these kind of data extracted and also considering the combination of the two.

Since the purpose was changed respect to the previous part of the project, here we looked for features able to capture how well an exercise was being performed. These were determined by observation of the recorded signals, analysis of what was shown to work on previous similar studies, as well as from the scoring criteria that would be used by the Tai Chi masters.

Range of acceleration is the only feature extracted in both the parts of our work, providing an idea of the orientation of the sensors.

Cross correlation was included in the set of features based the importance of symmetry (between left and right side of the body, but also between upper and lower limbs) in the scoring criteria. For this reason, cross correlation was calculated between different pairs of sensors, evaluating the maximum value of the resulting function.

Other meaningful aspects can be shown better in the following figures, realized by superimposition of the signals of different repetitions of the same exercise (from the same sensor and axis of course). Two figures are shown for each exercise, the first obtained with the signals from a subject with high proficiency, the second with a participant with limited experience, in order to allow a comparison between the two.

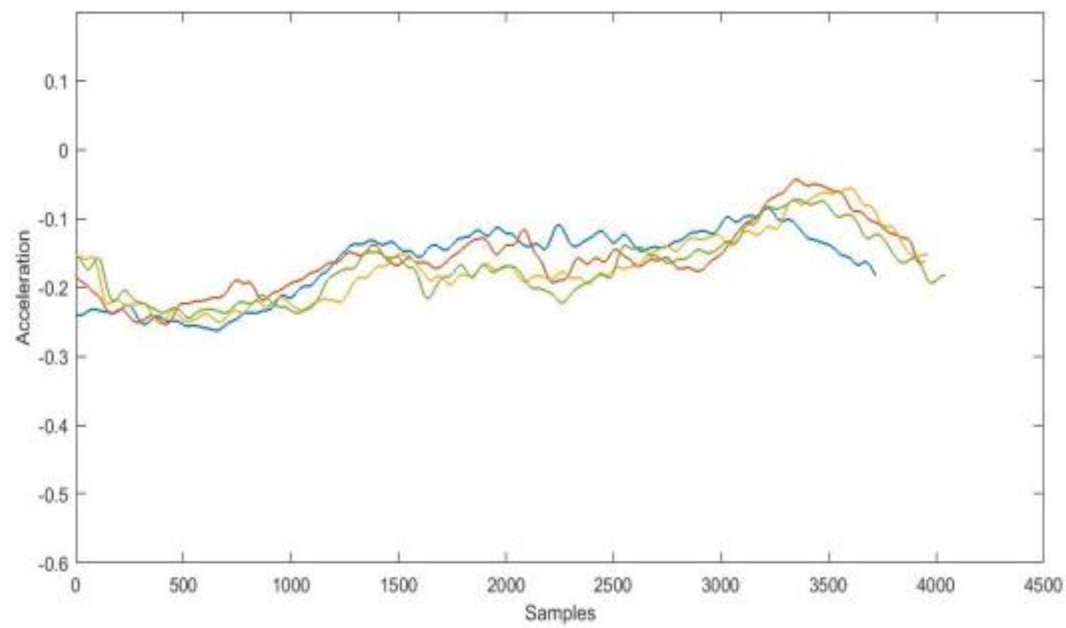


Figure 3.27: Acceleration on the x-axis of the sensor on the left wrist for different repetitions of RTP, for a subject with high proficiency level

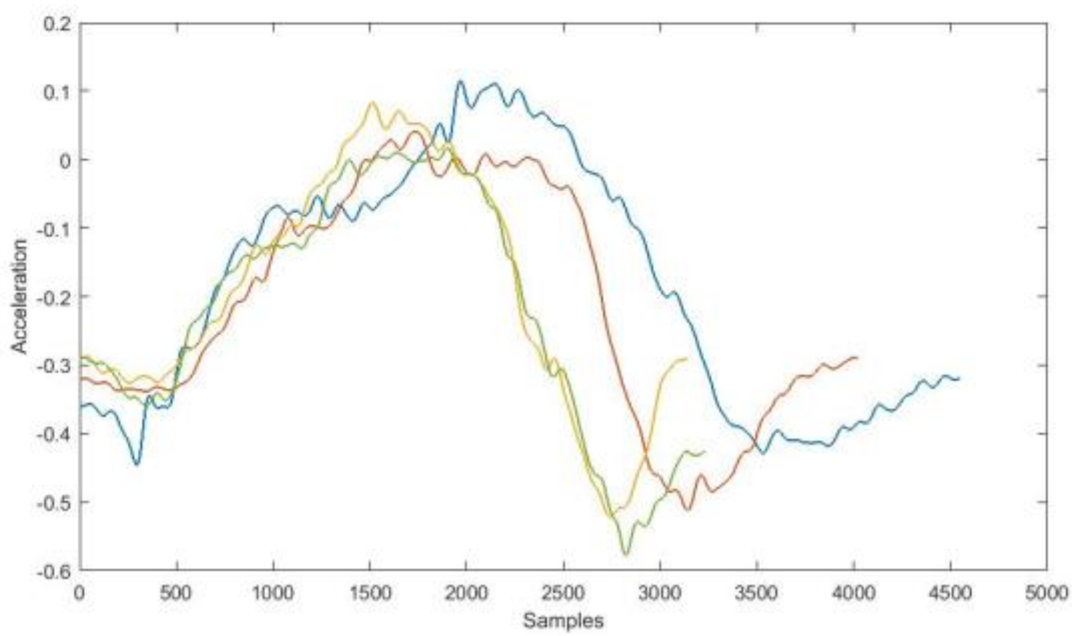


Figure 3.28: Acceleration on the x-axis of the sensor on the left wrist for different repetitions of RTP, for a subject with low proficiency level

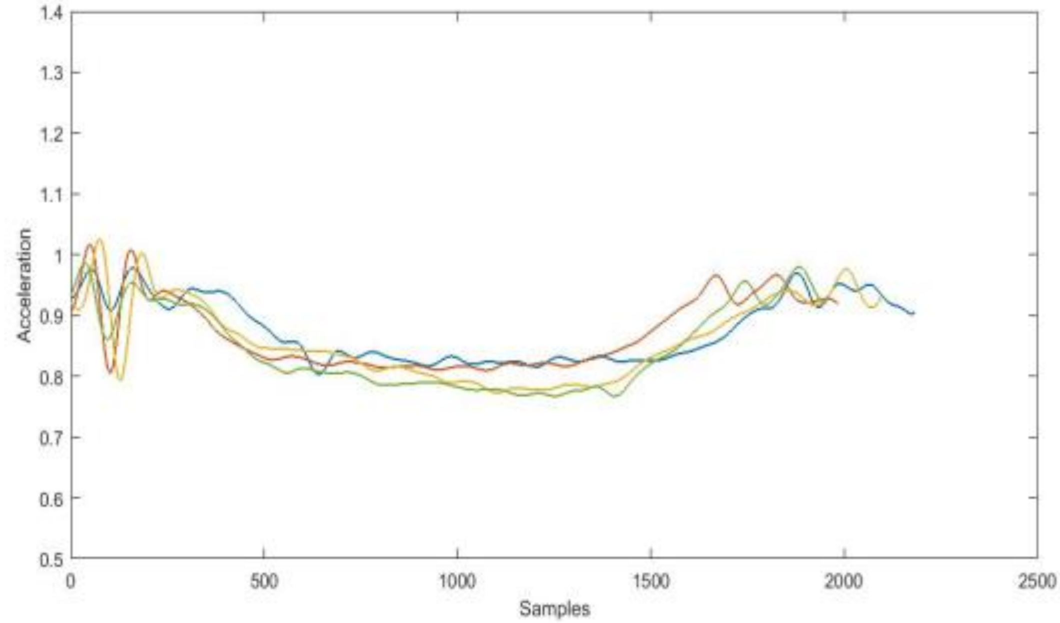


Figure 3.29: Acceleration on the x-axis of the sensor on the left ankle for different repetitions of GR_L for a subject with high proficiency level

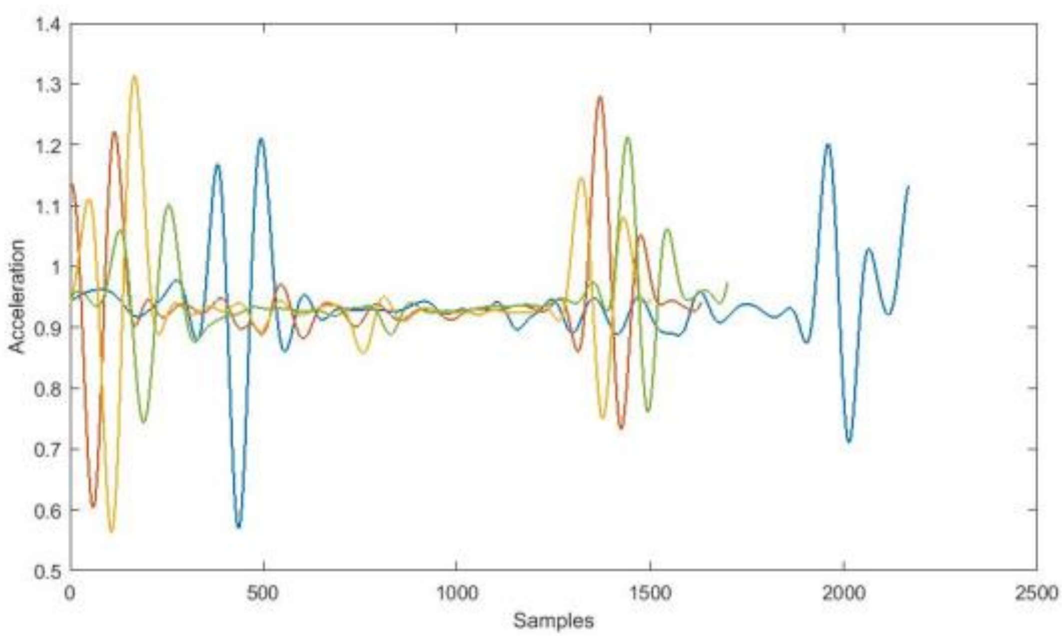


Figure 3.30: Acceleration on the x-axis of the sensor on the left ankle for different repetitions of GR_L for a subject with low proficiency level

The figures clarify why it was considered to be meaningful including how the different repetitions of a single exercise were different from one another, as we saw that in many cases more proficient practitioners were also more consistent in their performance. To quantify this, cross correlation between the signals of the same sensor for different repetitions was calculated. In this case both the maximum value and the delay were included as features. The difference in duration among the different repetitions was used as well for this purpose, with the maximum and the mean value as the two extracted features.

In the previous graphs, another fundamental difference is represented by the higher smoothness and regularity of the signals in the case of higher proficiency subject. To quantify this, the range of the jerk (jerk defined as the derivative of the acceleration) was also extracted, also because Tai Chi masters were supposed to take into account, in some way, this aspect (the flow and natural execution of the movements) in assigning scores to the subjects.

The last feature extracted was the autocorrelation; as shown in literature this parameter gives an idea of the randomness of a signal, so it could be useful to assess if there is a periodicity in the signals recorded or not.

3.2.4.3.2 Features selection

This stage was developed in the same two steps described in the previous part about the discrimination of the exercises, but this time with the aim of finding the most relevant features to use to assess the proficiency level of the practitioners.

First, the use of ReliefF algorithm allowed us to rank the features in a decreasing order of importance.

The second step of the features selection procedure consisted in the use of the Davies-Bouldin Index (DBI) that provided us an appropriate number of top ranked features, based on the results of the ReliefF algorithm.

At the end of the second step, the cardinality of the feature subset that produced the minimum DBI was selected.

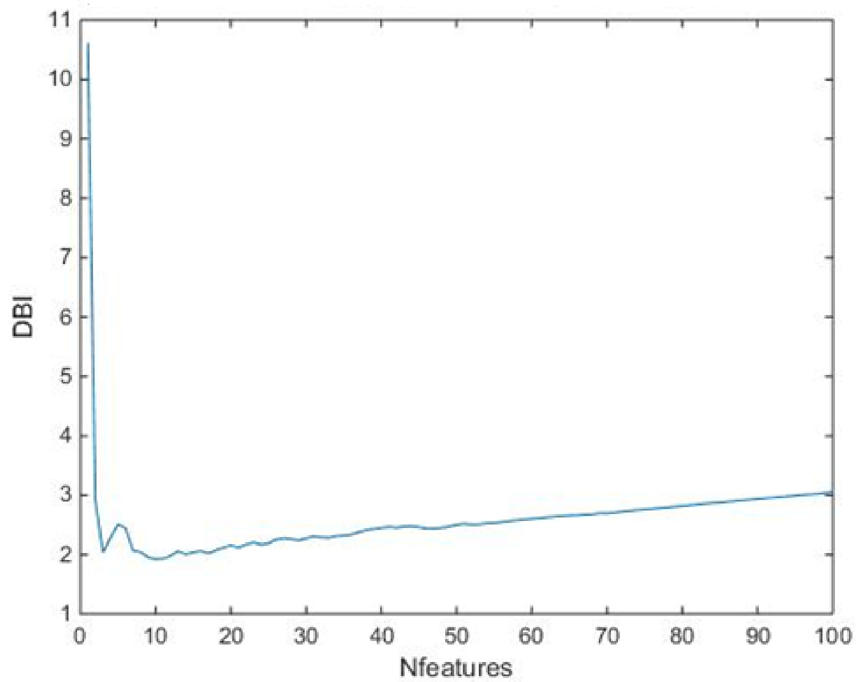


Figure 3.31: DBI plot for RTP exercise considering the medium proficiency score

This process was done evaluating separately the exercise on the basis of the medium scores, the sub scores and the general scores, as described in the scoring criteria paragraph.

3.2.4.3.3 Dimensionality reduction and data visualization

3D Sammon mapping algorithm was used also in this part of the project, with the purpose of visualizing the clusters correspondent to the different proficiency scores. In order to have the best separation of clusters, Sammon mapping was built by using the features selected in the previous step. These include the cross-correlation and the range of the acceleration, only for a subset of Shimmer sensors, that comprehends the ones on the ankles and the ones on the wrists, as was resulted and set also in the part of the project about the discrimination of the exercises.
In the figures below, an example is given by the Push exercise taking into account the five sub-scores separately, the medium and the general scores described before.

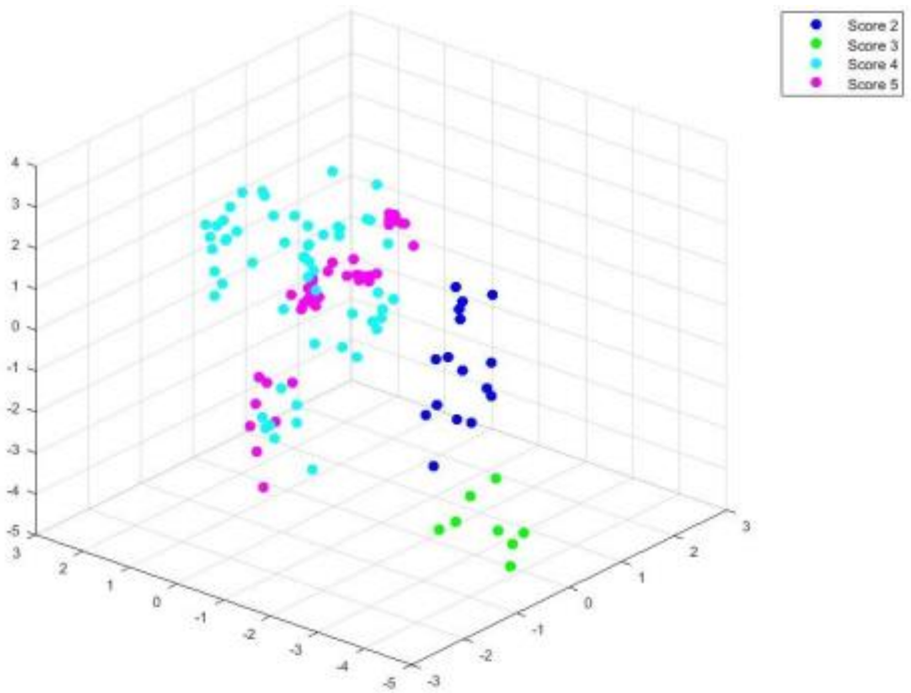


Figure 3.32: Sammon mapping of PUSH exercise considering gross competency sub-score using ankles and wrists accelerometers

In the figure, it is possible to distinguish clearly the clusters associated to the score equal to 2 and 3, while the highest scores (4 and 5) are less distinct and closer to each other.

The same happened for the other sub-scores considered.

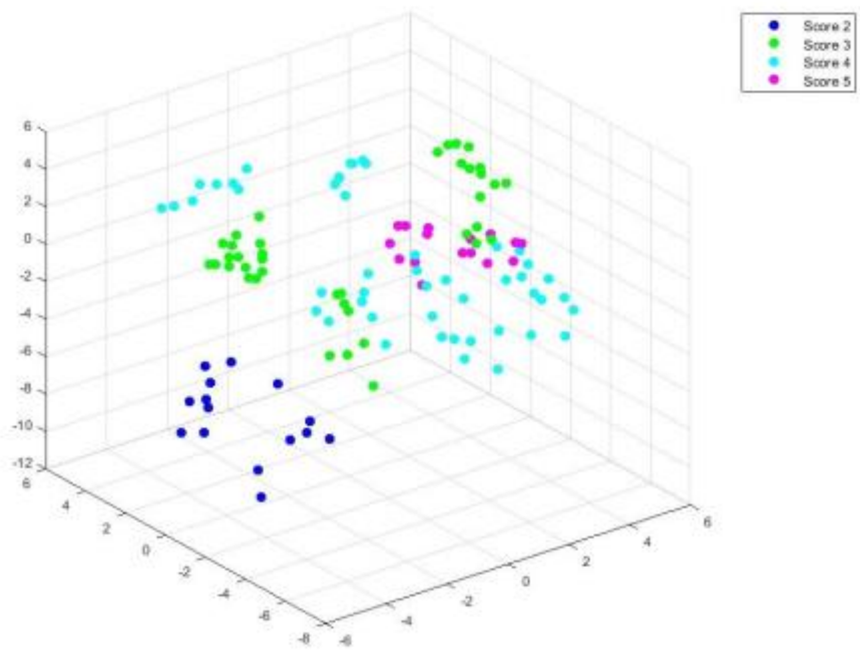


Figure 3.33: Sammon mapping of PUSH exercise considering Alignment/Posture sub-score using ankles and wrists accelerometers

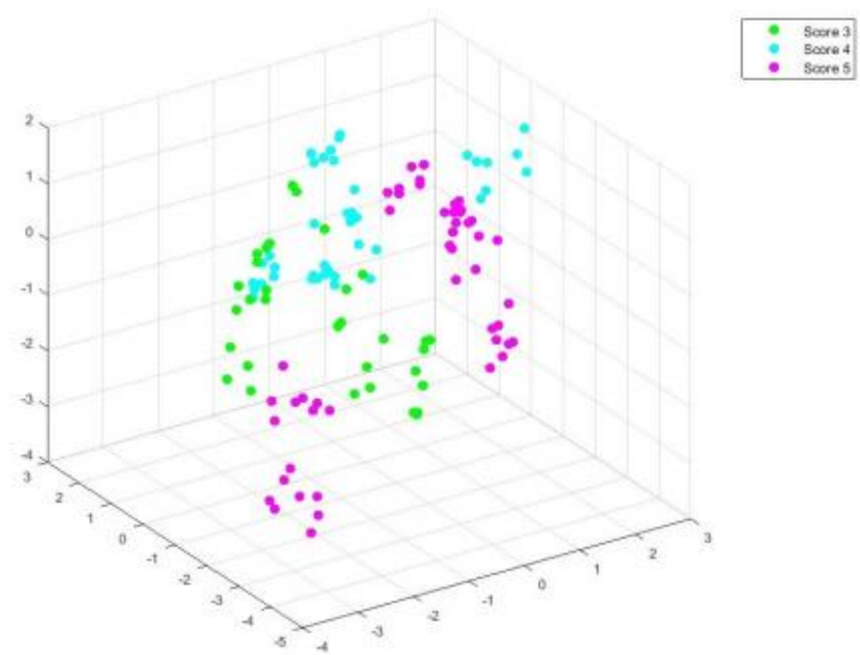


Figure 3.34: Sammon mapping of PUSH exercise considering Flow/Integration sub-score using ankles and wrists accelerometers

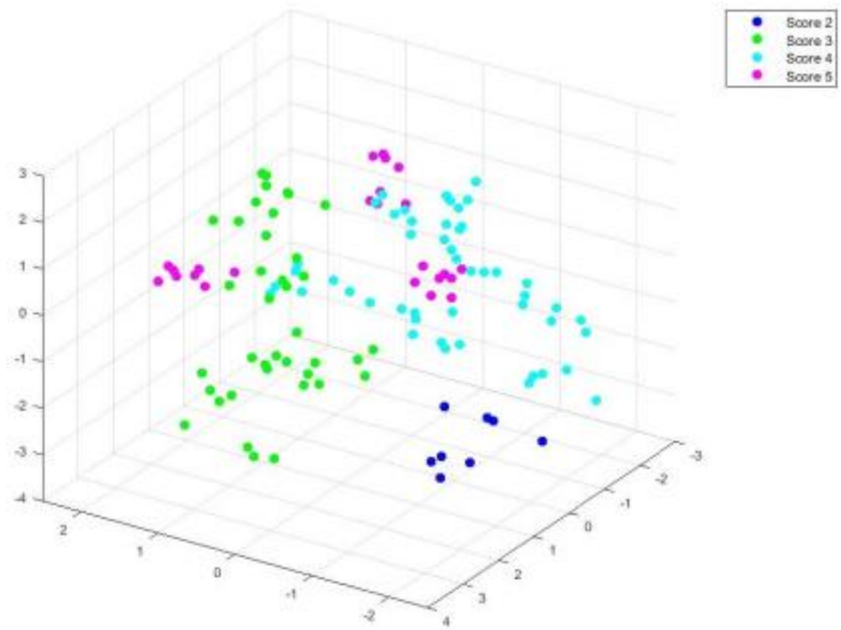


Figure 3.35: Sammon mapping of PUSH exercise considering ROM sub-score using ankles and wrists accelerometers

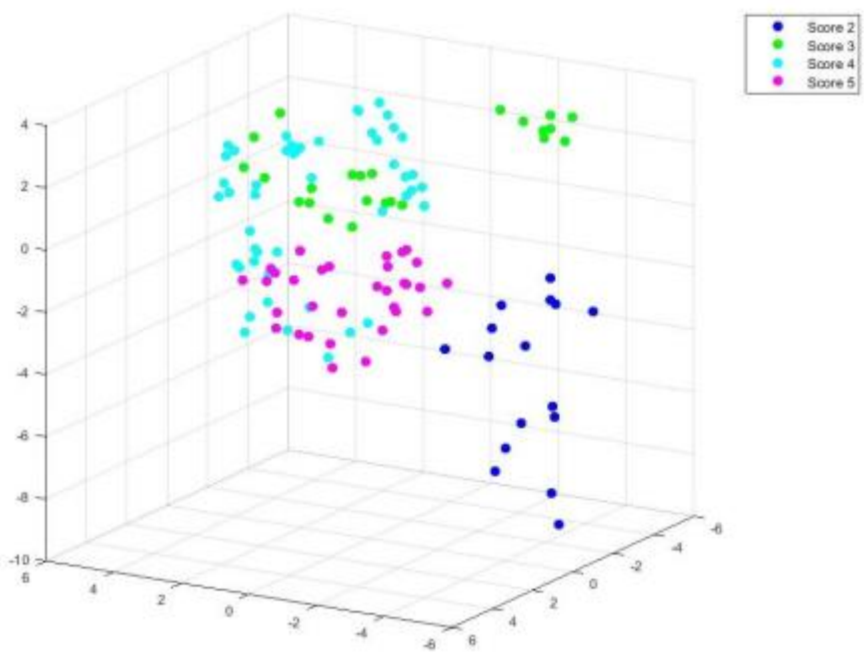


Figure 3.36: Sammon mapping of PUSH exercise considering Yin/Yang sub-score using ankles and wrists accelerometers

After the five sub-scores, the dimensionality reduction and the data visualization was carried out also for the medium and the general scores, and below there is an example considering the Push exercise, as done before.

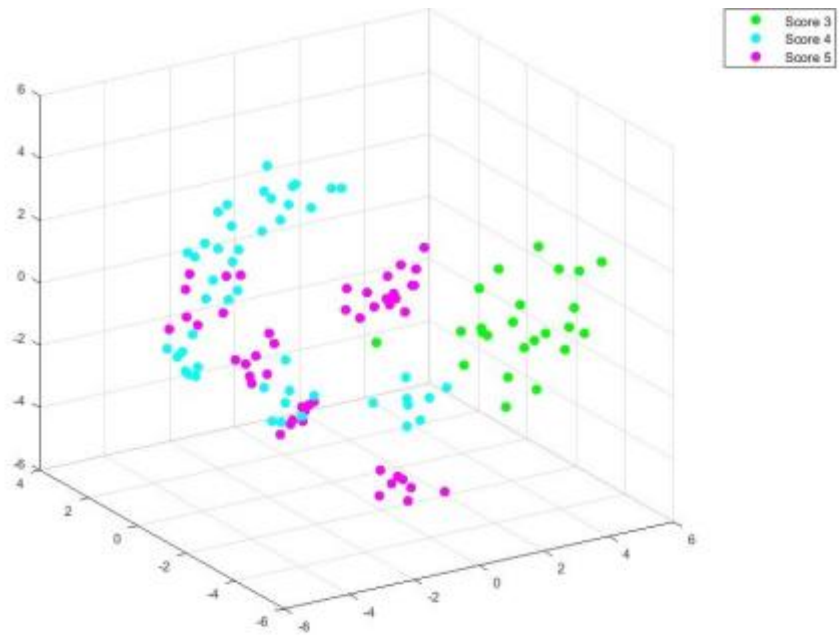


Figure 3.37: Sammon mapping of PUSH exercise considering the medium score using ankles and wrists accelerometers

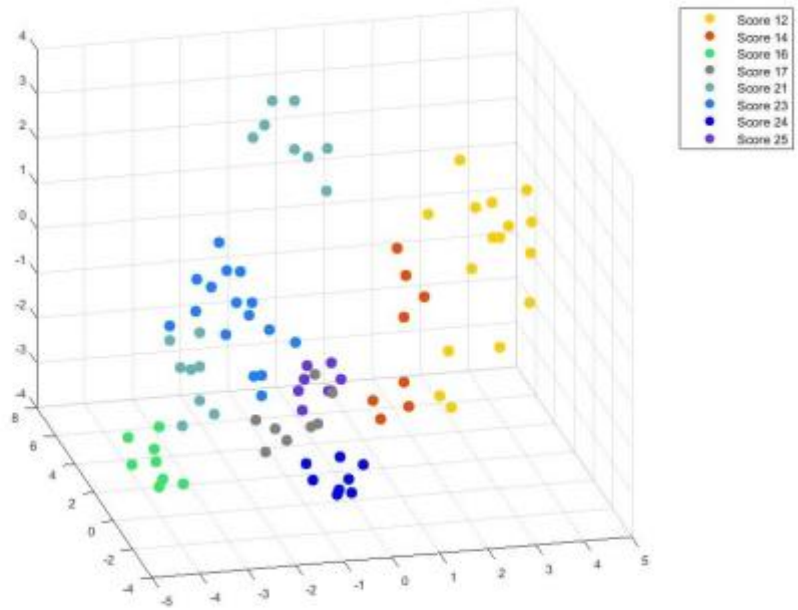


Figure 3.38: Sammon mapping of PUSH exercise considering the general score using ankles and wrists accelerometers

3.2.4.3.4 Predictive model

The Linear Discriminant Analysis (LDA) approach was applied as method of classification, as it has been done before in the discrimination of the exercises.

This time the extracted and ranked features had to be assigned to different classes corresponding to the proficiency scores provided by Peter Wayne. The classification was performed by using a subset of features, the most important ones coming from the implementation of the DBI algorithm, and it was done considering the five sub-scores as well as the medium and the general scores.

The selected features correspond to the maximum value of cross correlation, the root mean square of the autocorrelation, the range of acceleration and the range of jerk, whereas the subset of sensors is represented by the ones put on the ankles and on the wrists, and it is the same subset obtained for the discrimination of the exercises.

In addition, the classification was built taking into account the 3 axes separated of the accelerometers, the magnitude value of them and the combination of the two approaches.

To assess the performance of the classifier, two validation techniques were employed, as done before in the first part of our work: Leave-One-Trial-Out and the 10-Fold cross validation.
In this part, the Leave-One-Subject-Out was not applied since for some scores just one subject is present, thus making difficult the validation of the classifier.
For this reason, 10-Fold cross-validation was chosen instead of Leave-One-Subject-Out to evaluate the predictive model.
More specifically, in 10-Fold cross-validation the original sample is randomly partitioned into 10 equal size subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing the model and the remaining subsamples are used as training data.
The cross-validation is repeated 10 times (the number of folds) with each subsample used exactly once as validation data. The results coming from the folds are then averaged in order to produce a single estimation error. The main advantage of this method is that all observations are employed for both training and validation.
The results in terms of accuracy of the predictive model will be present in the next chapter.

Chapter 4: Results

4.1 Discrimination of the exercises

4.1.1 Predictive performances of the model

For the first aim of the project, both the Leave-One-Trial-Out and the Leave-One-Subject-Out validation methods were used to assess the performance of the classifier, and the process was repeated for the fifteen subjects.

Accuracy, calculated as the number of correctly classified observations divided by the total number of instances, was used to express the results.

As previously mentioned, the classifier was built by using the subset of features and sensors coming from the employment of the ReliefF algorithm and DB index together.

Specifically, the subset of features is represented by the range of acceleration and the root mean square, and the subset of sensors is constituted by the ones put on the ankles and on the wrists.

Furthermore, the classification has been carried out taking into account the 3 axes of the sensors, since it is important to maintain the orientation of the wearable platforms with the purpose of discriminating the different exercises.

The results presented are the ones concerning the use of the data of the 3 axes separated and in the following tables it is possible to see the accuracy related to the three different cases of classification described before: static/dynamic exercises, six exercises, twelve exercises.

	LEAVE-ONE-TRIAL-OUT	LEAVE-ONE-SUBJECT-OUT
STATIC/DYNAMIC EX	99.7%	98.9%
SIX EXERCISES	95.1%	89.3%
TWELVE EXERCISES	93.5%	88.5%

Table 4.1: Accuracy of the classifier, by using the Leave-One-Trial-Out and Leave-One-Subject-Out validation methods

As could have been foreseen, the best results were obtained in the discrimination between static and dynamic exercises; by the way the results can be considered good in general, in both the cases of validation method.

In the next tables, more detailed results are shown by the application of confusion matrices.

In machine learning, they allow the visualization of the performance of a classification method and they can give a better idea of what types of errors the classifier is making. Each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class. The counts of correct and incorrect predictions are then filled in the table, in particular the correct ones are located along the diagonal of the matrix.

The exercises are listed in order of similarity; the firsts are the static and then the dynamic ones. Furthermore, the closer the exercises, the more similar they are.

In this way, the errors further from the principal diagonal are considered worse respect to the ones closer to it.

In this part of the project they have been used to show the differences between predicted and actual exercise considering the static/dynamic discrimination, and then the same repeated for the discrimination of the six and the twelve exercises.

In the table below the results are shown.

PREDICTED EXERCISE			
TRUE EXERCISE		**STATIC**	**DYNAMIC**
	STATIC	480	0
	DYNAMIC	2	238

Table 4.2: Confusion matrix for static/dynamic exercises using Leave-One-Trial-Out algorithm

PREDICTED EXERCISE			
TRUE EXERCISE		**STATIC**	**DYNAMIC**
	STATIC	476	4
	DYNAMIC	4	236

Table 4.3: Confusion matrix for static/dynamic exercises using Leave-One-Subject-Out algorithm

	PREDICTED EXERCISE						
		RTP	PUSH	GST	WHLC	BKTS	GR
TRUE EXERCISE	RTP	60	0	0	0	0	0
	PUSH	4	114	2	0	0	0
	GST	0	3	117	0	0	0
	WHLC	0	1	8	171	0	0
	BKTS	0	1	1	0	111	7
	GR	0	0	0	0	8	112

Table 4.4: Confusion matrix for six exercises using Leave-One-Trial-Out algorithm

	PREDICTED EXERCISE						
		RTP	PUSH	GST	WHLC	BKTS	GR
TRUE EXERCISE	RTP	60	0	0	0	0	0
	PUSH	11	99	9	1	0	0
	GST	3	3	113	1	0	0
	WHLC	0	1	13	166	0	0
	BKTS	0	5	1	4	102	8
	GR	0	0	0	0	17	103

Table 4.5: Confusion matrix for six exercises, by using Leave-One-Subject-Out algorithm

		PREDICTED EXERCISE											
TRUE EXERCISE		RTP	PUSH_L	PUSH_R	GST_L	GST_R	WHLC_R	WHLC_L	WHLC_B	BKTS_L	BKTS_R	GR_L	GR_R
	RTP	60	0	0	0	0	0	0	0	0	0	0	0
	PUSH_L	4	56	0	0	0	0	0	0	0	0	0	0
	PUSH_R	0	0	59	0	0	0	0	0	0	0	0	0
	GST_L	0	0	0	60	0	0	0	0	0	0	0	0
	GST_R	0	0	0	0	56	4	0	0	0	0	0	0
	WHLC_R	0	0	0	0	4	56	0	0	0	0	0	0
	WHLC_L	0	0	0	1	0	0	59	0	0	0	0	0
	WHLC_B	0	0	1	0	0	0	0	59	0	0	0	0
	BKTS_L	0	1	0	0	0	0	0	0	51	4	4	0
	BKTS_R	0	0	0	0	0	0	0	0	4	52	0	4
	GR_L	0	0	0	0	0	0	0	0	3	1	52	4
	GR_R	0	0	0	0	0	0	0	0	2	2	4	52

Table 4.6: Confusion matrix for twelve exercises, by using Leave-One-Trial-Out algorithm

TRUE EXERCISE \ PREDICTED EXERCISE	RTP	PUSH_L	PUSH_R	GST_L	GST_R	WHLC_R	WHLC_L	WHLC_B	BKTS_L	BKTS_R	GR_L	GR_R
RTP	60	0	0	0	0	0	0	0	0	0	0	0
PUSH_L	4	53	0	1	2	0	0	0	0	0	0	0
PUSH_R	4	0	54	0	2	0	0	0	0	0	0	0
GST_L	3	4	0	53	0	0	0	0	0	0	0	0
GST_R	3	0	6	0	51	0	0	0	0	0	0	0
WHLC_R	0	0	0	0	0	56	4	0	0	0	0	0
WHLC_L	0	0	0	0	0	4	54	2	0	0	0	0
WHLC_B	0	0	1	0	0	1	0	58	0	0	0	0
BKTS_L	0	1	0	0	0	0	0	0	50	4	5	0
BKTS_R	0	0	0	0	0	0	0	1	4	51	0	4
GR_L	0	0	0	0	0	0	0	0	4	1	51	4
GR_R	0	0	0	0	0	0	0	1	5	1	4	49

Table 4.7: Confusion matrix for twelve exercises, by using Leave-One-Subject-Out algorithm

From the confusion matrices associated to both the validation methods it is evident that most of the exercises are always predicted correctly and, in the case this situation doesn’t occur, most of the errors are close to the principal diagonal; this means that the errors regard the misclassification of similar exercises

The accuracy was also calculated considering the subjects separately, in order to figure out if there was a high variability among the practitioners, and evaluate if this variability was correlated to a different proficiency level of the subjects.

The process was repeated for the three different classifications (static/dynamic, six exercises, twelve exercises) and the comparison was made considering the medium score of the proficiency level assigned by the Tai Chi master; this value ranks from 1 to 5, as described in the previous chapter.

ACCURACY				
	STATIC / DYNAMIC	**SIX EXERCISES**	**TWELVE EXERCISES**	**PROFICIENCY LEVEL (medium score)**
SUB1	100%	100%	100%	5
SUB2	100%	100%	100%	4
SUB3	98%	93.80%	91%	2
SUB4	100%	100%	100%	3
SUB5	100%	96%	96%	4
SUB6	100%	100%	100%	4
SUB7	100%	96%	93.80%	3
SUB8	100%	100%	98%	3
SUB9	100%	100%	100%	5
SUB10	98%	93.80%	93.80%	4
SUB11	100%	100%	100%	4
SUB12	96%	93.80%	89.80%	4
SUB13	100%	96%	98%	3
SUB14	100%	100%	93.80%	3
SUB15	93.80%	89.80%	89.80%	3

Table 4.8: Accuracy of the classifier subject-specific, by using Leave-One-Trial-Out algorithm

The results show a variability in the accuracy of the classifier taking into account one subject at a time; in general, a higher value of accuracy corresponds to subjects who have a higher level of proficiency. Practitioners who perform the exercises more properly are the ones with better results in terms of accuracy, as it could had been foreseen.

4.2 Proficiency level estimation

4.2.1 First method: template matching technique

In this part, the results coming from the application of the template matching technique are shown.

After the extraction of one template for each score, repeating the procedure sensor by sensor and exercise by exercise, DTW was applied in order to obtain the distances between signals and templates and at the end a specific score has been assigned to each signal according to the proximity to a specific template, thus searching for the minimum distance.

This analysis has been carried out considering one sensor at a time since we have to compare signals coming from the same sensor.

In addition, in this part of the analysis, the only scoring criteria taking into account was the medium score, in order to have a reasonable number of templates.

As mentioned in the previous chapter, only the first four repetitions of each exercise for the fifteen subjects were kept to have an equal number of signals.

In this way, each repetition was classified with a score based on the minimum distance from the templates and then a majority voting approach was applied to the different repetitions in order to have a final score for each subject.

The predicted scores have been compared with the scores provided by the Tai Chi master and a measure of error has been computed.

The following results show the accuracy obtained for each exercise by using the template matching technique.

EXERCISE	ACCURACY
RTP	50.4%
PUSH	49.7%
GST	57.7%
WHLC	48%
BKTS	46%
GR	46%

Table 4.9: Accuracy of the classifier for each exercise by using template matching technique

In general, the results in terms of accuracy are pretty low for each exercise considered and this is due to the fact that signals coming from practitioners with different proficiency level were usually not well separated and distinct; thus it was not unusual to have signals related to a practitioner with high proficiency score closer to the template referred to a lower class.

To better clarify the concept, an example is proposed in the figure below.

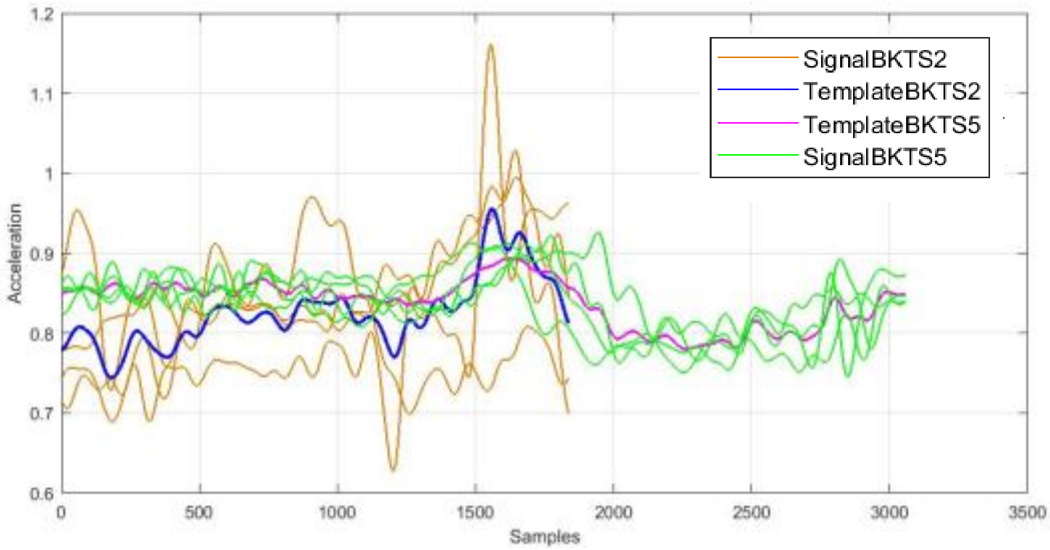


Figure 4.1: Signals coming from two practitioners with different proficiency level

In the figure, signals coming from two practitioners with different proficiency level (the lowest and the highest) are reported, as well as the two templates (in blue and in red) extracted for the two distinct scores.

The signals represented are the ones of the sensor put on the left ankle and the exercise considered is the BKTS.

Looking at the plot, it is clear that the signals related to the practitioner with the low score and the signals related to the one with high score are not well separated, as well as the two templates.

Thus, it is clear why the general accuracies are not good, since in a lot of cases we had the same situation.

Analyzing the results sensor by sensor, it is evident that there are sensors more important than others since they provided better results.

In the following table, results related to each sensor and each exercise are reported to have a better idea of the importance of the single Shimmer sensor.

	L Ankle	R Ankle	L Thigh	R Thigh	L Upper Arm	R Upper Arm	L Wrist	R Wrist	Waist
RTP	47%	33%	40%	60%	67%	53%	47%	60%	47%
PUSH	60%	53%	27%	53%	60%	47%	67%	60%	20%
GST	53%	53%	60%	60%	73%	53%	67%	60%	40%
WHLC	47%	53%	40%	53%	47%	40%	53%	67%	33%
BKTS	47%	47%	53%	60%	33%	47%	47%	47%	33%
GR	47%	40%	33%	47%	47%	60%	53%	47%	40%

Table 4.10: Accuracy of the classifier sensor-specific for each exercise, by using template matching technique

Looking at the table, it is clear that in general the accuracies are pretty low and in particular for some sensors, such as the one put on the waist that provides low accuracy for each exercise.

The results obtained by using the Shimmer sensors put on the wrists (left and right) are the highest ones throughout the six exercises.

Since the accuracies obtained by employing the template matching technique were not good enough, the estimation of the proficiency level has been carried out with another method, described in the previous chapter, and the results related to it will be shown in the following paragraphs.

4.2.2Second method: linear discriminant analysis

In this section, the results obtained by means of the second method applied to estimate the proficiency level will be discussed.

In order to verify the performance of the classifier used in the previous part, two validation methods were applied: the Leave-One-Trial-Out and the 10-Fold cross-validation and the results are presented in terms of accuracy, as done in the first section of the project.

As mentioned before, the classifier was built by using the subset of features and sensors coming from the employment of the ReliefF algorithm and DB index together.

Specifically, the subset of features is represented by range of acceleration and maximum value of cross-correlation, while the subset of sensors is constituted by the ones put on the ankles and on the wrists.

Furthermore, the classification was carried out taking into account the 3 axes of the sensors, the magnitude value and the combination of the two methods.

The first results presented are the ones concerning the use of the data of the 3 axes separated and in the following tables it is possible to see the accuracy obtained by means of the medium scores, the general scores and the sub-scores, by using the Leave-One-Trial-Out approach.

The decision to repeat the classification process for each specific sub-score was made to see if there was variability in terms of accuracy of the classifier among the different sub-scores, so that to evaluate which were the Tai Chi peculiarities which are better captured through the sensors.

EXERCISE	ACCURACY
RTP	98.3%
PUSH	98.3%
GST	95.8%
WHLC	100%
BKTS	87.5%
GR	96.7%

Table 4.11: Accuracy of the classifier for the medium scores, by using Leave-One-Trial-Out algorithm (3 axes)

EXERCISE	ACCURACY
RTP	98.3%
PUSH	96.7%
GST	96.7%
WHLC	99.4%
BKTS	94.2%
GR	95%

Table 4.12: Accuracy of the classifier for the general scores, by using Leave-One-Trial-Out algorithm (3 axes)

For the results related to the use of the five sub-scores, one exercise was chosen (PUSH) as example and the accuracies are shown below (Table 4.13).

SUB-SCORE	ACCURACY
Gross Competency	90.8%
Yin/Yang	97.5%
Alignment/Posture	97.5%
Flow/Integration	99.2%
Range Of Motion	96.7%

Table 4.13: Accuracy of the classifier for the five sub-scores of PUSH, by using Leave-One-Trial-Out algorithm (3 axes)

For the Leave-One-Trial-Out method some examples of confusion matrices are presented below.

	PREDICTED LEVEL		
TRUE LEVEL	**3**	**4**	**5**
3	23	0	1
4	0	47	1
5	0	0	48

Table 4.14: Confusion matrix for PUSH exercise considering the medium score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
TRUE LEVEL	**2**	**3**	**4**	**5**
2	16	0	0	0
3	0	8	0	0
4	0	0	47	9
5	0	0	2	38

Table 4.15: Confusion matrix for PUSH exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

The same procedure was followed for the assessment of the classifier by means of 10-Fold cross-validation, by using the three kinds of scores and the results are shown in the tables below.

EXERCISE	ACCURACY
RTP	98.3%
PUSH	95.8%
GST	97.5%
WHLC	100%
BKTS	76.7%
GR	86.7%

Table 4.16: Accuracy of the classifier for the medium scores, by using 10-Fold cross-validation algorithm (3 axes)

EXERCISE	ACCURACY
RTP	98.3%
PUSH	94.2%
GST	95%
WHLC	98.9%
BKTS	94.2%
GR	93.3%

Table 4.17: Accuracy of the classifier for the general scores, by using 10-Fold cross-validation algorithm (3 axes)

SUB-SCORE	ACCURACY
Gross Competency	96.7%
Yin/Yang	98.3%
Alignment/Posture	96.7%
Flow/Integration	99.2%
Range Of Motion	97.8%

Table 4.18: Accuracy of the classifier for the five sub-scores of PUSH, by using 10-Fold cross-validation algorithm (3 axes)

Examples of confusion matrices are proposed also for the 10-Fold cross-validation, in order to verify what kinds of mistakes were done during the classification.

		PREDICTED LEVEL		
		3	**4**	**5**
TRUE LEVEL	**3**	23	0	1
	4	0	42	6
	5	0	3	45

Table 4.19: Confusion matrix for PUSH exercise considering the medium score, by using 10-Fold cross-validation algorithm (3 axes)

	PREDICTED LEVEL				
		2	**3**	**4**	**5**
TRUE LEVEL	**2**	16	0	0	0
	3	0	8	0	0
	4	0	0	52	4
	5	0	0	0	40

Table 4.20: Confusion matrix for PUSH exercise considering the gross competency sub-score, by using 10-Fold cross-validation algorithm (3 axes)

It is clear, looking at the results, that the best case is the one in which the Leave-One-Trial-Out was applied because it provides very good results in terms of accuracy of the classifier.

The validation by means of the other approach, the 10-Fold cross-validation, is good too, since the lowest accuracy is around 76% and just for one exercise (BKTS).

In general, the results obtained with both the validation methods are good, especially considering that the errors that were committed when assigning a class to a new input observation were mostly of only one class of difference.

More significant mistakes (with a difference between predicted and real class bigger than two) were rarely committed.

Furthermore, the choice of applying two different validation methods is due to the risk of overfitting, since the dataset used in the analysis is small.

In the following graph, the accuracies related to the six exercises and obtained by means of the two validation methods applied are shown, to better visualize the difference between the two.

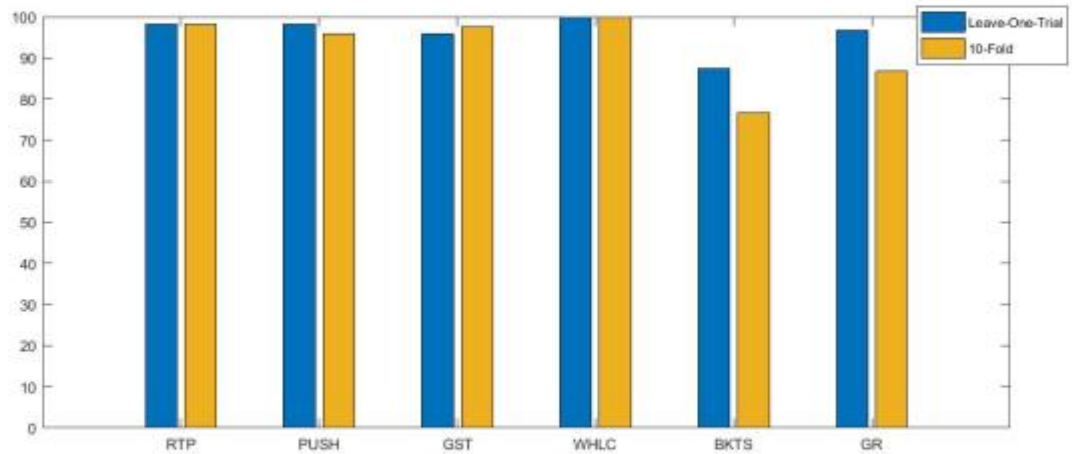


Figure 4.2: Accuracy of the classifier for the medium score (six exercises), by using the two validation methods (3 axes)

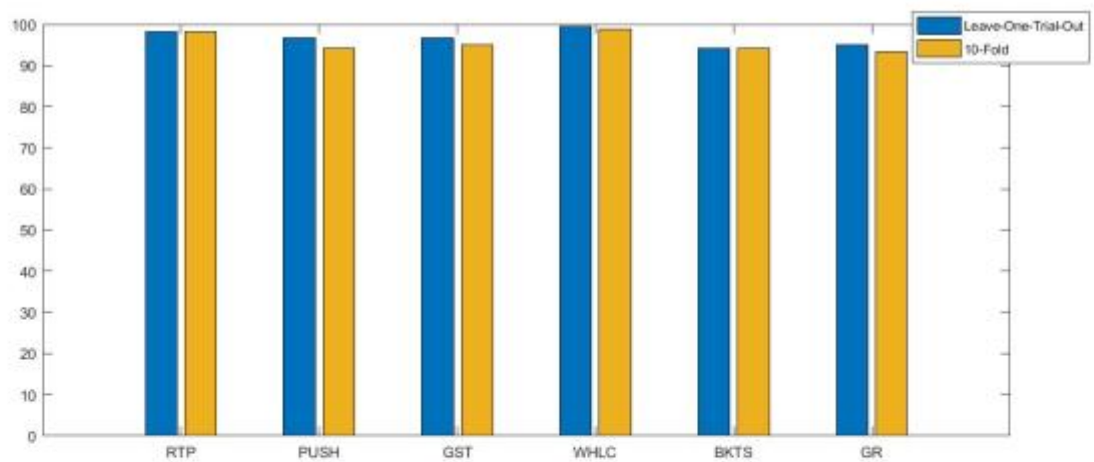


Figure 4.3: Accuracy of the classifier for the general score (six exercises), by using the two validation methods (3 axes)

The same approach was followed considering the magnitude of the axes, and some results are shown below in terms of accuracy and confusion matrices, taking into account the three types of scoring system.

The first tables referred to the results obtained by means of Leave-One-Trial-Out method.

EXERCISE	ACCURACY
RTP	83.3%
PUSH	90.8%
GST	88.3%
WHLC	91.7%
BKTS	94.2%
GR	86.7%

Table 4.21: Accuracy of the classifier for the medium scores, by using Leave-One-Trial-Out algorithm (magnitude of axes)

EXERCISE	ACCURACY
RTP	98.3%
PUSH	95.8%
GST	93.3%
WHLC	95%
BKTS	96.7%
GR	97.5%

Table 4.22: Accuracy of the classifier for the general scores, by using Leave-One-Trial-Out algorithm (magnitude of axes)

For the five sub-scores, one exercise between the six has been picked as example to show the results and in this case the PUSH exercise is the one selected, as done before.

SUB-SCORE	ACCURACY
Gross Competency	89.2%
Yin/Yang	95.8%
Alignment/Posture	93.3%
Flow/Integration	93.3%
Range Of Motion	88.3%

Table 4.23: Accuracy of the classifier for the five sub-scores of PUSH, by using Leave-One-Trial-Out algorithm (magnitude of axes)

Examples of confusion matrices are presented in order to better understand which scores were misclassified and how important is the error of misclassification.

The matrices referred to the PUSH exercise, since it has been taken as example in the previous analysis.

		PREDICTED LEVEL		
		3	**4**	**5**
TRUE LEVEL	**3**	22	1	1
	4	2	45	1
	5	0	6	42

Table 4.24: Confusion matrix for PUSH exercise considering the medium score, by using Leave-One-Trial-Out algorithm (magnitude of axes)

		PREDICTED LEVEL			
		2	**3**	**4**	**5**
TRUE LEVEL	**2**	15	0	0	1
	3	0	8	0	0
	4	0	0	55	1
	5	0	0	3	37

Table 4.25: Confusion matrix for PUSH exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (magnitude of axes)

The confusion matrices underline that just in two cases a low score of proficiency level were classified as the highest score and in general the errors regard proficiency levels that are very close.

Same approach was carried out using the 10-Fold cross validation technique and the results in terms of accuracy are shown in the following tables.

EXERCISE	ACCURACY
RTP	81.7%
PUSH	87.5%
GST	82.5%
WHLC	90.5%
BKTS	93.3%
GR	85.8%

Table 4.26: Accuracy of the classifier for the medium scores, by using 10-fold cross validation algorithm (magnitude of axes)

EXERCISE	ACCURACY
RTP	98.3%
PUSH	95%
GST	90.8%
WHLC	96.7%
BKTS	95%
GR	96.7%

Table 4.27: Accuracy of the classifier for the general scores, by using 10-Fold cross validation algorithm (magnitude of axes)

As done before, examples of confusion matrices for the PUSH exercise are reported below considering the medium score and one of the five sub-scores.

		PREDICTED LEVEL		
TRUE LEVEL		**3**	**4**	**5**
	3	21	2	1
	4	2	44	2
	5	1	7	40

Table 4.28: Confusion matrix for PUSH exercise considering the medium score, by using 10-Fold cross-validation algorithm (magnitude of axes)

		PREDICTED LEVEL			
		2	3	4	5
TRUE LEVEL	2	15	0	0	1
	3	0	8	0	0
	4	0	0	56	0
	5	0	0	3	37

Table 4.29: Confusion matrix for PUSH exercise considering the gross competency sub-score, by using 10-Fold cross-validation algorithm (magnitude of axes)

In the first confusion matrix presented, it is possible to see that there are more misclassification errors, compared to the errors obtained through the application of Leave-One-Trial-Out technique.

Results for the six Tai Chi exercises are presented in the figures below, comparing the two validation techniques.

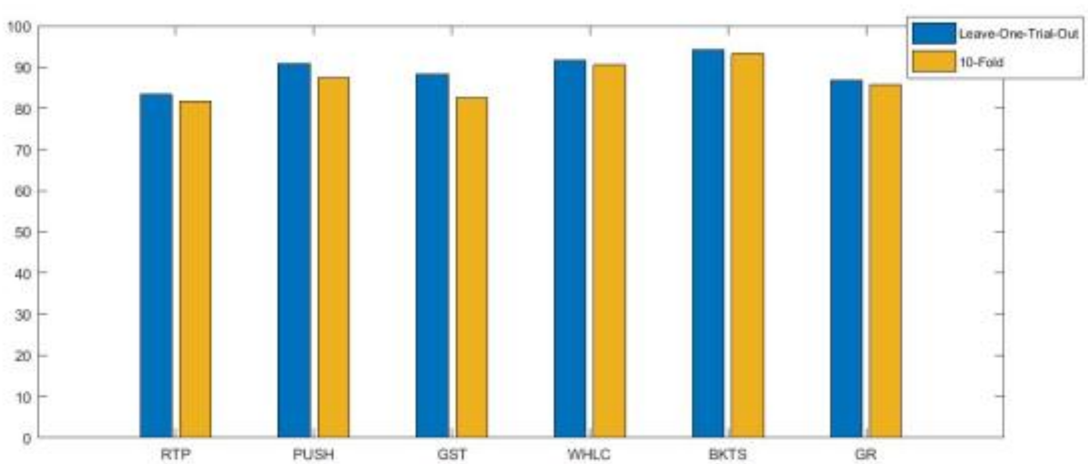


Figure 4.4: Accuracy of the classifier for the medium score (six exercises), by using the two validation methods (magnitude of axes)

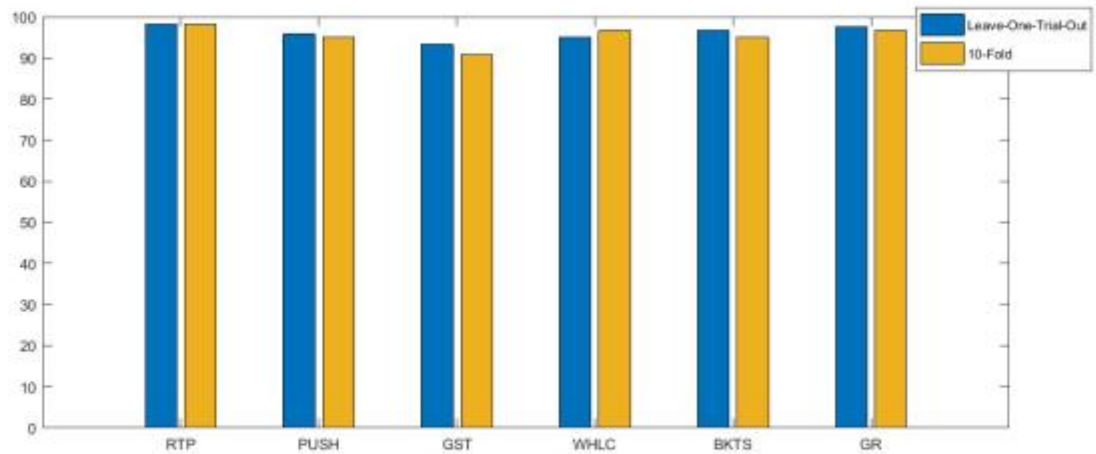


Figure 4.5: Accuracy of the classifier for the general score (six exercises), by using the two validation methods (magnitude of axes)

The last case analyzed is represented by the combination of features extracted for each axis and features extracted for the magnitude value and the results are shown below, both the ones coming from the implementation of Leave-One-Trial-Out method and the ones coming from the 10-fold cross validation technique.

The first tables show the accuracy of the classifier for each exercise using the Leave-One-Trial-Out validation method and then an exercise is picked as example in order to visualize the results using the five distinct sub-scores.

EXERCISE	ACCURACY
RTP	80%
PUSH	92.5%
GST	73%
WHLC	96.7%
BKTS	96%
GR	85%

Table 4.30: Accuracy of the classifier for the medium scores, by using Leave-One-Trial-Out algorithm (magnitude + 3 axes)

EXERCISE	ACCURACY
RTP	98.3%
PUSH	98.3%
GST	96.7%
WHLC	98.3%
BKTS	93.3%
GR	99%

Table 4.31: Accuracy of the classifier for the general scores, by using Leave-One-Trial-Out algorithm (magnitude + 3 axes)

SUB-SCORE	ACCURACY
Gross Competency	92%
Yin/Yang	97%
Alignment/Posture	87%
Flow/Integration	95%
Range Of Motion	92.5%

Table 4.32: Accuracy of the classifier for the five sub-scores of PUSH, by using Leave-One-Trial-Out algorithm (magnitude + 3 axes)

The confusion matrices referred to PUSH exercise after the implementation of Leave-One-Trial-Out algorithm are shown below.

	PREDICTED LEVEL			
TRUE LEVEL		**3**	**4**	**5**
	3	24	0	0
	4	0	43	5
	5	0	4	44

Table 4.33: Confusion matrix for PUSH exercise considering the medium score, by using Leave-One-Trial-Out algorithm (magnitude + 3 axes)

	PREDICTED LEVEL				
TRUE LEVEL		**2**	**3**	**4**	**5**
	2	15	0	0	1
	3	0	8	0	0
	4	0	0	56	0
	5	0	0	3	37

Table 4.34: Confusion matrix for PUSH exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (magnitude + 3 axes)

In the following section, results obtained by means of the 10-Fold cross-validation method are presented for the different type of scores employed during the analysis.

EXERCISE	ACCURACY
RTP	77%
PUSH	84%
GST	84%
WHLC	92%
BKTS	96%
GR	81%

Table 4.35: Accuracy of the classifier for the medium scores, by using 10-Fold cross-validation (magnitude + 3 axes)

EXERCISE	ACCURACY
RTP	100%
PUSH	96.7%
GST	92.5%
WHLC	96.7%
BKTS	93.3%
GR	99%

Table 4.36: Accuracy of the classifier for the general scores, by using 10-Fold cross-validation (magnitude + 3 axes)

The last results shown are the ones regarding the five sub-scores, taking as example the PUSH exercise.

SUB-SCORE	ACCURACY
Gross Competency	92%
Yin/Yang	97%
Alignment/Posture	87%
Flow/Integration	95%
Range Of Motion	92.5%

Table 4.37: Accuracy of the classifier for the five sub-scores of PUSH, by using 10-Fold cross-validation (magnitude + 3 axes)

The following tables show the correct and incorrect number of classified instances for PUSH exercise.

	PREDICTED LEVEL			
TRUE LEVEL		**3**	**4**	**5**
	3	24	0	0
	4	0	39	9
	5	0	10	38

Table 4.38: Confusion matrix for PUSH exercise considering the medium score, by using 10-Fold cross-validation (magnitude + 3 axes)

		PREDICTED LEVEL			
		2	**3**	**4**	**5**
TRUE LEVEL	**2**	16	0	0	0
	3	0	8	0	0
	4	0	0	46	10
	5	0	0	1	39

Table 4.39: Confusion matrix for PUSH exercise considering the gross competency sub-score, by using 10-fold cross-validation algorithm (magnitude + 3 axes)

As done before, a comparison between the two validation techniques is reported in the graphs below for the six exercises.

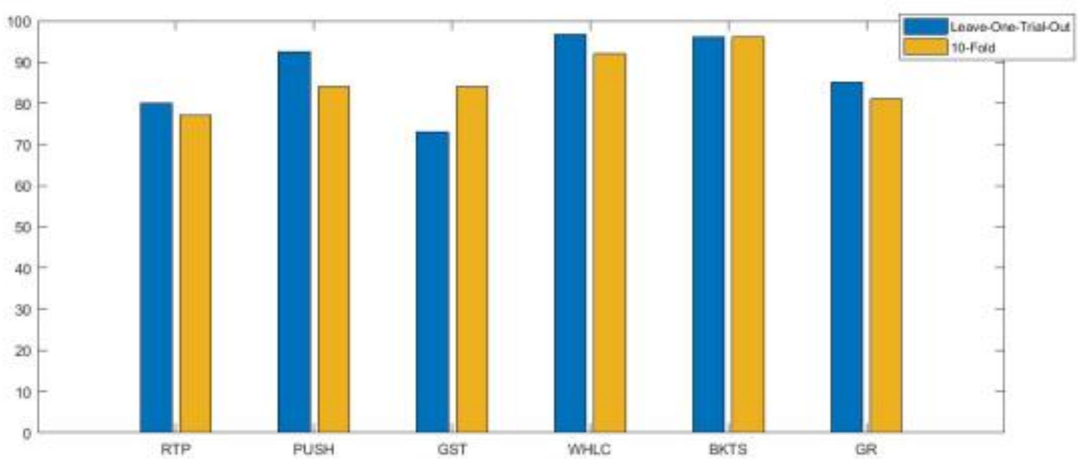


Figure 4.6: Accuracy of the classifier for the medium score (six exercises), by using the two validation methods (magnitude + 3 axes)

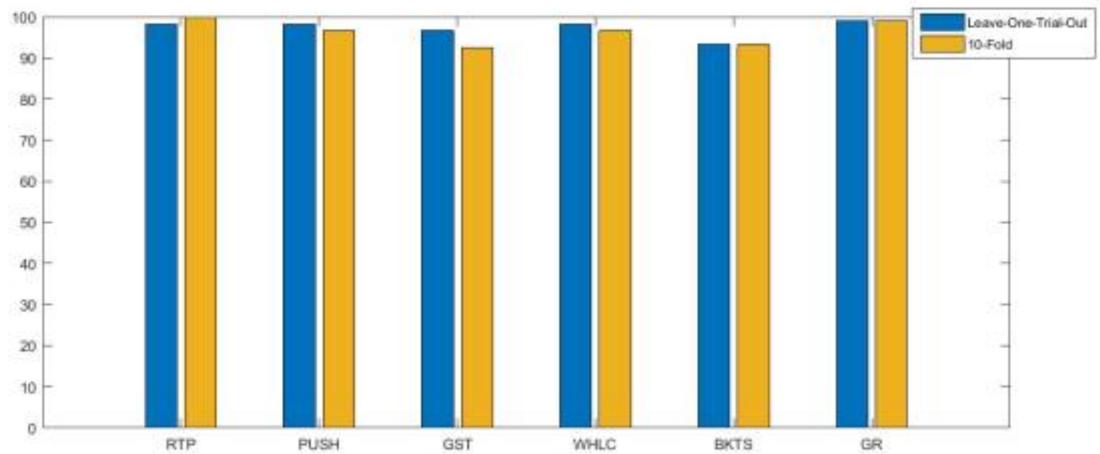


Figure 4.7: Accuracy of the classifier for the general score (six exercises), by using the two validation methods (magnitude + 3 axes)

Looking at the results obtained by using three distinct kinds of scores and considering two validation methods, the highest accuracies have been obtained in the case in which the three axes of the sensor were considered separated, even if the results coming from the other two cases are pretty close and so they are considered acceptable too.

This underlines that it is important to keep the orientation of the sensors during the analysis, both for the discrimination of Tai Chi exercises and for the estimation of the proficiency level of each practitioner.

In addition, the results show that some exercises gave much better accuracy compared to others, both by means of Leave-One-Trial-Out and 10-Fold cross-correlation technique.

In conclusion, the second method has provided much better results compared to the first one, the template matching.

All the results concerning the assessment of the proficiency level for the six exercises obtained keeping the three axes separated are reported in the appendix section.

In general, the accuracies are high and it is not present a high variability between the six Tai Chi exercises and among the different scoring criteria employed.

However, an interesting aspect regards the accuracies obtained using the different sub-scores; even if there is not a great variability among them, it was evident in most of the cases that the best results were obtained considering the Yin/Yang and the Flow/Dynamic Integration sub-scores.

These are the most philosophical aspects among the scoring criteria; discussing about this fact with the Tai Chi master, it was deduced that the sensors are apparently able to capture very well some features related to these sub-scores, such as the neuromuscular activity and coordination and the connection of the different parts of the body.

Some more attention should be put in the evaluation of the scoring criteria and which kind of biomechanical aspects they refer to.

Chapter 5: Discussion

In this project, a wearable system to monitor Tai Chi practitioners has been discussed, dividing the work in two main parts: the discrimination of twelve Tai Chi exercises and the assessment of the proficiency level of the practitioners while performing them.

The results regarding the two big aims of the thesis suggest that monitoring Tai Chi practice by means of wearable sensors is feasible, even if there are some limitations that affect the significance of the results.

For the discrimination of the different Tai Chi exercises, the results obtained are satisfactory and the values of the accuracy are high. In general, higher accuracies have been obtained for practitioners who have a higher proficiency level.

For the second part of the work, the proficiency level estimation, the results obtained by using two different methods are quite different.

By using the template matching technique, the results show a general low accuracy due to signals coming from subjects with different proficiency levels that are not well distinct.

Another reason why the obtained results are not good enough lays on the template used in the analysis. Indeed, the templates have been obtained by averaging the signals coming from the same sensor, as described in the previous chapters.

Thus, the main drawback is that we lost the shape of the template since it results to be attenuated compared to the other signals, making the classification more difficult.

An improvement to overcome this limitation is represented by the use of more templates (maybe one for each subject), not just one for each score, to not lose important characteristics of the signals and to achieve better results in terms of accuracy.

The second method applied to assess the proficiency level has provided much better results in terms of accuracy.

In particular, the best results have been obtained by using the three axes of the sensor separated, underlining that keeping the orientation of the sensors is important during the analysis.

In general, the accuracies are high and it is not present a high variability between the six Tai Chi exercises and among the different scoring criteria employed.

A general limitation of our analysis is represented by the starting position of the fifteen practitioners. Indeed, the subjects do not start the Tai Chi exercises with the same positions. Thus, it could be difficult to discriminate the different exercises since we have different starting movements.
Another possible improvement regarding the discrimination of the exercises can be the application of the template matching technique, not used in this part of the project, mainly due to a lack of time.
This approach can be promising since the Tai Chi exercises analyzed provide signals with different shapes from each other, allowing a clear discrimination among exercises.
Thus, it can be useful to see whether or not this different technique can give better results compared to the analysis carried out in this project.
In our analysis, due to the big amount of data, some of the recorded signals (ECG, GSR and toe/heel pressure) were not used. In future developments, they can be employed to observe if they can add significant information and provide better results, both for the discrimination of exercises and the proficiency level assessment.
Other limits regarding both the discrimination of exercises and the proficiency level estimation lay on the small dimension of the dataset analyzed, composed by fifteen subjects, thus making possible the occurrence of overfitting.
To overcome this problem, in the future a recruitment of more subjects should be done, to assess the analysis carried out in this project with a bigger dataset.
Another possible improvement to deal with the limit mentioned before can be the employment of other classification methods, such as Random Forests, and then comparing the obtained results to verify which is the best one.
Furthermore, discussing with the Tai Chi master, it has been deduced that adding one Shimmer sensor to put on the head of the subjects can be advisable to capture information related to some sub-scores considered in the analysis, such as the verticality of the head compared to the hip (as regards the proficiency level part). In this way, the sensor on the head could improve the results obtained for the assessment of the proficiency level.

Chapter 6: Appendix

6.1 Second method: Predictive performance of the model

SUB-SCORE	ACCURACY
Gross Competency	98.3%
Yin Yang	98.3%
Alignment/Posture	100%
Flow/Integration	100%
Range Of Motion	96.7%

Table 6.1: Accuracy of the classifier for the five sub-scores of RTP, by using Leave-One-Trial-Out algorithm (3 axes)

SUB-SCORE	ACCURACY
Gross Competency	93.3%
Yin Yang	97.5%
Alignment/Posture	95.8%
Flow/Integration	95%
Range Of Motion	90.8%

Table 6.2: Accuracy of the classifier for the five sub-scores of GST, by using Leave-One-Trial-Out algorithm (3 axes)

SUB-SCORE	ACCURACY
Gross Competency	98%
Yin Yang	98.3%
Alignment/Posture	77%
Flow/Integration	96.7%
Range Of Motion	91.7%

Table 6.3: Accuracy of the classifier for the five sub-scores of WHLC, by using Leave-One-Trial-Out algorithm (3 axes)

SUB-SCORE	ACCURACY
Gross Competency	96.7%
Yin Yang	97.5%
Alignment/Posture	95%
Flow/Integration	99.2%
Range Of Motion	90%

Table 6.4: Accuracy of the classifier for the five sub-scores of BKTS, by using Leave-One-Trial-Out algorithm (3 axes)

SUB-SCORE	ACCURACY
Gross Competency	94%
Yin Yang	99.2%
Alignment/Posture	95%
Flow/Integration	91.7%
Range Of Motion	78.3%

Table 6.5: Accuracy of the classifier for the five sub-scores of GR, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL		
ACTUAL LEVEL		**4**	**5**
	4	40	0
	5	1	19

Table 6.6: Confusion matrix for RTP exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

		PREDICTED LEVEL			
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	4	0	0	0
	3	0	19	1	0
	4	0	0	24	0
	5	0	0	0	12

Table 6.7: Confusion matrix for RTP exercise considering the Yin/Yang sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

		PREDICTED LEVEL			
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	4	0	0	0
	3	0	24	0	0
	4	0	0	20	0
	5	0	0	0	12

Table 6.8: Confusion matrix for RTP exercise considering the Alignment/Posture sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL		
ACTUAL LEVEL	**3**	**4**	**5**
3	12	0	0
4	0	36	0
5	0	0	12

Table 6.9: Confusion matrix for RTP exercise considering the Flow/Integration sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
ACTUAL LEVEL	**2**	**3**	**4**	**5**
2	4	0	0	0
3	2	14	0	0
4	0	0	24	0
5	0	0	0	16

Table 6.10: Confusion matrix for RTP exercise considering the ROM sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	4	0	0
	4	1	27	0
	5	0	0	28

Table 6.11: Confusion matrix for RTP exercise considering the medium score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
ACTUAL LEVEL		**2**	**3**	**4**	**5**
	2	15	0	0	1
	3	0	24	0	0
	4	0	0	46	2
	5	0	0	0	32

Table 6.12: Confusion matrix for PUSH exercise considering the Yin/Yang sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
ACTUAL LEVEL	**2**	**3**	**4**	**5**
2	15	0	1	0
3	0	39	1	0
4	0	1	47	0
5	0	0	0	16

Table 6.13: Confusion matrix for PUSH exercise considering the Alignment/Posture sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL		
ACTUAL LEVEL	**3**	**4**	**5**
3	32	0	0
4	0	39	1
5	0	0	48

Table 6.14: Confusion matrix for PUSH exercise considering the Flow/Integration sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

ACTUAL LEVEL \ PREDICTED LEVEL	2	3	4	5
2	8	0	0	0
3	0	40	0	0
4	0	0	47	1
5	0	0	0	24

Table 6.15: Confusion matrix for PUSH exercise considering the ROM sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

ACTUAL LEVEL \ PREDICTED LEVEL	2	3	4	5
2	23	1	0	0
3	2	37	1	0
4	1	3	44	0
5	0	0	0	8

Table 6.16: Confusion matrix for GST exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

ACTUAL LEVEL \ PREDICTED LEVEL	2	3	4	5
2	14	0	1	1
3	1	55	0	0
4	0	0	24	0
5	0	0	0	24

Table 6.17: Confusion matrix for GST exercise considering the Yin/Yang sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

ACTUAL LEVEL \ PREDICTED LEVEL	2	3	4	5
2	8	0	0	0
3	1	63	0	0
4	0	4	28	0
5	0	0	0	16

Table 6.18: Confusion matrix for GST exercise considering the Alignment/Posture sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	8	0	0	0
	3	0	44	4	0
	4	0	0	48	0
	5	0	2	0	14

Table 6.19: Confusion matrix for GST exercise considering the Flow/Integration sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	28	4	0	0
	3	0	44	4	0
	4	0	3	13	0
	5	0	0	0	24

Table 6.20: Confusion matrix for GST exercise considering the ROM sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	4	0	0
	4	1	27	0
	5	0	0	28

Table 6.21: Confusion matrix for GST exercise considering the medium score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	8	0	0
	4	0	31	1
	5	0	0	20

Table 6.22: Confusion matrix for WHLC exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
ACTUAL LEVEL	2	3	4	5
2	4	0	0	0
3	0	20	0	0
4	0	0	20	0
5	0	1	0	15

Table 6.23: Confusion matrix for WHLC exercise considering the Yin/Yang sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
ACTUAL LEVEL	2	3	4	5
2	7	0	0	1
3	0	18	3	3
4	0	6	14	0
5	0	1	0	7

Table 6.24: Confusion matrix for WHLC exercise considering the Alignment/Posture sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	15	1	0
	4	0	28	0
	5	0	1	15

Table 6.25: Confusion matrix for WHLC exercise considering the Flow/Integration sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
ACTUAL LEVEL		**2**	**3**	**4**	**5**
	2	4	0	0	0
	3	0	14	2	0
	4	0	2	29	1
	5	0	0	0	8

Table 6.26: Confusion matrix for WHLC exercise considering the ROM sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	8	0	0
	4	0	36	0
	5	0	0	16

Table 6.27: Confusion matrix for WHLC exercise considering the medium score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL						
ACTUAL LEVEL		**1**	**2**	**3**	**4**	**5**
	1	24	0	0	0	0
	2	0	29	3	0	0
	3	0	1	31	0	0
	4	0	0	0	24	0
	5	0	0	0	0	8

Table 6.28: Confusion matrix for BKTS exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

ACTUAL LEVEL \ PREDICTED LEVEL	2	3	4	5
2	39	1	0	0
3	0	54	0	2
4	0	0	8	0
5	0	0	0	16

Table 6.29: Confusion matrix for BKTS exercise considering the Yin/Yang sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

ACTUAL LEVEL \ PREDICTED LEVEL	2	3	4	5
2	19	5	0	0
3	0	55	1	0
4	0	0	32	0
5	0	0	0	8

Table 6.30: Confusion matrix for BKTS exercise considering the Alignment/Posture sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
ACTUAL LEVEL	2	3	4	5
2	16	0	0	0
3	1	79	0	0
4	0	0	8	0
5	0	0	0	16

Table 6.31: Confusion matrix for BKTS exercise considering the Flow/Integration sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

	PREDICTED LEVEL			
ACTUAL LEVEL	2	3	4	5
2	6	1	1	0
3	6	18	0	0
4	3	1	60	0
5	0	0	0	24

Table 6.32: Confusion matrix for BKTS exercise considering the ROM sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	7	1	0	0
	3	5	45	13	1
	4	3	3	34	0
	5	0	0	0	8

Table 6.33: Confusion matrix for BKTS exercise considering the medium score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	8	0	0	0
	3	0	66	6	0
	4	0	1	31	0
	5	0	0	0	8

Table 6.34: Confusion matrix for GR exercise considering the gross competency sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	16	0	0
	4	0	95	1
	5	0	0	8

Table 6.35: Confusion matrix for GR exercise considering the Yin/Yang sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
ACTUAL LEVEL		**2**	**3**	**4**	**5**
	2	13	2	0	1
	3	1	70	1	0
	4	0	1	23	0
	5	0	0	0	8

Table 6.36: Confusion matrix for GR exercise considering the Alignment/Posture sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	16	0	0	0
	3	0	36	4	0
	4	0	5	50	1
	5	0	0	0	8

Table 6.37: Confusion matrix for GR exercise considering the Flow/Integration sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL					
		2	**3**	**4**	**5**
ACTUAL LEVEL	**2**	7	1	0	0
	3	5	45	13	1
	4	3	3	34	0
	5	0	0	0	8

Table 6.38: Confusion matrix for GR exercise considering the ROM sub-score, by using Leave-One-Trial-Out algorithm (3 axes)

PREDICTED LEVEL				
ACTUAL LEVEL		**3**	**4**	**5**
	3	45	3	0
	4	1	63	0
	5	0	0	8

Table 6.39: Confusion matrix for GR exercise considering the medium score, by using Leave-One-Trial-Out algorithm (3 axes)

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