POLITECNICO DI TORINO

Master course in ICT for Smart Societies

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Mobile health support for post injury rehabilitation

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A mio padre e mia madre che mi hanno sempre teso la mano quando la salita diventava più ripida. Grazie per avermi sempre fatto credere di potercela fare. A mia nipote Greta che è riuscita a strapparmi un sorriso anche nei momenti più cupi.

Abstract

In rehabilitation field there is a need to improve the efficiency of treatments and speed up the healing processes. Providing a support compares normal functional abilities with reduced ones after a musculoskeletal problem is becoming a useful way to increase patient motivation and adherence to the recommended exercise. Human biomechanical parameters such as body balance disorder and range of motion (ROM) can give useful information regarding the health status of the individual. Their estimation helps in detecting disease and in assessing people training activities before and after injuries. Those parameters also play an important role in evaluating people's rehabilitation process and in detecting anomalous conditions.

In sports, providing a support that can help the athlete following an injury represents a way to make faster the healing process. Furthermore, having an instrument able to evaluate movements and their characteristics can match normal functional abilities with the ones after an injury.

In this thesis, conceived together with LINKS Foundation, a mobile health tool was developed to assist Dinamo Sassari basketball athletes and the sport club in evaluating some movements to compare pre and post injury functionalities using a "wearable" smartphone.

The three main athlete movements during a basketball match are:

- jumping
- throws of the ball, through flexion of the arm
- running

The thesis focused on the jumping act, by analyzing the movement and estimating the height of the jump, and the arm movements.

The tool measures the postural sway angles by applying a trigonometric formula and the maximum height of a countermovement jump implementing an algorithm able to calculate the flight time. Furthermore, it integrates an artificial intelligence algorithm to detect the correctness of the elbow joint range of motion while performing a specific rehabilitation exercise. The parameters of the One-Class Support Vector Machine algorithm have been optimized to reduce the misclassification in both correct and incorrect exercise repetitions. The comparison between normal athlete's functionalities and reduced abilities after an injury can help in making aware sportsperson of his total functional recovery.

Contents

Acronyms

ROM Range of motion

COP Centre of pressure

COG Centre of gravity

COM Centre of mass

LOS Limits of stability test

SVM Support Vector Machine

PD Parkinson's disease

OT Orthostatic tremor

MEMS Micro-electro-mechanical System

CMJ Countermovement jump

IMU Inertial Measurement System

NDI Numerical double integration

TOV Take-off velocity

FT Flight Time

APP Application

AP Anteroposterior

ML Medial-lateral

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Chapter 1

Introduction

Rehabilitation is the restoration of the optimal form (anatomy) and function (physiology) [1]. The process aims at minimizing the loss associated with acute injury by restoring the functional capacity.

In rehabilitation context, a clinician prescribes a collection of rehabilitation exercises to a patient, performing the movements in front of him to strengthen his perception. In this way, the patient becomes familiar with the exercise and able to correctly reproduce it. Then the patient has the task of performing the prescribed set of exercises at home. It is essential to face a correct rehabilitation program following injuries or orthopedic surgery.

Physiological recovery times of the body and individual assessment must be taken into account. It is essential not to "run too fast" with the times and accept that each person reacts and recovers in a different way than any other, even if the physical problem is the same. Factors that affect recovery times can be physical, physiological, character and psychological; what makes a rehabilitation process functional is above all the personal predisposition. Doctors ask patients to record their daily progress following each type of rehabilitation exercise. Patients will then have to visit the clinic periodically to evaluate progress with a doctor after a series of exercises.

Numerous medical sources [2] [3] report low levels of patient motivation in performing the exercises recommended for in-home rehabilitation. This lack of adherence leads to prolonged treatment times and increased health care costs. Many factors contribute to this problem, but the main one is the absence of continuous feedback and timely supervision of patients' exercises in a domestic environment by a healthcare professional. This continuous feedback aims also at identifying if the patient has recovered its total functional abilities.

Athletes are the individuals most exposed to musculoskeletal injuries, often due to a strong force - such as fall, accident, and laceration. Nowadays, inertial sensor components, such as accelerometers and gyroscopes, are embedded into smartphones. They can register position as acceleration and inclination. Subsequently, a great number of mobile applications has been developed and, any of the uses of these applications include a great capacity for tracing human motion variables for both investigation and medical uses.

In the sports scenario, it could be useful to provide athletes with an instrument that can assist them during sports preparation, monitoring their movements. The main purposes that are closely interconnected are performance optimization and accident prevention. The monitoring of movements certainly provides a useful tool of applicative interest when the athlete suffers an injury during the course of his activity.

Rehabilitation in this case plays a fundamental role in order to return to sporting activity. Early in rehabilitation, resistance training is typically of lower intensity and supervised by an athletic trainer or physical therapist. Exercises are prescribed for a number of reasons: the restoration of balance, the development of reflex control, the redevelopment of neuromuscular control and function, and the development of endurance in injured tissues. Unfortunately, athletes often pay the price for poorly coordinated recovery plans within the return-to-play process or lack of adherence to them. Return from athletic injury can be a difficult and lengthy process.

The injured athlete receives care from several clinicians during rehabilitation. As their condition improves, injured athletes recover strength programs for return to play. Although the athlete may have recovered in medical terms (improvements in flexibility, range of motion, functional strength), preparation for competition requires the restoration of strength, speed and power at levels exhibited in sport. When athletes resume team-based activities, emphasis should be on generic movements (exercises inherent to most sports, such as jumps and squats) and sport-specific movements that compose the complete strength training program for an athlete.

In this sense it would be useful to provide technological support to the athlete who keeps track of his functional abilities. Awareness of the state of health and recovery is a vital factor. A lack of awareness can slow or prevent athletes from returning to peak capability and increase the risk of new injuries and even more devastating musculoskeletal problem.

The thesis has been conceived together with LINKS Foundation and aims at supporting a basketball team called Dinamo Sassari. The purpose of the thesis is to provide athletes and the sport club with a tool capable of evaluating movements and their characteristics in a simple and intuitive way. Providing an evaluation of the movement makes the athlete aware of the skills and abilities he possesses in every situation. An instrument capable of evaluating movements is of fundamental importance following an injury, when the functional abilities of the sportsman are compromised. The mobile health support evaluates physical capacities in both static and dynamic situations.

The first ones regard the measurement of the postural sway in anteroposterior and medial-lateral directions. Control of balance is complex and involves maintaining postures, facilitating movement, and recovering equilibrium. Balance control consists of controlling the body's center of mass over its limits of stability. The tool will support athletes in maintaining balance providing sound feedbacks and calculating the postural sway angles along the two body directions. This functionality becomes important in the case of injury to the lower limbs, a condition in which athletes find it difficult to intentionally shift their weight along anteroposterior and medial-lateral directions or maintain balance by placing themselves on one foot.

Furthermore, for the same purpose, the tool will provide with an automatic calculation of the maximum vertical displacement of the centre of mass during a countermovement jump. The comparison between the maximum height under the "normal" condition of the athlete and the functional capabilities after an orthopedic injury could motivate the patient.

These two activities have been carried out by following the procedures found in the literature. The postural sway angles have been calculated through a trigonometric formula, while the maximum height of a vertical jump was evaluated by implementing an algorithm that allows to detect the flight time of the jump and applying the physical formula of motion in free fall.

The dynamic activity developed in the tool, instead, consists of implementing a machine-learning algorithm to automatically detect the correctness of a specific rehabilitation exercise. The chosen exercise is the flexion-extension of the elbow. This exercise becomes difficult to be performed following an injury at the upper limbs. Elbow health represents one of the most important things for a basketball player. The correctness of the specific rehabilitation exercise allows to give athletes an index of the total recovery following an injury. The idea was to build an ad-hoc machine that recognizes the normal functionality of the athlete. At the beginning of the sporting season, the athlete records the data needed for training the machine learning algorithm. It is assumed that the athlete is at the top of his functional abilities and can perform the exercise without any difficulty. The machine learns that this is the right movement and identifies an anomaly if the exercise were performed differently. In this way, when athlete suffers an injury and is aware of not succeeding in the correct performance of the exercise, the machine recognizes the error, up to the moment of its total recovery. To pursue the goal, a semi-supervised machine learning algorithm was explored. Only the correct exercises have been used to train the machine. Since the tool was designed as an ad-hoc machine built for a specific athlete, only the data of a single individual were used to conduct the work.

1.1 State-of-Art

This section aims at describing which technologies have been used in the literature to evaluate the parameters which have been subject of study in this thesis. It describes the sensors-based devices usage in detecting and calculating balance disorders, height of a vertical jump and elbow joint range of motion. Regarding the postural control, the chapter explains the importance of continuously monitoring balance disorders as a consequence of disease and injuries.

1.1.1 Postural control

Maintaining proper standing balance requires a series of sensory processing and motor executing. Balance control is given by the input coordination from multiple sensory systems: the vestibular, somatosensory and visual systems. Different studies [4] [5] have shown the feasibility of using smartphone-based accelerometers to identify body movement changes while performing different tasks.

Basketball is one of the most popular sports in the world. Basketball players must adjust their body position rapidly and continuously during the game. They must maintain their center of gravity within the base of support while performing very rapid and asymmetrical lower limb movements. Therefore, body balance is crucial for basketball skill advancement, sports performance, and injury prevention.

Postural sway is a very interesting parameter to identify balance disorders given by many different diseases and injuries. Orthostatic tremor, Parkinson's disease, and stroke are the main fields of postural sway in the literature. Patients affected by Orthostatic tremor occur in instability problems while standing and walking. The continuous monitoring of this problem by a smartphone-based accelerometer increases the possibility of detecting limits and serious situations.

For orthostatic tremor (OT), [6] showns the feasibility of detecting stand/gait pattern by measuring acceleration values of a 3-axis accelerometer embedded in an iPhone 6s, fastened tightly on the sacrum area via a running belt waist pack. The sacrum area has been chosen since it is considered the location of the centre of mass of the body, so the centre of balance control. All research participants had to perform two conditions: standing and walking. During the first one, persons had to close their eyes for 20 seconds after 20 seconds of opened eyes. The research demonstrates that patients with OT significantly increased their accelerations in the medial-lateral direction than healthy ones. This outcome has verified that using smartphone-based accelerometers can identify the standing balance and gait changes in patients with OT. Another research asserts that the balance control can be performed by subjects with chronic stroke [7] supported with the help of a smartphone-based accelerometer. Patients that survive a stroke - a cerebral artery disease - usually suffer balance impairments, which affect their performance in daily living activities and life quality. A smartphone HTC 10 - fixed to the back of subjects at the second sacral spine - was used to perform the balance assessment in [7]. Data coming from its built-in accelerometer and gyroscope were recorded to measure postural sway. Accelerometer and gyroscope changes were the parameters used for asserting disorders: higher values indicate more instability. Measurements of anteroposterior and medial-lateral acceleration changes have been compared with the Berg Balance Scale (BBS): a widely used clinical test to measure a person's static and dynamic balance abilities. Acceleration changes recorded by smartphone have shown significant differences between healthy and ill patients. Outcome of the study was the feasibility of smartphone as an instrument to assess balance for patients affected by chronic stroke. Furthermore, the rating of postural instability is an important concept if also related to people with Parkinson's disease.

A research article proved the utility of wearable sensors for evaluating standing balance and walking stability in patients affected by Parkinson's disease [8]. During this study, sway was assessed with a wearable inertial sensor, positioned with an elastic belt at the level of the fourth and fifth lumbar spine segment. Two different metrics were considered to calculate postural balance: the root mean square of acceleration values and the jerkiness of sway. The last one represents the first derivative of the acceleration signal which indicates the smoothness of postural sway. The study showed that body sway, measured by wearable sensors, was not significantly different in PD patients and healthy ones during standing conditions. On the contrary, it has been founded the difference between the two groups while performing dynamic tasks.

Postural control assessment study for chronic ankle instability [9] has stated that identifying decreased postural control ability could help in planning a correct rehabilitation process. The result of the research was the statement that the smartphone is a feasible device for monitoring postural balance. The study has proved that the mobile phone has a good correlation compared to the force platform when recording the performance of a single leg stance balance test.

Efficacy of smartphone usage has been proved also if located at a different place concerning the centre of mass [10]. Smartphone LG G3 - fixed in the centre of a balance platform - was used to record data coming from its built-in gyroscope. The results of the research have shown a significant relationship between body sway variability measured by the platform and the mobile phone in both frontal and sagittal planes. Once again the Micro-Electro-Mechanical Systems (MEMS) embedded in the before-mentioned smartphone has been considered to have the potential for accurate assessment of postural balance.

1.1.2 Countermovement Jump

Countermovement jump, also known as CMJ, is a jump that contains a countermovement. A countermovement can be described as composed by a downward action followed by a reciprocal upward action (more explanation about it will be given in Chapter 2).

Functional deficits following an injury, have been associated with decreases in jump height and sprint speed. Athlete's readiness to return-to-play and later return-to-performance is one of the most important aspect to be taken into account.

Literature [11] has shown the feasibility of using wearable sensors in calculating the maximum height reached by the jumper and the flight time recorded during the jump. Force platforms allow to accurately determine the vertical acceleration of the centre of mass, but they are often expensive.

Nowadays, inertial measurement units (IMUs) have become popular for the jump parameters analysis, probably because of reduced size and ease of use. IMU sensors feasibility and reliability have to be proven.

Different are the methodologies to evaluate the maximum displacement of the centre of mass during a vertical jump. These methods could rely on numerical double integration (NDI), take-off velocity (TOV) and flight time (FT). Many studies have validated IMU and smartphone-based sensors to determine CMJ height, comparing the results with a force platform, considered as a gold standard. Countermovement jump estimated with an IMU can be used to evaluate functional performance in the lower limbs. The estimation of height using the numeric double integration method has been considered as the best way to evaluate maximum vertical displacement in [12]. This outcome can be doubted because there are conflicting opinions in asserting the best manner for evaluating jump maximum height. The NDI approach introduces drifts due to rounding errors. On the other hand, no study has shown which is the best location of the body to wear the sensor.

The identification of take-off and landing during vertical jump via foot-worn inertial sensing - mounted on the toe and the heel - has shown excellent agreement with the gold standard optical motion capture system measurements [13]. At the same time, the choice to mount an IMU device close to the ankle has showed an elevate accuracy in detecting jump events [14]. In this case, landing and take-off were estimated from the acceleration in the vertical direction and flight time was calculated as the elapsed time between the two events plus 20ms of correction factor because of the delay in onboard data. Inertial sensors integrated into the iPhone 4S - fixed at L5-S1 level attached to a belt - has been used to describe and analyze kinematics characteristics [15]. The research has described contact mat variables (jump height and jump time) to highlight the differences in kinetic and kinematic measurements in men and women.

Limitations: Calculation of the height during a vertical jump requires the exact identification of take-off and landing instants if the calculation is based on the flight time method. The identification of these two instants from wearable sensors is often really hard, since it is required to detect a threshold in acceleration values that can trigger the jump event. At the same time, if the maximum vertical displacement of the centre of mass is calculated with the numerical double integration, it is necessary to take into account the introduction of drifts due to rounding errors. Furthermore, take-off velocity method also requires the identification of take-off. Therefore the limitation found in the calculation of the height is the same as that found in the time of flight method.

1.1.3 Limb Range of Motion

In rehabilitation process, another parameter to take into account is human movement analysis. It has been subject of study and it is still being explored by clinicians and researchers. One of the most important aspects of the before mentioned analysis is joint angle measurement.

Information of limb range of motion is helpful since it allows to detect movement disorders and it gives information about the achieved state of healing. The conventional gold standard for monitoring and measuring the changes in the joints' angle is optically based. Alternatively, it is possible to use an electrogoniometers which is an electronic device that uses angle sensors, such as potentiometers and, more recently, accelerometers to record such measurements. While the first standard is not so practical since it requires a specific gait laboratory and an expensive setup, the second method requires a trained clinician to operate. To overcome these limitations, literature has explored alternative methods of measuring the joint angle. Micro-electromechanical systems have become practical solutions for clinical use.

The model used in [16] was composed of two wooden bars of the same dimension jointed by a hinge. Sensors were attached to the bars using double-sided adhesives and accelerometer values were used to calculate joint angles from a trigonometric relationship. For validating the results, a flexible goniometer was used as the gold standard. The research proved that acceleration values coming from the model confirmed the goniometer readings. At the same time, studies based on the calculation of joint angles from smartphone applications have shown that mobile devices are reliable and valid for clinical use[17].

Smartphones are provided by sensor inertial measurement units able to support medical researches and studies. Goniometer apps have become very useful because they represent a portable instrument acting as the goniometers usually used in clinical practice. Accelerometers, magnetometers and optical sensors contained inside the mobile devices have been exploited to measure the body movements. DrGoniometer[18] measures knee flexion positioning a virtual goniometer, visible on the smartphone screen, on a photo taken by the smartphone camera.

Clinometer [19], KneeGoniometer[20] and Angle [21] are accelerometer-based goniometer applications able to measure knee flexion using acceleration values coming from the inertial measurement unit embedded into the smartphone.

SimpleGoniometer [22] and GetMyROM[23] are also based on accelerometer developed for the same purpose.

On the contrary, Compass[24] is an application that uses the magnetometer to measure cervical range of motion (ROM) on the horizontal plane. A thesis [25] based on the development of an application for home training has shown the potentiality of the smartphone for measuring the limb joint. In particular, the mobile application aims at calculating the knee joint angles from the combination of a smartphone and an IoT device. The system showed an average standard deviation of $\pm 4.55°$ in the seated position when starting the procedure for evaluating the joint angles. At the same time, also the elbow joint angles were calculated through a smartphone inclinometer and the outcomes have shown that despite smartphone applications are reliable tools for this type of calculation, they overestimate flexion angles (mean of $6.4° \pm 1.0°$) with respect to the gold standard goniometer [28]. The extension angles measured by both the instruments, instead, have shown no particular differences in measurements.

Limitations: Different methods for measuring limb movements have been investigated. The disadvantage of the photographic method is its time consuming and set up that could be complex to use for oneself. Magnetometer-based methods, instead, perform as reliable tools if compared to universal goniometer but they are not widely used and considered more complex to get precise measurements.

For this purpose, accelerometer-based modalities have shown the highest degree of correlation with respect to the usual clinicians' method. The mentioned researches have proved the reliability of the smartphones in calculating the limb joint angles, but none of these focused on providing the patient with information about the correctness of elbow flexion-extension movement. Several studies in the literature employed machine learning methods that implement a time-delay neural network for predicting real-time joint angles [29].

Other studies classify an exercise repetition into correct or incorrect classes of movements, but no studies have focused on the classification of the correctness of the specific rehabilitation exercise analyzed in this thesis (the exercise will be described in Chapter 2).

Chapter 2

Methods

This chapter aims at describing the entire process that was followed to develop the mobile health tool in its three different parts: postural control, countermovement jump and elbow range of motion.

These three activities were chosen to give an index of functional recovery after an injury to basketball athletes. Functional recovery regards the lower limbs when talking of postural control and countermovement jump and the upper limbs when addressing the problem of the elbow range of motion.

The mobile health tool was developed with Android Studio with a smartphone provided with Android v7 operating system and three different sensors: accelerometer, gyroscope and magnetometer. Each section of this chapter explores the technologies and the procedures used to collect, analyze and process data.

Section 2.1 explains the calculation of postural sway angles obtained from the application of a trigonometric formula found in the literature.

Section 2.2 focuses on countermovement jump performance analysis given by the calculation of the flight time and the maximum height reached by the jumper. It describes the threshold chosen for identifying the instants of take-off and landing and how the calculation of the height has been derived from the flight time.

Section 2.3 describes how the model for training the machine learning algorithm in detecting the correctness of the elbow range of motion has been built and tuned. It explains how data was processed before the training of the machine and which features have been selected to build the model.

2.1 Postural Control

2.1.1 Introduction

This section aims at describing the procedure that was done to calculate the postural sway angles. Postural balance is the ability to control and maintain the body centre of gravity toward the base of support. The postural sway [26], in terms of the human sense of balance, is a measure of how much the body oscillates around the center of gravity.

For a person the maintenance of balance requires input coordination from multiple sensory systems: the vestibular, somatosensory and visual systems. The first one controls balance and directional information concerning the position of the head and the middle ear. The second detects information on the relative movement of the supporting surface and the position of the different parts of the body with respect to each other. Visual system, on the other hand, refers to the verticality of body and head movement. These systems coordinate together to allow us to maintain balance: the postural oscillation is more balanced.

Loss of effectiveness of postural control, due to advanced age or to effects of some pathologies, has led researchers to investigate the functioning of postural control. The aim is to be able to determine and quantify the balance at every moment. Patients affected by vestibular disorders rely excessively on visual system and this leads them to have stability problems when they close their eyes.

An individual in his upright position maintains balance thanks to small but continuous oscillations, counterbalancing the weight force that would tend to make it fall, due to gravity. Weight force and constraining reaction of the ground apply respectively to its center of gravity (CoG) and the center of pressure (CoP).

Centre of gravity is defined as the point of application of the resultant of the forces acting on the body; while centre of pressure is the point of application of the ground reaction force vector.

Many studies are based on measuring the parameters that are involved in detecting balance disorders through the usage of a smartphone [27] [30]. These researches demonstrated the validity of the use of the smartphone [32], comparing the results with measurements taken from a force platform [31].

In sport, the balance control is an index to be taken into account. It is not always the vestibular disorders that can cause stability problems. This condition can be compromised following an injury at the lower limbs. Athletes are the individuals most exposed to musculoskeletal injuries and in this situation, basketball players have difficulty maintaining balance, for example by standing on one leg.

Limits of Stability (LoS) are important parameters defined in postural control. They are defined as the points at which the center of gravity (CoG) approaches the limits of the base of support (BoS).

LoS are defined as the amount of maximum excursion a person is able to intentionally cover in any direction without losing balance or taking a step. The two directions that play a key role in investigating the stability impairment are the anteroposterior and the medial-lateral ones (Figure 2.1[1]). The normal sway angle in the two before mentioned directions is approximately 12.5° and 16° respectively. The "Cone of Stability" is defined as the area of stable swaying (12.5° in anteroposterior direction and 16° in medial-lateral direction). LoS is a reliable variable of stability that provides important information about voluntary motor control in the dynamic state. LoS helps assess balance in the dynamic state by instantaneously tracking the change in COM velocity and COM position.

The reduction in LoS for sportive athletes may be because of the weakness of foot muscles and musculoskeletal problems of the lower limb. These impairments may help physicians to correlate with the medical examination findings and serve as an important outcome measure for the rehabilitation of these specific underlying body impairments. This is the reason why the postural sway angles have been considered a measurement to be included in the development of the mobile health tool.

During human quiet standing, postural sway is indeed often quantified by measuring the motion of centre of pressure, strongly related to the sway of the center of mass (CoM). In this study, the postural control has been carried on by measuring the anteroposterior (AP) and the medial-lateral (ML) sway angles, by the only usage of sensors embedded in the smartphone.

2.1.2 Technologies

A smartphone was attached to the body with a belt at the centre of gravity height. The orientation of the axes (x,y,z) is defined as: the X-axis is horizontal and points to the right, the Y-axis is vertical and points downwards and the Z-axis points towards the outside of the screen face. In this system, the coordinates in front of the screen have negative Z values.

A triaxial accelerometer sensor was used to measure the sway angles of

[1]Source: `https://images.app.goo.gl/MAvJPU3TxibyvHfo9`

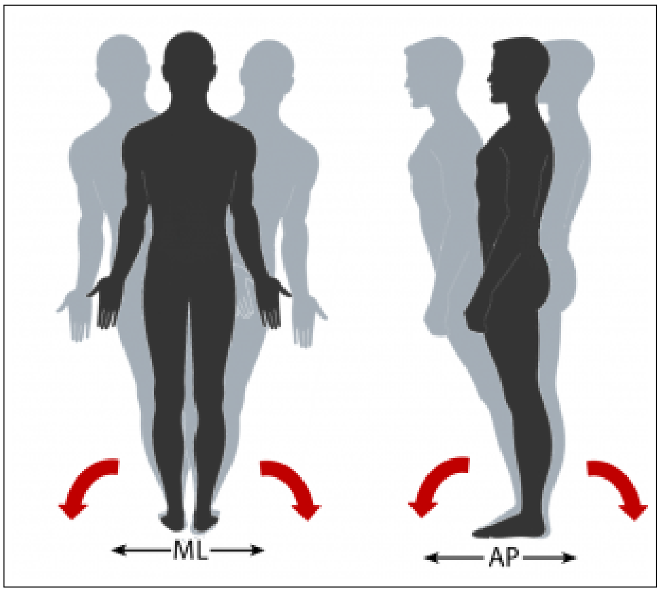


Figure 2.1: Cone of Stability for antero-posterior and medial-lateral directions

interest because the used trigonometric formula is based on accelerometer values. This smartphone sensor measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity.

In standing position, the smartphone thus placed records an acceleration along the y-axis equal to the gravity. A 100Hz sample frequency was used for carrying on the study.

2.1.3 Procedure

2.1.3.1 Removing offsets

Acceleration values measured by the triaxial accelerometer were treated to remove the offsets to reduce noise in acceleration signal. During the standing position, linear acceleration values along the three-axes were recorded for ten seconds and averaged. Linear acceleration value is defined as the acceleration force along the 3-axes (excluding gravity).

The resulted correction factor were subtracted from all the subsequent measurements. Correction factor was calculated as the summation of the linear acceleration values divided by the number of recorded samples.

Three different correction factors were obtained, one for each Cartesian axis (x,y,z).

2.1.3.2 Real-time processing

The cleaned acceleration values along the 3-axes were used in the calculation of the sway angles.

Real-time in processing allows to have the displacements of sagittal and coronal planes of the body (Figure 2.2[2]) using only the instantaneous acceleration values along the 3-axes. In this way, the individual can have information about the postural sway at any instant of the dynamic state.

Calculated sway angles are the anteroposterior and the medial-lateral angles. AP and ML sway angles are the angles between a line projecting vertically from the center of foot support and a line from the center of foot support to the center of gravity (COG) position on the body in the anteroposterior and medial-lateral directions respectively.

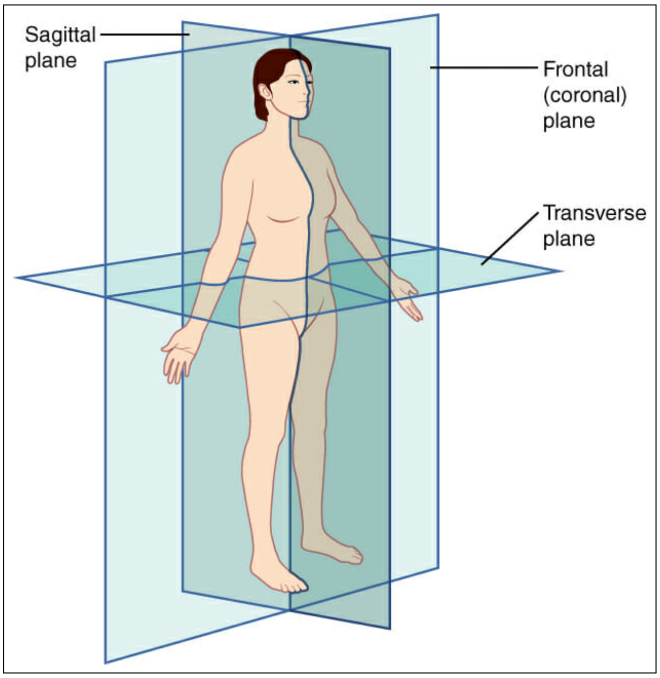


Figure 2.2: Anatomical planes configuration

The trigonometric formulas used for evaluating the postural anteroposterior (Equation 2.1) and medial-lateral (Equation 2.2) angles were respectively:

$$AP_{angle}[deg] = |90° - |\frac{atan2\frac{acceleration_y}{acceleration_z}}{\frac{pi}{180}}|| \tag{2.1}$$

$$ML_{angle}[deg] = |90° - |\frac{atan2\frac{acceleration_y}{acceleration_x}}{\frac{pi}{180}}|| \tag{2.2}$$

[2]Source: `https://images.app.goo.gl/GTGPnGPbgnB3iUAu9`

The two formulas (Equations 2.1 and 2.2) were applyed on cleaned data after the offsets remotion.

The mobile health tool was also provided by a sound feedback that warns the athlete when he is moving away from the initial position.

An example would be to keep the balance on one leg. If the athlete moves away from the initial position - as a result of an injury to the lower limbs it could be difficult to maintain the posture - the sound feedback will increase its frequency in correspondence with an increase in distance.

2.2 Countermovement Jump

2.2.1 Introduction

This section converges its focus on the main components that were analyzed in the study of the countermovement jump performance.

Countermovement Jump (CMJ) is an excellent movement for evaluating athletes in several scenarios. It is a very simple and reliable measure for evaluating lower-body power. Studies proved that it is the most indicated measure of lower-body power compared to other jump tests.

Contact mats, force platforms, accelerometers, high-speed cameras, and infrared platforms showed to provide a valid measure of CMJ performance – through force platforms which are considered as the gold standard. During CMJ (Figure 2.3[3]), the jumper starts from an upright standing position (Figure 2.3 (a)), makes a preliminary downward movement by flexing at the knees and hips (Figure 2.3 (b-c)), then immediately extends the knees and hips again to jump vertically up off the ground (Figure 2.3 (d-e-f)).

Athletes, especially basketball players, rely a lot on lower-body power during the matches. Giving them an instrument able to evaluate the maximum height reached during a vertical jump allows them to compare their body capabilities in top conditions with respect to the ones under a post-injury situation.

During the rehabilitation program, an individual must be able to recover all its functionalities and can be interesting to keep continuously track of previous and present motor skills. In this way the rehabilitation process is tuned to readjust the athlete's features and recover normal abilities. Countermovement jump tests are commonly used to assess recovery of muscle function following musculoskeletal injury. Traditionally CMJ performances were evaluated by a vertical structure where athletes jump to touch a peg to evaluate their maximum centre of mass vertical displacement. According to Section 1.1.2,

[3]Source: `https://images.app.goo.gl/mmrCaoSceKt5529p6`

different devices[4] were used to evaluate CMJ performances. Surely, the usage of inertial sensors to assess CMJ recovery in athletes offers several advantages over the other methods. Inertial devices are small, portable and wearable. Data, derived from these sensors, agrees well with simultaneously recorded data by force plate, even if they slightly underestimate jump height compared to the force plate. Studies showed the calculation of jump height using different methodologies: take-off velocity, numeric double integration and flight time.

To carry on the development of the mobile health tool, the method relies on flight time was chosen. To estimate the flight time, it was necessary to identify the take-off and landing instants. It can be said that the jump is identified by three phases: the take-off, the flight and the landing ones. The flight time is defined as the elapsed time between the instant of take-off and the instant of landing. To estimate this time, it was necessary to identify the two main before mentioned moments. In physics, when the sensed acceleration is 0 or approximately 0 - it is equal or approximately equal to the acceleration of gravity of Earth - this means that the jumper is either standing on the ground, or is reaching the highest point in the air, or is falling back on the floor. What is found out in literature is that the accelerometers in the smartphone can measure the time of the flight with reasonable precision.

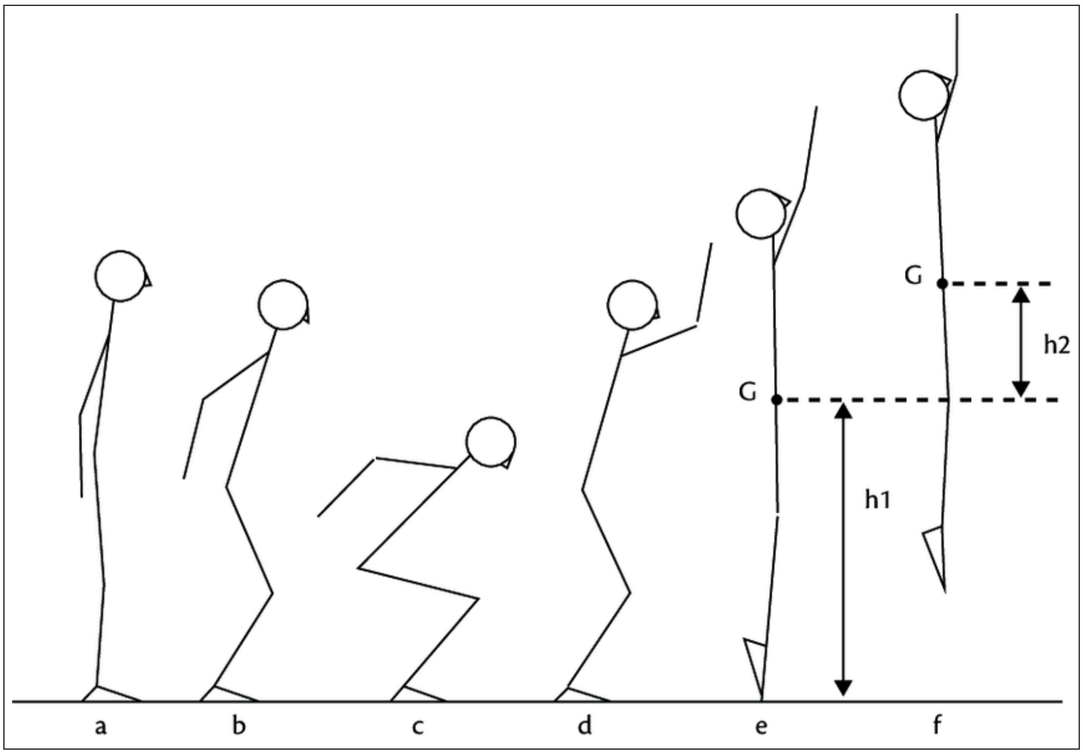


Figure 2.3: Countermovement jump phases illustration

[4]contact mats, force platforms, accelerometers, high-speed cameras, and infrared platforms

2.2.2 Technology

A smartphone was attached to the body with a belt at the height of the centre of mass. The orientation of the axes (x,y,z) is defined as: the X-axis is horizontal and points to the right, the Y-axis is vertical and points downwards and the Z-axis points towards the outside of the screen face. In this system, the coordinates in front of the screen have negative Z values (as mentioned in Section 2.1.2).

A triaxial accelerometer sensor was used to measure the maximum vertical displacement of centre of mass during the vertical jump. This smartphone sensor measures the acceleration force in m/s2 that is applied to a device on all three physical axes (x, y, and z), including the force of gravity. In standing position, the smartphone thus placed records an acceleration along the y-axis equal to the gravity.

A 100Hz sample frequency has been used for carrying on the study.

2.2.3 Procedure

2.2.3.1 Removing offsets

Acceleration values measured by the triaxial accelerometer were treated to remove the offsets. During the standing position, linear acceleration values along the three-axes were recorded for ten seconds and averaged.

In this way, it was possible to obtain three different correction factors for removing the offsets values from the three-axes measurements. The resulted correction factor was subtracted from all the subsequent acceleration values measured by the accelerometer during the vertical jump.

The correction factor was calculated as the summation of the linear acceleration values divided by the number of recorded samples.

2.2.3.2 Data processing

After the offsets remotion, cleaned acceleration values were recorded for six seconds during which the subject performs the countermovement jump. Data was sent in real-time to a personal computer through a Bluetooth connection and processed offline using Python code to tune the algorithm for calculating the vertical height.

A 1st-order Butterworth low-pass filter with a cut off frequency of 10Hz was used to smooth the acceleration signals. A cut off frequency of 10 Hz was shown to be the best cut off frequency when analyzing accelerometer data [33].

Figure 2.4 shows the acceleration values along the 3-axes during a countermovement jump lasts six seconds. While it can be said that the acceleration values along the X-axis are not particularly relevant because of its orientation, the accelerometer records a signal along the Z-axis that is consistent because of the trunk bending during the vertical jump.

Figure 2.5 shows the module of the three axes acceleration values, calculated as in Equation 2.3.

$$A[m/s^2] = \sqrt{accX^2 + accY^2 + accZ^2} \tag{2.3}$$

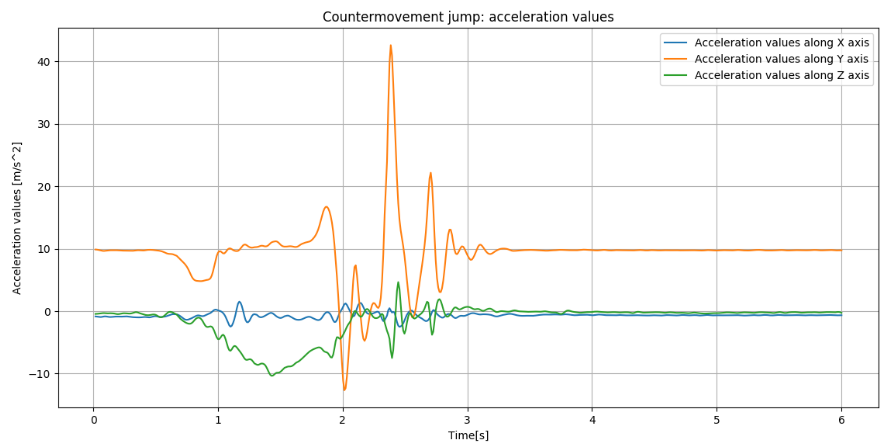


Figure 2.4: Acceration values along the 3-axes performing a countermovement jump

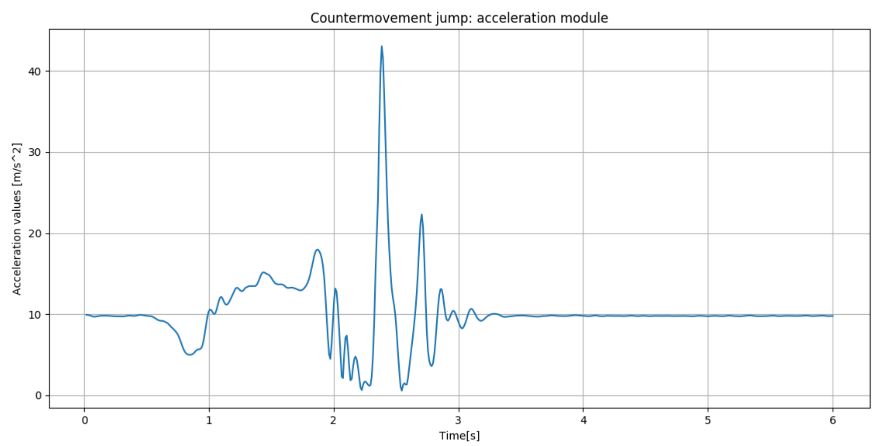


Figure 2.5: Acceration module during countermovement jump performance

To calculate the maximum displacement of the centre of mass during the countermovement jump, only the acceleration value along the Y-axis was taken into account. Finding the maximum height of the jump by using the method based on the flight time means identifying the instants of take-off and landing.

The take-off instant is defined as the moment in which the feet come off the ground before the jump. The landing moment instead is the moment in which the feet touch again the ground after the jump. Therefore the flight time is defined as the elapsed time between these two moments.

All of the conducted researches in literature had the aim of correlating as much as possible the outcomes of the body-mounted accelerometer with the force platform used as a gold standard. The force platform allows perfectly to detect the flight time because of the take-off coindices with the moment in which the subject leaves the platform and registers a force equal to zero. For carrying on the calculation of the flight time, the instants of take-off and landing were identified as the moments in which the acceleration values along the Y-axis cross half of the gravity [34]. This identification allowed improving the calculation of jump height for greater accordance with a force platform. Force values recorded with force platform allows perfectly to detect the flight event (force values equal to zero). Figure 2.6[5] shows the recorded vertical force values during a countermovement jump with a force platform. It is clearly visible which are the instants of take-off and landing that trigger the jump event. The same consideration cannot be done for body-mounted accelerometer (Figure 2.4) with which is very hard to find exactly take-off and landing moments.

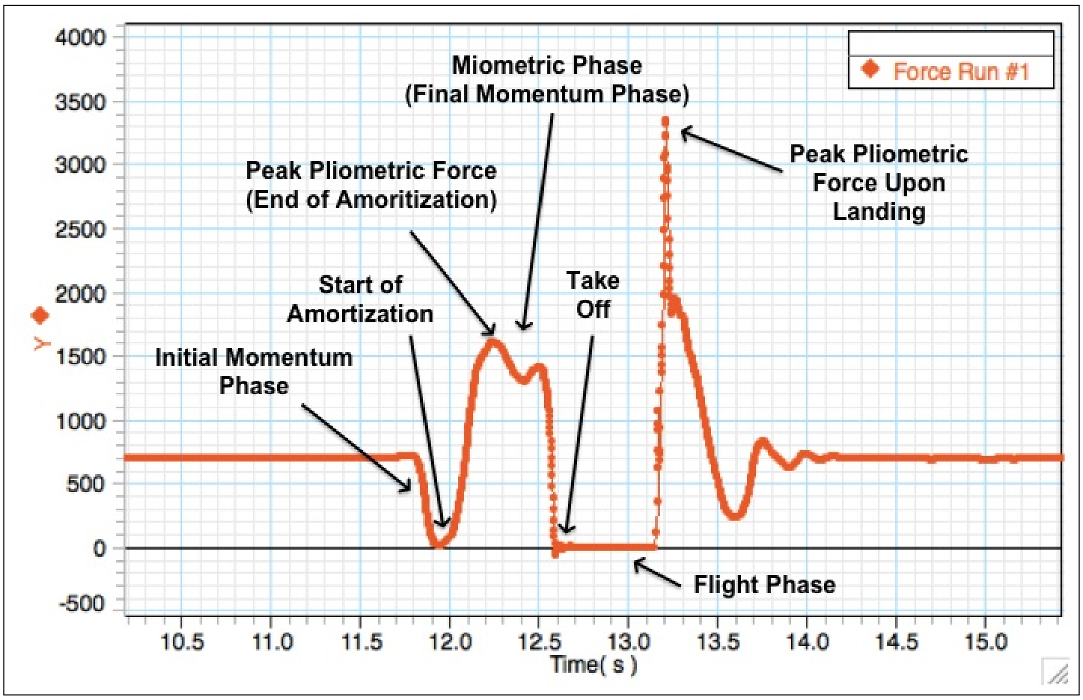


Figure 2.6: Countermovement jump recorded by a force platform

[5]Source: `https://images.app.goo.gl/4T1wxHcAfr6pJ9gH6`

Equation 2.4 shows the formula used to calculate the flight time. This formula contains a subjective error because the athlete can fold his legs during the falling and then extend the fall time.

The assumption that must be performed is in fact that the body configuration is the same at the instant of take-off than at landing. The maximum height of the jump, instead, was calculated with the formula of free-fall motion (Equation 2.5) where gravity is the only acceleration acting on the body.

$$t_f[s] = Tlanding - Ttakeoff \tag{2.4}$$

$$h[m] = \frac{1}{2} * g * \frac{t_f^2}{4} \tag{2.5}$$

An algorithm that detects automatically four main points in Y-axis acceleration values was developed. The threshold to identify take-off and landing has been set when the acceleration values cross an half of the gravity. Figure 2.7 shows the outcome of the algorithm developed for the identification of the acceleration values and correspondent instants of time to calculate the flight time. These four main points are: maximum peak before the jump (orange point), take-off point (green point), landing point (red point) and maximum peak after the jump (purple point).

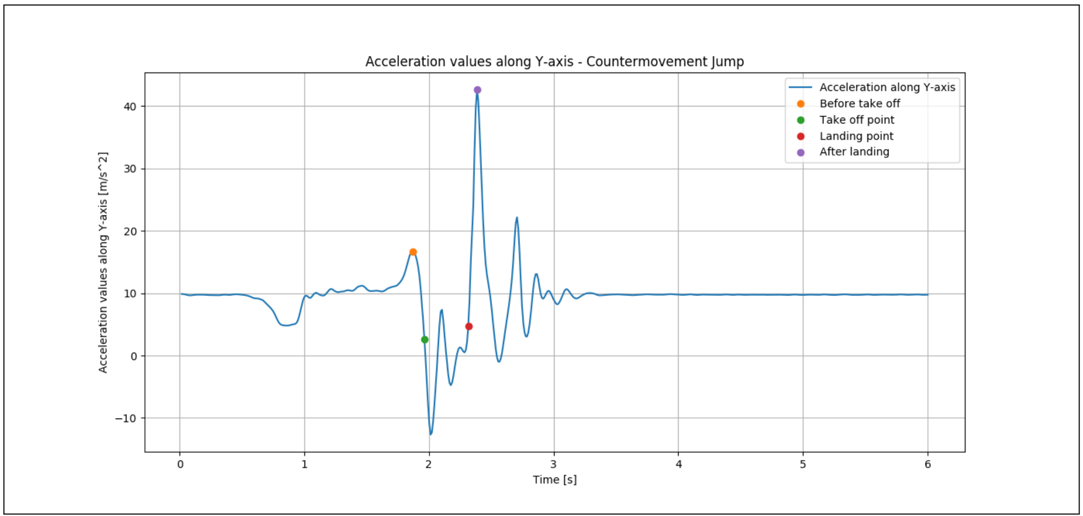


Figure 2.7: Automatically detection of maximum peak before the jump, take off instant, landing instant and maximum peak after jump in Y-axis accelerometer values.

The maximum peak before take-off identifies the end of the downward phase performed by the jumper. Landing corresponds to feet contact with the ground following the jump.

Despite the offsets remotion and the low-pass filtering, the acceleration values exhibit a step trend in some points. This behavior could be due to the body position to which the smartphone is attached. Oscillations of the accelerations may be due to normal abdominal breathing, during which there is a slight protrusion of the abdominal wall. Furthermore, these oscillations in the accelerometer signal during flight are due to the wobbling of the device with respect to the pelvis.

2.3 Elbow joint range of motion

2.3.1 Introduction

This section aims at describing the entire methodology that was developed to create an ad-hoc machine able to recognize the correctness of a specific rehabilitation exercise.

The chosen exercise as case study was the flexion-extension of the elbow.

Basketball players rely heavily on the elbow as it is one of the main parts of the body used in this type of sport. For this reason it was decided to conduct the work focalizing on the elbow functionalities.

The elbow swings 180 degrees in a direction for the forearm and it helps turn to the point where the the radius and ulna meet. The analyzed movement consists in starting from a position in which the arm is completely extended at shoulder height with the hand facing upwards. By mantaining the arm orthogonal to the shoulder, the forearm must fold completely over the arm until it touches the shoulder and goes back to the initial position.

This movement can completely performed in normal condition (i.e. when the subject does not have any musculoskeletal problems on the arm or elbow injury), while it becomes difficult when a problem at the upper limbs occurs. The machine learning algorithm was developed ad-hoc on the single athlete.

This concept allowed to consider as valid only the data coming from a single subject. The idea was to assume that at the beginning of the sportive season, athlets - not affected by any kind of problems - perform the exercise to populate the dataset that will be used for training the machine learning algorithm. In this way if N is the number of athlets, N will be also the number of trained machine learning algorithms. Under this hypothesis, the training phase of the machine learning algorithm ends when an injury occurs to the athlete and the event will be triggered by the individual with a flag inserted in the mobile health tool. There exists different types of machine learning algorithm and they can be grouped into two main categories: supervised and unsupervised ones.

Supervised learning algorithms aim at identifing objects of a specific class amongst all objects, by primarily learning from a training set containing only the objects of that class. Unsupervised learning algorithms, instead, aim at finding previously unknown patterns in data set without pre-existing labels.

In biomedical field, often, data for other classes can be difficult or impossible to obtain. In particular in binary classification, data for the second labeled class can be hard to collect. In the specific case of study tought for the mobile health tool, the machine learning algorithm should be able to classify correct and uncorrect movements to make aware the athlete of its elbow functional recovery after an injury.

Since it is not possible to obtain data of the individual after injury before it occurs, it has been necessary to identify a solution for modelling the problem. The so-called tipicality approach has been demonstrated to be the most useful in analysing biomedical data [36]. It is based on the clustering of data by examining data and placing it into new or existing clusters [37]. To apply the approach to one-class classification, each new observation y0 is compared to the target class C and identified as an outlier or a member of the target class.

The algorithm chosen for detecting anomalies in performing the arm motion was the one-class Support Vector Machine. It is a semisupervised algorithm that learns a decision function for novelty detection: classifying new data as similar or different to the training set. Hyper parameters of the one-class SVM are the kernel type, which specified the kernel to be used in the algorithm, η that represents an upper bound on the fraction of training errors and a lower bound on the fraction of support vectors and γ which is the kernel coefficient. The η parameter tunes the trade off between overfitting and generalization. Indeed, a decrease in training error is to be expected by decreasing η, since more training data points fall on the correct side of the hypersphere. But assuming a too small outlier ratio can easily result in many negatives also falling on this side of the hypersphere, causing a higher test error. Therefore it was necessary to tune the values of η and γ to not fall into overfitting and underfitting situations.

2.3.2 Technology

A smartphone, during arm flexion-extension motion, was held in the hand. The orientation of the axes (x,y,z) is defined as: the X and the Y axes are in the horizontal plane and points to the right and downwards rispectively. The Z axis points towards the outside of the screen face. In this system, the coordinates in front of the screen have negative Z values (as mentioned in Section 2.1.2). When the arm is in the initial position - completely extended at shoulder height - the accelerometer values recorded from the Z-axis are equal to the gravity.

2.3.3 Procedure

2.3.3.1 Data collection

Data coming from accelerometer, gyroscope and magnetometer was gathered while performing the exercise. For each sensor, values along 3-axes (x, y and z) were sent with a sample frequency of 10Hz via a Bluetooth connection to a personal computer on a running Python code.

Each repetition of arm flexion-extension has a time duration of twelve seconds and therefore a total of 120 samples have been counted. In the case in which the number of samples was different from 120 in a reasonable range, data was interpolated to have the same size. 208 exercise correct repetitions and 162 uncorrect repetitions have been gathered from the smartphone by a single subject to train and test the machine learning algorithm. Repetitions of incorrect exercise have been recorded as simulating an elbow injury.

2.3.3.2 Data processing

Acceleration values along the 3-axes were filtered by a median filter with a window lenght of 5 and subsequently by a 1st order low-pass Butterworth filter to remove noisy signal. The Median Filter is a non-linear digital filtering technique used to remove noise from a signal[6]. A low-pass filter, instead, passes signals with a frequency lower than a certain cut-off frequency and attenuates signals with frequencies higher than the cut-off frequency. The cut-off frequency of the filter was changed systematically in a range [0.1,1] and a frequency of 0.5Hz was chosen to filter out outliers and to smooth acceleration values. Figures 2.8, 2.9 and 2.10 show the comparison between filtered acceleration values (red line) and not filtered ones (blue line) for x,y and z axes respectively. As it clear from Figure 2.8, 2.9 and 2.10 the filter allowed to make smoothier the acceleration values. Oscillations that they initially presented may be caused by the precision and measurement accuracy of the sensors integrated in the smartphone.

[6]Source: `https://en.wikipedia.org/wiki/Median_filter`

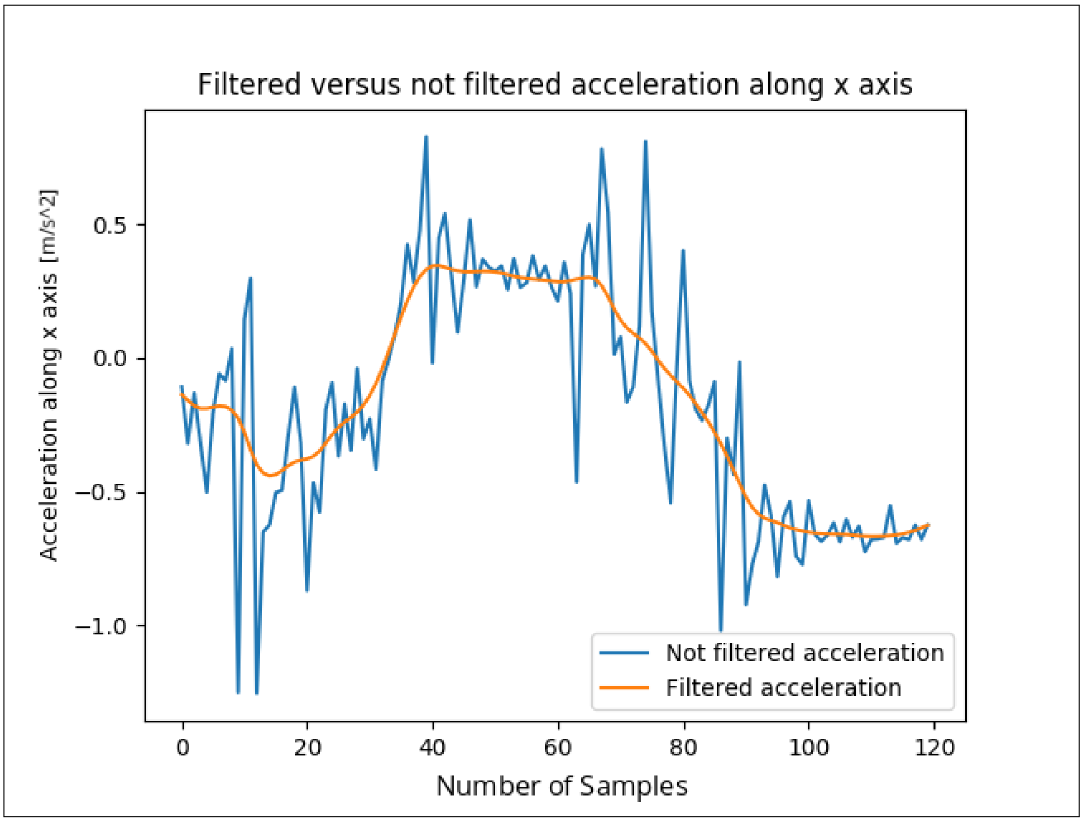


Figure 2.8: Filtered acceleration values compared to original acceleration values along the X-axis.

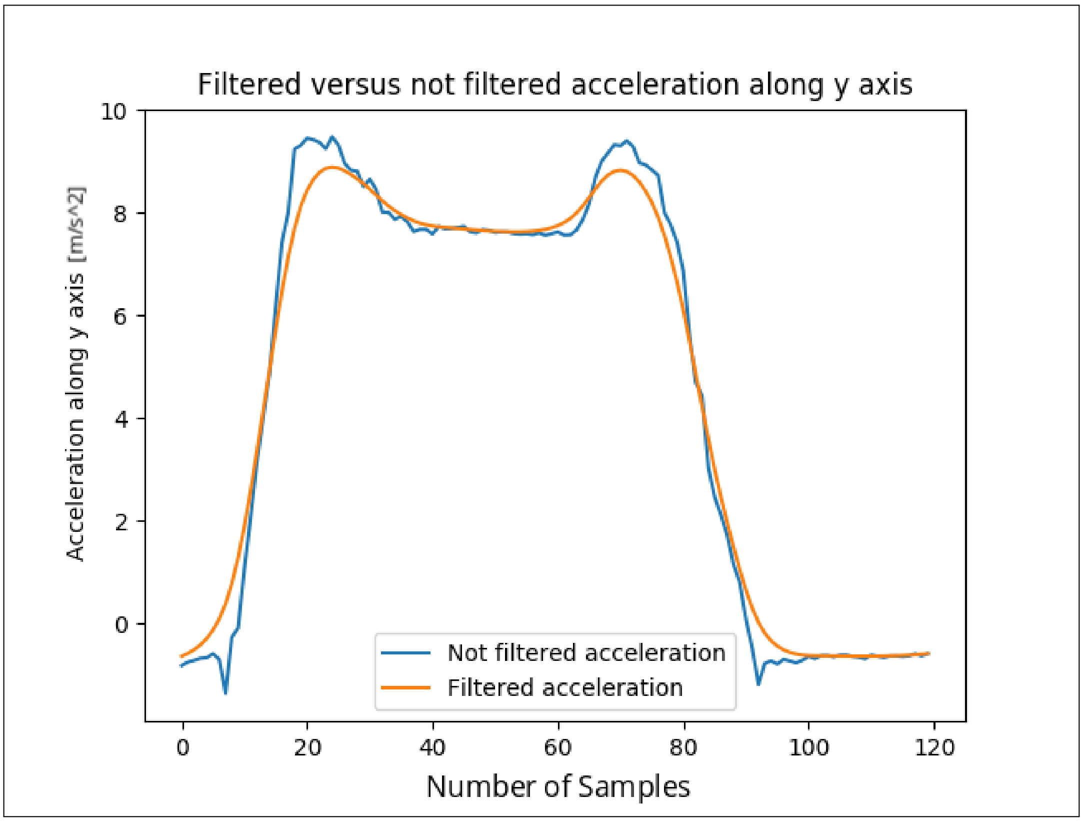


Figure 2.9: Filtered acceleration values compared to original acceleration values along the Y-axis.

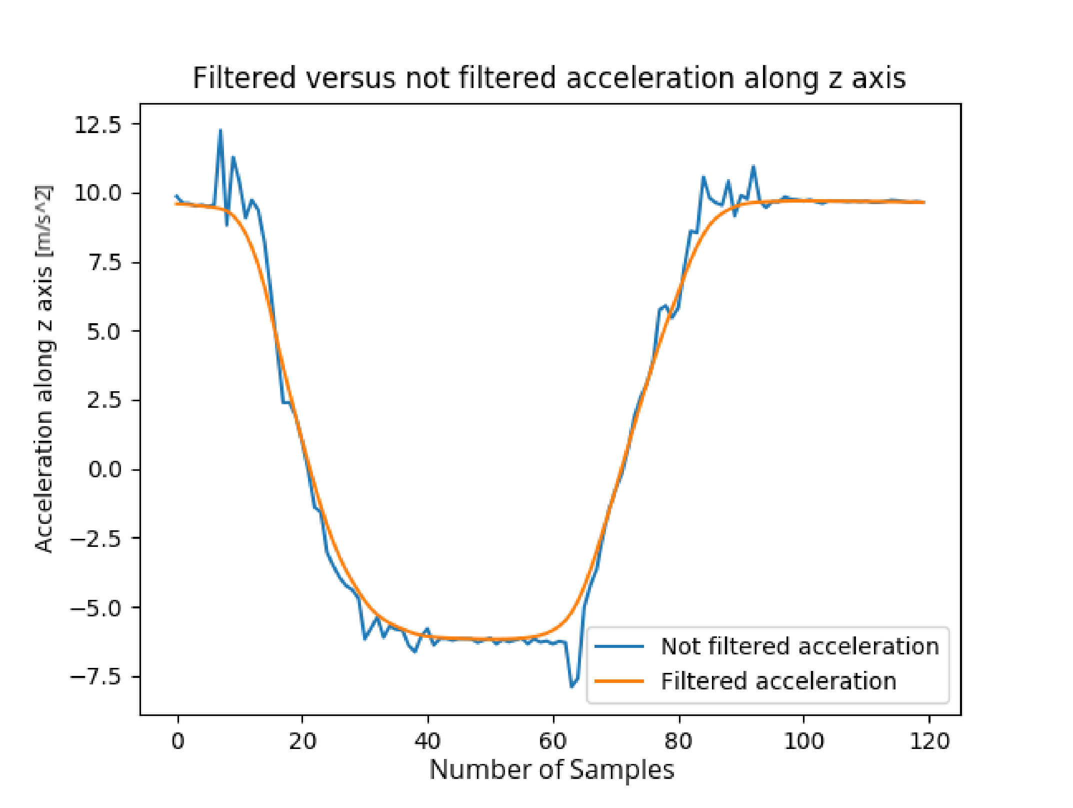


Figure 2.10: Filtered acceleration values compared to original acceleration values along the Z-axis.

A feature extraction was performed from existing features. Joint angles of the elbow and the tilt angles along x,y and z axes were calculated as Equation 2.6, 2.7, 2.8 and 2.9 respectively.

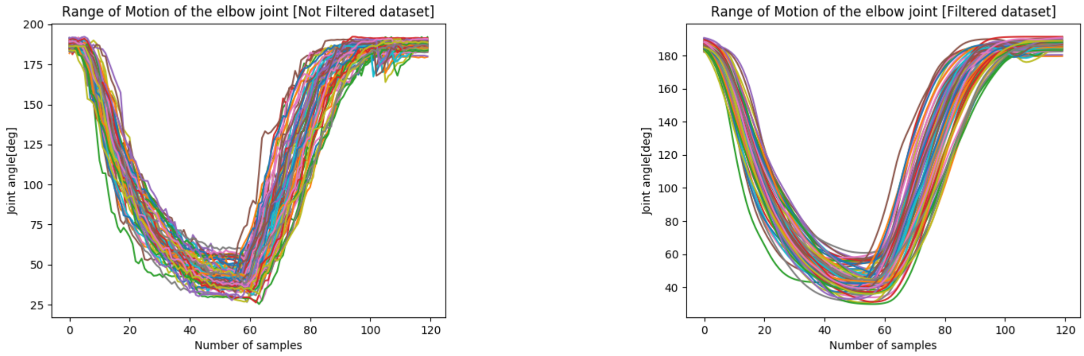
$$JointAngle[deg] = |180° - |\frac{atan2\frac{acceleration_y}{acceleration_z}}{\frac{pi}{180}}|| \tag{2.6}$$

$$TiltAngle_x[deg] = atan\frac{acceleration_x}{\sqrt{acceleration_y^2 + acceleration_z^2}} \tag{2.7}$$

$$TiltAngle_y[deg] = atan\frac{acceleration_y}{\sqrt{acceleration_x^2 + acceleration_z^2}} \tag{2.8}$$

$$TiltAngle_z[deg] = atan\frac{acceleration_z}{\sqrt{acceleration_x^2 + acceleration_y^2}} \tag{2.9}$$

The calculation of the elbow joint angle was done before and after the data filtering and Figure 2.11 shows the calculation of the elbow joint angle before that acceleration values have been filtered (Figure 2.11 (a)) and after the processing (Figure 2.11 (b)). It can be seen that the calculation of the angle was also affected by the oscillations due to error in sensor measurements.



(a) Elbow joint angle calculation from not filtered acceleration values

(b) Elbow joint angle calculation from filtered acceleration values

Figure 2.11: Elbow joint angle calculation from filtered acceleration values toward not filtered ones.

At the end of the features extraction, the dataset was made of 208 repetitions of the correct exercise and 162 repetitions of the uncorrect exercise with 120 samples and 13 features each. The features are: 3-axes accelerometer values, 3-axis gyroscope values, 3-axis magnetometer values, elbow joint angle and 3-axes tilt angle.

2.3.4 Artificial Intelligence

2.3.4.1 Support Vector Machine

As mentioned in Section 2.3.1, the machine learning algorithm chosen for carrying on the study was the one-class Support Vector Machine.

The algorithm is particularly useful when there are a lot of "normal" data and a lack of anormalities that have to be detected. In the specific case analyzed in this thesis, data after injuries can be difficult to be obtained. This is because there are different levels of severity and different types of injuries that can affect the upper limbs and it is not possible to explore all of them. Therefore, in one-class SVM, the support vector model is trained on data belonging to only one class, which is the "normal" class (i.e. the class of correct exercise repetitions). It infers the properties of normal cases and from them, it can predict which examples are unlike the normal ones. This is useful for anomaly detection because of the lack of training examples that are defined anomalies.

In this regard, only the data concerning the correct repetition of the exercise was used to train the machine learning algorithm since this data represents the athlete fully of his functional abilities. On the contrary, data which simulate an injury at the upper limbs was used to test the machine in detecting anomalies.

At the beginning, all of the 13 features were used in training the machine learning algorithm and to tune η and γ by choosing the Radial Basis Function Kernel (RBF). RBF kernel on two samples x and x' is represented as feature vectors in some input space and it is defined as Equation 2.10, where the term in the denominator of the exponential argument represents instead the gamma coefficient of the kernel (Equation 2.11).

$$K(x, x') = \exp(-\frac{||x - x'||^2}{2\sigma^2}) \tag{2.10}$$

$$\gamma = \frac{1}{2\sigma^2} \tag{2.11}$$

The terms ||x-x'|| and σ in Equation 2.10 represent the Euclidean distance between the feature vectors and a free parameter respectively. η and γ parameters were tuned to reduce as much as possible the number of misclassified training examples and to decrease the error in the test set.

Training set was composed by only correct data, while the test phase has been made on two different datasets: a dataset containing correct exercise repetitions and a dataset with uncorrect ones. Since the One-class SVM requires a 2 dimensional vector as input, it was necessary to reshape each repetition made of 120 samples and 13 features into a single row data. At the end, the training set was made of 166 rows and the test sets were made by 42 "normal" rows data and 162 anomalies rows data respectively, each of length 1560.

At the beginning, a randomly range of values for η and γ was selected to train the SVM. Different proves have been done and a finally value of $7.4*10^-3$ for η and a value of $9*10^-6$ for γ were chosen for tuning the machine.

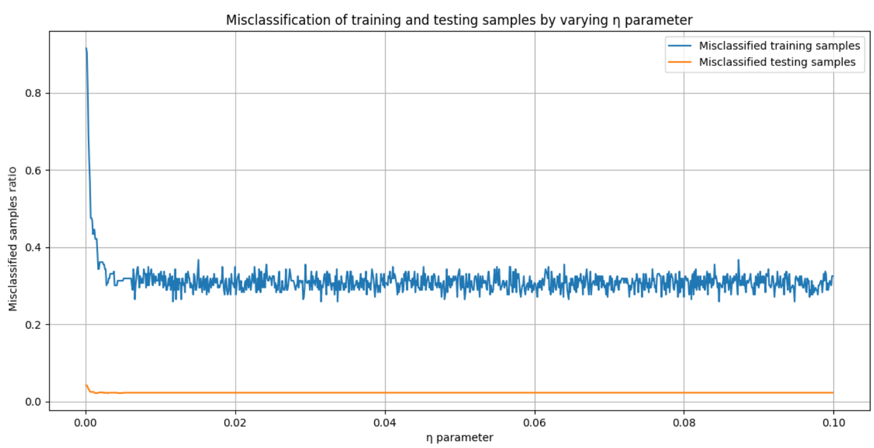


Figure 2.12: Misclassification samples with a fixed γ by varying η in a range [0.0001,0.1]

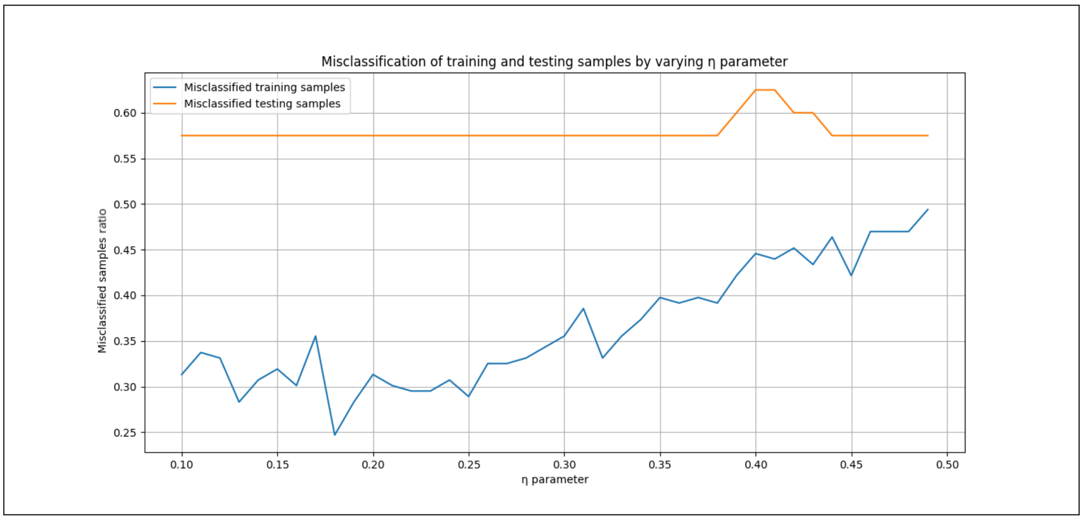


Figure 2.13: Misclassification samples with a fixed γ by varying η in a range [0.1,0.5]

Figures 2.12 and 2.13 show how the error ratio on training and test set varies with respect to a fixed γ and by varying η. As expected a decrease in training error is shown by decreasing η and the same concept applies for the error ratio in the test set.

What is visible from Figure 2.12 is that the so-built model is affected by underfitting, since the error in test phase is much lower than the one in training phase. On the contrary, Figure 2.13 shows an inverse situation for the model that is affected by overfitting (i.e. the test set has poor performance with respect to training set one). To find a trade off between the two performances, it has been tought to fix the η parameter to minimize the error in the training set and by varying gamma ($\eta = 7.4 * 10^-3$).

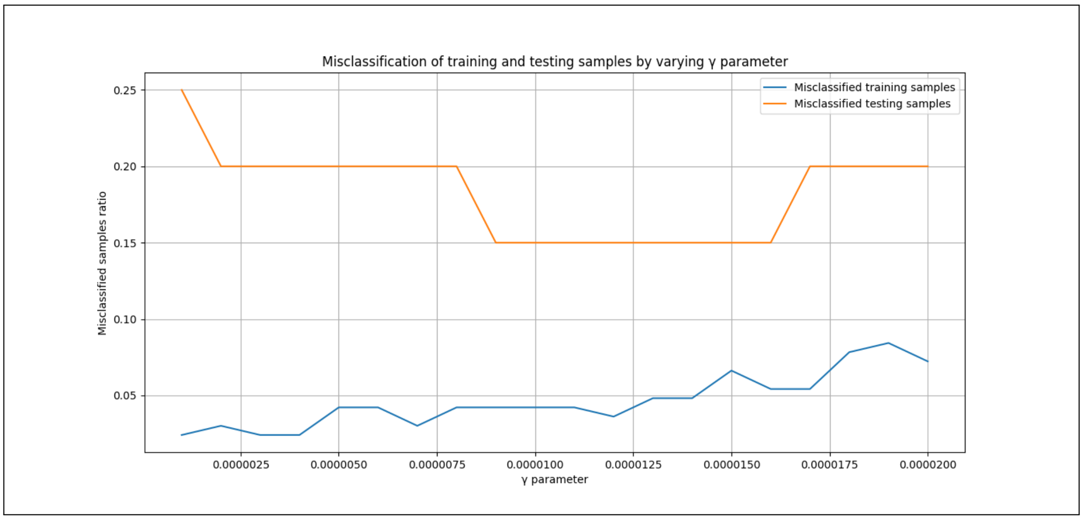


Figure 2.14: Misclassification samples with a fixed η by varying γ in a range [0.000001,0.00002]

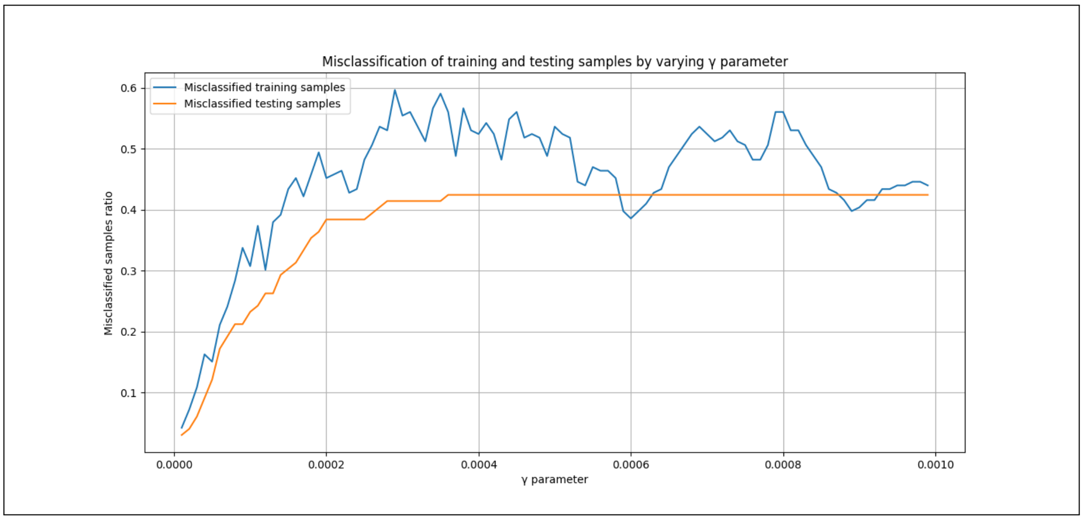


Figure 2.15: Misclassification samples with a fixed η by varying γ in a range [0.00001,0.001]

Figures 2.14 and 2.15 show the variation of the error ratio for both training and test set by fixing the value of η and varying γ. As it clear, an increasing error in both training and test set is given by increasing the value of γ.

To overcome underfitting, the value of γ was chosen such that the performance in training set is greater than the ones in testing set.

At the same time, γ had to be selected such that the distance between the the two sets error was relatively small. Under this hypothesis, the values for η and γ were fixed to 7.4*10−3 and 9*10−6 respectively. Table 2.1 shows the test results for the one-class SVM by considering all the features to train the machine. The value for the True Negative shows that the machine is able to recognize all the anomalies, without misclassified them.

	TP	TN	FP	FN	Sensivity	Specificity
Test	39	162	0	3	0.9285	1

Table 2.1: Metric evaluation One-class SVM with all features.

As the machine learning algorithm will be run on a smartphone, it would be useful to reduce the amount of data used to train the machine to reduce the computational time and the heaviness of the algorithm.

For this reason, it was necessary to explore different features combinations to understand if a feature reduction could maintain the same accuracy on training and test set or even reduce it. In this regard, it has been necessary to evaluate the correlation matrix of the features to see which of them could be selected.

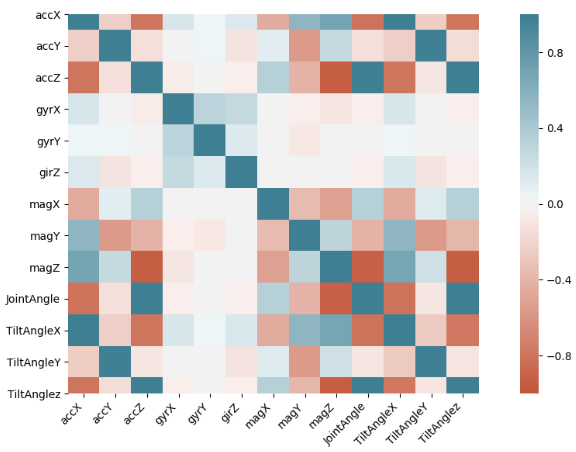


Figure 2.16: Features correlation matrix

Figure 2.16 shows the correlation of the features that were used in the construction of the model. Starting from the less correlated feature (gyroscope values along Y-axis), different combinations were explored to select the most suitable ones and to reduce the amount of data used for the model.

	TP	TN	FP	FN	Sensivity	Specificity	Accuracy	ErrorRate
$[gyrY, gyrZ, TiltAngleZ, accZ]$	42	152	10	0	1	0.9382	0.9509	0.049
$[gyrY, TiltAngleZ, accZ]$	42	152	10	0	1	0.9382	0.9509	0.049
$[gyrY, gyrZ, accZ]$	42	152	10	0	1	0.9382	0.9509	0.049
$[gyrY, accZ]$	42	152	10	0	1	0.9382	0.9509	0.049
$[gyrY, gyrZ]$	0	152	10	0	0	1	0.7941	0.2058
$[gyrY, accY]$	42	160	2	0	1	0.9876	0.9901	0.0098

Table 2.2: One-class SVM testing set metric evaluation with different features combination.

Table 2.2 shows the different proves that were done to reduce the amount of data to train the one-class SVM algorithm.

As it is clear, using only the gyroscope values and the acceleration values along the Y-axis it is possible to have an accurancy on the testing set equal to 99.01 percentage. Based on these results, the two features used to ultimately train the algorithm were, as mentioned before, the gyroscope and the accelerometer values along the Y-axis.

Chapter 3

Results

This chapter aims at describing and discussing the results obtained from the development of the mobile health tool in its three different parts.

Outcomes concerning postural control regard the calculation of AP and ML angles while performing one of the most sophisticated tests to assess balance (Limits of Stability Test).

Analyzed results for countermovement jump performance analysis were acquired from the comparison between the mobile health tool and a commercial mobile application named MyJump2 and with a built video-system. A video-system was built because of the large differences in calculating flight time and height between the mobile health tool and the MyJump2 mobile application. Calculated flight times overestimated the ones obtained by the commercial application.

The last section of the chapter analyzes the machine learning algorithm performances when 16 different models are built on 16 different subjects. Models were trained by using the best parameters and the selected features mentioned in Section 2.3.4. After that, because of the low performances in training and test phases when building the model on a reduced dataset, a chosen subject was asked to record other repetitions of the normal exercise (i.e. arm flexion-extension).

3.1 Postural Control

This section focuses on the results obtained during the implementation of the postural control part of the mobile health tool. Postural control study was considered a valid analysis when it comes to support athletes suffering from a musculoskeletal problem. Healthy individuals do not present any kind of problem in postural control. This condition can instead be violated following a problem of various natures. One of the injuries that most affects athletes is the one that affects the lower limbs. As a result of this injury, athletes are unable to make movements like when they are at the height of their functional abilities and motor skills. For this reason, providing them with an index that can make them aware of their pre and post-injury skills can encourage physical recovery.

The Limits of Stability Test is one of the most sophisticated tests to assess balance. During the test, the individual is asked to intentionally shift his body weight in the cued direction. It was interesting to see if the anteroposterior and medial-lateral angles calculated with the mobile health tool could be in line with the maximum limits denoted by the Limits of Stability test. For this reason, an individual was asked to shift the weight of the body first in the anteroposterior direction and then in the mediolateral direction with a smartphone attached as described in Chapter 2. After having pressed a start button and waited for the calibration of the device, the subject was asked to make the agreed movement.

Figure 3.1 shows data gathered from the mobile health tool while performing a task of the LOS test, shifting the body forward. The task was performed by a healthy subject, so an individual who has not been affected by an injury at the lower limbs. Performing this task would become more difficult if the subject shows pain following a musculoskeletal problem.

The mobile health tool records a minimum angle which is approximately $0.05°$ and a maximum one $12.59°$. Since the normal sway angle, while performing the specific task, should be approximate of $12.5°$ (as mentioned in Section 2.1), on one hand, it can be concluded that the mobile health support is able of calculating this postural sway maximum excursion with large reliability. On the other hand, the graph (Figure 3.1) shows noisy acceleration values despite the offset remotion performed. This is reasonable since data has not post-processed by filtering out the noise, but the sway angles were calculated in real-time.

With the same purpose, Figure 3.2 shows postural sway in medial-lateral direction while performing Limits of Stability test shifting the body weight to the right. In this case, the normal sway angle should be $16°$, and the maximum recorded from the support is $15.53°$.

Anteroposterior and medial-lateral angles (Equation 2.1-2.2) were then translated into a quality score, by calculating the equilibrium score for both anteroposterior and medial-lateral directions. Equilibrium score for the anteroposterior direction was subsequently calculated as a percentage, which compares the peak amplitude of AP sway to the theoretical AP limits of stability using the formula 3.1, while for the medial-lateral direction using 3.2 with the same principle.

$$EquilibriumScore_{AP} = \frac{12.5^\circ - [APangle_{max} - APangle_{min}]}{12.5^\circ} * 100 \quad (3.1)$$

$$EquilibriumScore_{ML} = \frac{16^\circ - [MLangle_{max} - MLangle_{min}]}{16^\circ} * 100 \quad (3.2)$$

A high score of 100 represents no postural sway, and lower scores indicate a poor balance or postural instability.

These are only representative examples that show the potential of calculating postural sways with the only usage of a smartphone to support the athletes in post-injury rehabilitation, giving it an index which compares the normal functionalities (i.e. in healthy individual condition) with respect to compromised capabilities of a person under musculoskeletal problems.

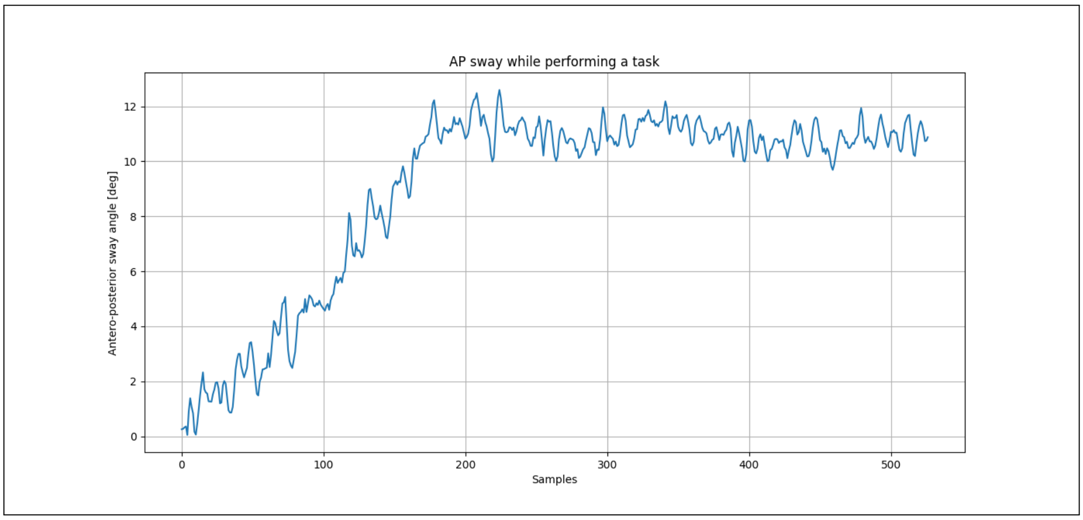


Figure 3.1: Antero-posterior sway during LOS test

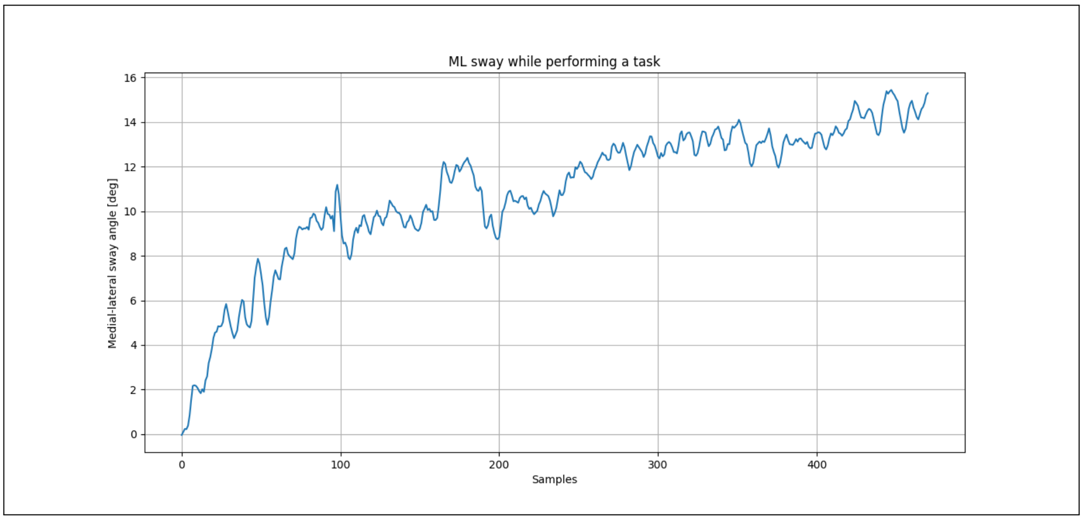


Figure 3.2: Medial-lateral sway during LOS test

The mobile health support was also provided with sound feedback to guide the subject to maintain balance with respect to an initial position. Sound feedback was set so that an increase in the frequency corresponds to an increase in the distance with respect to the initial position. In this way, the athlete can recognize if he can maintain a given posture after an injury at the lower limbs or if the total functional abilities have not been recovered yet.

3.2 Countermovement Jump

This section analyzes the results obtained with the comparison between the countermovement jump performances given by the mobile health tool and the ones calculated with a commercial mobile application. Countermovement jump test was considered a valid tool to analyze to support athletes in post rehabilitation process. Knowing the normal performance of the athlete, following an injury, it is possible to understand when all the motor skills are restored through this test. If athlete before the injury could reach an average height of 40 cm during the jump, following the traumatic event he will have to slowly recover his skills.

Heights calculated with the mobile health tool were compared with the ones calculated with MyJump2 application. MyJump2 is an application developed for iPhone and Android that gives advanced information of jumps using the camera on smartphones or tablets [35]. Just recording a jump and selecting accurately take-off and landing, the application evaluates the maximum vertical displacement of the centre of mass during a countermovement jump using the flight time method. Flight time method allows the calculation of the maximux height by using the physical formula of motion in free-fall that takes into account the time spent in air by the jumper. Furthermore, the commercial application calculates the height, flight time, velocity, force and power of the vertical jumps. MyJump2 showed to have a good agreement in measures of jump height with compared to force platform data in terms of Pearson's product-moment correlation coefficient (r = 0.80). One of the limitations of this application is having to necessarily be assisted during the jump. A second person, in fact, has to record the performance and the individual cannot be able to do it alone.

To test the concurrent validity of the mobile health tool, Pearson's product-moment correlation coefficient (r) was performed. It is a measure of the linear correlation between two variables X and Y. According to the Cauchy–Schwarz inequality, the coefficient has a value between +1 and -1, where 1 is a total positive linear correlation, 0 is no linear correlation, and -1 is the opposite of 1. Pearson's correlation coefficient, when applied to a sample, is commonly represented by equation 3.3 and may be referred to as the sample correlation coefficient.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \hat{x})(y_i - \hat{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \hat{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{3.3}$$

In Equation 3.3, n is the sample size, x and y are the individual sample points and $\hat{x}$,$\hat{y}$ are the sample mean. Ten repetitions of countermovement jump were performed with the mobile health tool attached with a belt at the height of the centre of mass. At the same time, the individual repetitions were recorded with the MyJump2 and the instants of take-off and landing were identified by following the procedure explained in the commercial application. Ten heights obtained from the two different instruments were gathered, matched and Pearson's correlation coefficient has shown a correlation equal to 0.57 between them.

Table 3.1 shows the comparison between the mobile health tool and MyJump2 in evaluating the flight time and the height during a vertical jump. Outcomes show that flight times and heights calculated with the mobile health tool overestimate the ones evaluated with the MyJump2 application. For the flight time, an average overestimation of 0.038 seconds is shown with a standard deviation of 0.015. Height, instead, is overestimated with a mean of 3.58 centimeters and a standard deviation of 1.40. Figures 3.3 and 3.4 show the flight times and the heights calculated with the mobile health tool (blue line) and MyJump2 (red line) application respectively. As it is clear, both the calculations performed with the mobile health tool are overestimated with respect to the ones evaluated with the commercial application.

	Countermovement Jump			
	Mobile health tool		MyJump2	
	Flight Time[ms]	Height[cm]	Flight Time[ms]	Height[cm]
1	409	20.59	354	15.38
2	400	19.60	346	14.67
3	409	20.59	350	15.02
4	401	19.68	354	15.38
5	430	22.8	400	19.62
6	411	20.69	375	17.24
7	380	17.68	358	15.75
8	382	17.87	354	15.38
9	382	17.87	371	16.86
10	392	18.82	350	15.02

Table 3.1: Countermovement Jump: comparison between the Mobile Health tool and MyJump2 in evaluating flight time and height

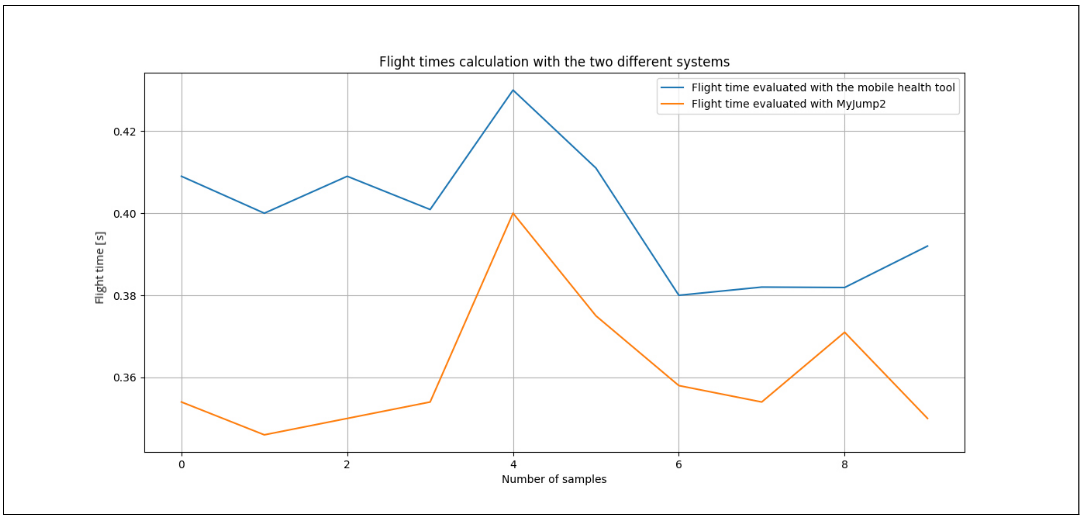


Figure 3.3: Flight time calculated with the mobile health tool compared to MyJump2 evaluation

From the moment that the searches made on MyJump2 showed a correlation with force platform equal to 0.8, but did not indicate whether the maximum height during the jump overestimated or underestimated those of the gold standard, it cannot be stated with certainty which of the two are closer to reality.

It was necessary to perform another test to conclude if the mobile health tool gives reasonable results in evaluating the height during a countermovement jump. A system that recorded the jumper while it performed the jump with the smartphone attached to the body was built. Two cameras were placed: one at feet height and one at the location of the head. Moreover, a meter tool was been attached to the wall to observe the displacement of the head with respect

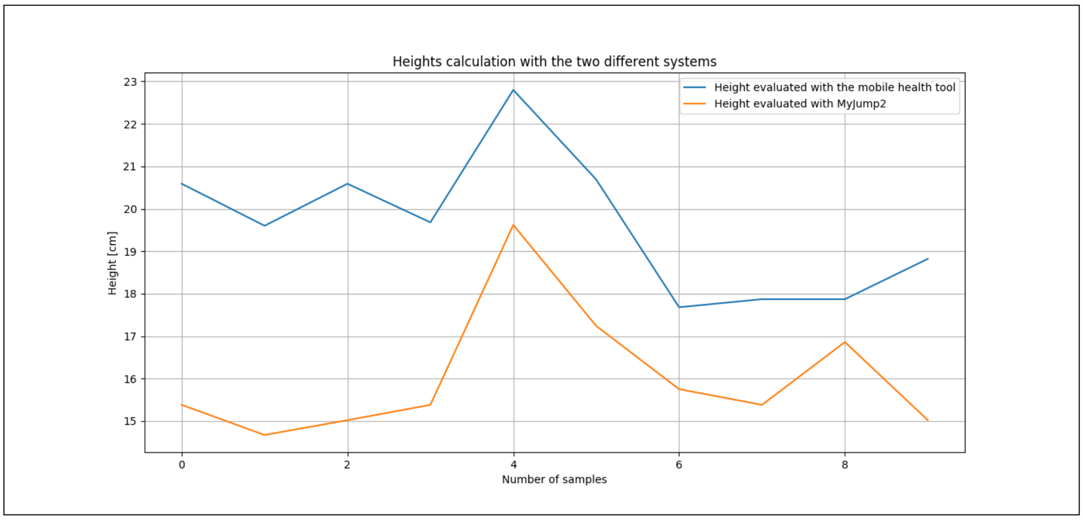


Figure 3.4: Height calculated with the mobile health tool compared to MyJump2 evaluation

to the initial position. Camera placed at the height of feet allowed to identify take-off and landing instants. The one placed at head height allowed to observe how much was the maximum movement achieved during the jump. Looking at the camera placed at head height, in fact, from the empirical research it was deduced that the data calculated with the mobile health tool came closer to reality, compared to those obtained by MyJump2. This result, although interesting, is to be considered subject to observation errors.

Furthermore, the obtained flight times from the smartphone - calculated as explained in Section 2.2.3 - were compared with the ones obtained from the recorded videos. The videos were processed with a video-editing program to identify the exactly instants for take-off and landing by extracting the elapsed time between the frames which identified the two before mentioned moments. A total of 5 vertical jump repetitions were made and Table 3.2 shows the percentage of error between the flight times evaluated with the two different systems.

Countermovement Jump: percentage error				
1st jump	2nd jump	3rd jump	4th jump	5th jump
0%	0.2%	1.5%	0.8%	1.2%

Table 3.2: Countermovement Jump: comparison between the flight times calculated with the Mobile Health tool and the ones calculated from recorded video

The low percentage error shows a great agreement between the mobile health support and the built video-system in evaluating the flight time and, subsequently, in calculating the maximum height reached by the jumper during the countermovement jump.

It can be concluded that, despite the assumption that the body configuration is the same at the instant of take-off and landing, the chosen threshold for detecting the jump event can identify the flight time with reasonable precision if compared to the built video-system.

3.3 Elbow Joint Range of Motion

Chapter 2 focused on the importance of supporting athletes during rehabilitation post-injury. Postural control and countermovement jump performance analysis was proved to be useful in assessing functional recovery after musculoskeletal problems at the lower limbs. As with the lower limbs, it is important to have a support that evaluates the skills of the upper limbs. Basketball players rely heavily on the elbow because it is one of the most stressed parts of the body during their sporting activity. In this regard, it was decided to provide the mobile health tool to guide the sportsman to make him aware of his total functional recovery following a traumatic event.

Eight males and eight females were asked to do a set of normal repetitions of the arm flexion-extension exercise followed by 5 repetitions in which subjects had to simulate an arm injury. The aim was to see if the fixed values for η and γ (η=7.4exp -3 and γ=9exp -6) and the selected features (gyroscope and acceleration values along Y-axis) could be fine to train 16 different machine learning algorithms (one for each individual involved in the experiment).

The followed protocol asked the subjects to do the exercise in question with naturalness and maximum of their functionality. Subjects were asked to extend their arms to shoulder height with their hands facing upwards and to press a start button that started the exercise. Once the start button was pressed, the mobile health tool emitted a sound indicating the beginning of repetition. At that point, subjects were asked to bring their hand as close to their shoulders and wait for the second sound to return to their initial position. The mobile health tool was set to make a beep 6 seconds after the first sound. Once back in the initial position, the individuals had to wait for 2 consecutive beeps that denoted the end of a single repetition.

Incorrect repetitions, indeed, were performed by asking to subjects to perform 5 specific movements:

- First exercise: Inward rotation of the forearm.
- Second exercise: Outward rotation of the forearm.
- Third exercise: Half elbow flexion

- Fourth exercise: Forearm flexion-extension with the hand rotated 90 degrees with respect to the normal position

- Fifth exercise: A complete flexion-extension at high speed

Incorrect repetitions that were taken into account represent some of the many problems that could affect the elbow following an injury. The choice of these exercises was made solely to test the machine and to evaluate its performance.

After the data collection, 16 machine learning algorithms were trained and subsequently tested. Each training set was made of all the correct repetitions of a single subject, while each test set with injury simulations. Percentage errors for both the training and test phase were evaluated. They were calculated as the number of misclassified samples out the total number of samples respectively for training and test phases.

	Arm flexion-extension: percentage error					
	RBF		Linear		Sigmoid	
	Training set	Test set	Training set	Test set	Training set	Test set
1	100%	20%	0%	20%	12.5%	20%
2	13.33%	40%	13.33%	60%	100%	0%
3	100%	0%	0%	40%	25%	40%
4	93.33%	0%	6.6%	40%	93.33%	20%
5	100%	0%	13.33%	40%	80%	40%
6	73.33%	0%	13.33%	20%	60%	0%
7	6.6%	0%	0%	0%	6.6%	0%
8	86.6%	0%	6.6%	80%	66.6%	60%
9	100%	0%	6.6%	60%	40%	60%
10	100%	0%	13.33%	60%	93.33%	20%
11	20%	0%	6.6%	80%	93.33%	40%
12	13.33%	40%	13.33%	60%	100%	0%
13	73.33%	0%	6.6%	80%	60%	20%
14	66.6%	0%	6.6%	0%	60%	0%
15	0%	100%	6.6%	60%	66.6%	40%
16	100%	0%	0%	40%	26.66%	40%

Table 3.3: Arm flexion-extension training and testing error on population of 16 subjects

Table 3.3 shows the resulted percentage errors while performing the training and the test phase on a population of 16 subjects. Chosen parameters and selected features to build the model were the ones selected in Section 4.3.3 (η=7.4exp −3, γ=9exp −6, features=[gyrY, accY]).

Table 3.3 suggests low performance for both training and test when using the Radial Basis Function (RBF) as a kernel type. Radial Basis Function was chosen in the development of the model in Section 4.3.3 and it gave great performance in both training and test set when the dataset was composed of 208 correct exercise repetitions.

The poor results obtained from training 16 machine learning algorithms can be considered reasonable if thinking that the machine was trained on a reduced training set.

As is known, few samples allow different models to "explain" the data, but they will probably malfunction compared to the test data. Outliers are extreme values that fall a long way outside of the other observations. In a small dataset, the impact of an outlier can be much greater, since it will have a heavyweight for the model.

For this reason, the machine learning algorithm was, firstly, trained by choosing a different kernel parameter. Table 3.3 shows the percentage errors on training and test sets, using the linear kernel and the sigmoid kernel. The Linear kernel is the simplest kernel function and it is given by the inner product <x,y> plus an optional constant c (Equation 3.4). The sigmoid kernel, instead, acts similar to the sigmoid function in logistic regression (Equation 3.5 when γ and r are kernel parameters).

$$K(x, y) = x^T y + c \tag{3.4}$$

$$K(x, y) = tanh(\gamma * x^T y + r) \tag{3.5}$$

The Linear kernel, despite the reduced dimension of the training set, showned best results if compared to the RBF and sigmoid kernels. The error in the training set using the linear kernel can be considered reasonably low if one considers the low number of examples on which to train the machine. As far as the error of the test set is concerned, it is obtained on a number of samples equal to 5. A percentage error of 20 indicates that one of the exercises simulating an elbow injury was misclassified by the machine.

To see if the percentage error decreases with the increasing of the training set size, a subject of the 16 was asked to perform other 10 repetitions of the exercise. In this way, the machine learning algorithm was trained on a dataset of 25 samples and tested on the same 5 incorrect exercises. Once again the percentage errors were calculated for both training and test set.

Table 3.4 shows the obtained percentage error when increasing the training set of 10 samples. It compares the training and the test phase of the machine of a 15 samples training set with a dataset made of 25 samples. As it is clear, the percentage error decreases with the increase in training set size. With a

	Arm flexion-extension: percentage error					
	RBF		Linear		Sigmoid	
	Training set	Test set	Training set	Test set	Training set	Test set
15-samples	13.33%	40%	13.33%	60%	100%	0%
25-samples	8.3%	20%	4.16%	60%	41.66%	20%

Table 3.4: Arm flexion-extension percentage error increasing training set size

dataset made of only 15 rows data, it is possible to notice overfitting of the machine learning algorithm. The training phase, in fact, performs much better than the test one. Furthermore, it is possible to underline that, enlarging the dataset, the best performance is given when the model is built using a Radial Basis Function kernel, as specified in Section 2.3.4.

Since the machine was an ad-hoc machine, it is reasonable thinking that the accuracy of the algorithm could be lower at the beginning of the data collection. As mentioned in Chapter 2, athletes will be asked to record the repetitions of the exercise until an injury occurs. The unpleasant event will be triggered by a flag inserted in the mobile health tool. The larger the training set, the greater the accuracy of the algorithm in detecting an anomaly and therefore an incorrect movement of the elbow following an injury.

Chapter 4

Conclusions

This thesis proposes the smartphone as a powerful device in supporting post-injury rehabilitation and evaluating movements in sports. A mobile health tool has been developed, made of three main parts. The first one evaluates the postural sway angles, by measuring the movements of the trunk with respect to the support base. The second part focuses on the countermovement jump performance analysis with the calculation of the maximum height reached by the jumper. The last part provides the detection of anomalies while performing an arm flexion-extension rehabilitation exercise.

Athletes are the individuals most exposed to musculoskeletal injuries and it is useful to make them aware of their functional abilities before and after a musculoskeletal problem. In sports, providing a tool that helps the athlete following an injury represents a way to make the healing process faster.

Postural control was addressed by measuring the postural sway angles in the anteroposterior and medial-lateral directions by using a trigonometric formula. Calculated angles have been compared, while performing the Limits of Stability Test (LoS), with the maximum angles that an individual should be able to cover when he shifts intentionally his body weight in a given direction. Meausures have shown near-perfect agreement within the normal maximum limits.

Countermovement jump performance analysis has been carried out implementing an algorithm that calculates the maximum height reached by the jumper using the flight time method. Flight time method is based on the identification of take-off and the landing instants. It was necessary to set a threshold to exactly define the beginning and the end of the jump. The threshold has been set to define take-off and landing when the acceleration value along Y-axis crosses half of the gravity. This threshold has been considered in the literature to have a great agreement in the calculation of the flight time with a body-mounted accelerometer when compared with a force platform.

Once the algorithm was implemented, flight times and resulting heights were compared with those calculated by a commercial application called MyJump2. Our study presented a correlation between the two of 0.57 in terms of Pearson's correlation coefficient. Under this result, the mobile health tool has shown a discrete agreement with the commercial application.

MyJump2 calculated flight times starting from the identification of the frames representing the take-off and landing instants. Previous research conducted on the validity of MyJump2 had shown a correlation index of 0.8 with the force platform. This good but not excellent correlation of MyJump2 with the force platform has fueled the need of a different way to validate the results obtained with the mobile health tool.

A video system was designed that recordes the vertical jump parallel to the data gathered with the mobile health tool.

By placing two cameras, one at head height and one at foot height and a meter tool, it was possible to assess the maximum displacement during the jump. Looking at the camera placed at head height, from the empirical research it was deduced that the data calculated with the mobile health tool came closer to reality, compared to those obtained by MyJump2.

This result, although interesting, is to be considered subject to observation errors. The recorded video from the second camera has been, instead, post-processed with a video-editing program to calculate the flight time by detecting take-off and landing moments in the frames.

Resulted flight time was in line with the one calculated by the tool. At the same time, the maximum displacement observed from a camera placed at head height was found to be in great agreement with that calculated by the device.

A lot of improvements could be implemented in the countermovement jump performance analysis. The first one could be to tune the data from the mobile health tool with a force platform to be used as a gold standard. In this way, it would be possible to find a different way to calculate the height with better precision and reliability. Furthermore, it would be useful to calculate, in addition to height, other characteristic parameters such as explosive power and force. These two parameters would give a greater indication of the recovery of the functional abilities of the athlete following an injury.

A third activity included in the mobile health tool was the use of artificial intelligence to detect the correctness of a specific rehabilitation exercise. Following an injury, it is useful to know if the athlete has managed to recover the total functional capacity. By training a machine learning algorithm, the application was provided with a useful tool to make the athlete aware of post-injury functional recovery. The machine learning algorithm used was the

One-class Support Vector Machine. This algorithm required the setting of three main parameters: the type of kernel, *eta*, and *gamma*. Optimization of these parameters had the purpose of minimizing the misclassification error in the training and in the testing phases. Afterward, the main features were selected in order to reduce the amount of data needed to train the machine.

The purpose of integrating artificial intelligence was to train an algorithm for each athlete. At the beginning of the season, in fact, every athlete is required to do a series of repetitions of flexion and extension of the arm. The collection of these data ends when an injury occurs. The experiment was performed training 16 models, collecting data from 16 different subjects. Subjects were asked to do 15 repetitions of the correct exercise and 5 in which they simulated an arm injury. The model, using the parameters that had been set to reduce errors in training and testing, showed low performance when trained on the few data collected by each individual subject. The reason of the bad performance is possibly due to the reduced training set size. It was choosen a different type of kernel and then to enlarge the dataset to see how the error behaved in the training and testing of the algorithm. From the first solution, it emerged that the type of kernel that most reduced misclassification errors was the linear type. However, this solution introduced overfitting.

Expanding the dataset, asking one of the subjects to record additional repetitions, it is clear instead that the kernel Radial Basis Function is the one that introduces fewer misclassification errors both in the training and in the testing set.

A possible extension of the mobile health tool concerning the identification of the anomaly in the repetition of the rehabilitation exercise, could be to associate a quality score to the movement. This solution can be implemented by founding metrics to quantify movement performance and mapping them into numerical scores of movement quality. At that point, it would be interesting to train a deep neural network for regressing quality scores of input movements.

It is possible that the generation of quality scores could encourage athletes to follow meticulously the rehabilitation program to recover the functional abilities. Moreover, reinforcing the perception of the individual in performing the movement more correctly and closer to normality, could push him to recover his initial abilities much faster.

It can be concluded that a portable mobile health tool that brings together the three activities implemented during this thesis work is able to provide support to basketball athletes in evaluating movements and, above all, in post-injury rehabilitation concerning both lower and upper limbs. Before this thesis work, there was no mobile application that focused on post-injury rehabilitation, integrating the mentioned three specific activities in a single instrument.

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