Master Science in Biomedical Instrumentation

Towards Wearable Intelligent System for Human Activity Recognition and Prediction

An Internship Report submitted in order to obtain the degree
of Master Science in Biomedical Instrumentation

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"Never regard your study as a duty, but as the enviable opportunity
to learn the liberating beauty of the intellect for your own personal joy
and for the profit of the community to which your later work will belong."
- Albert Einstein

ABSTRACT

Nowadays with the advancement in areas as sensing, wearable and wireless communication, it is possible to conceive intelligent systems to continuously monitor human being activities in real-time.

In the world of sports, improving athletes's performance is one of the main challenges for coaches, specially due to the variability in performance which can affect the end-result, where an inadequate decision-making can lead to under-performing players, which can affect the whole team. Identifying how athletes behave during training and matches and how they respond to training loads, prevent injuries and predict how athletes will perform, are key points to achieve an overall better collective performance, and, as consequence, better results. For this purposes wearable devices can help us with the acquisition and analysis of physiological, biomechanical and position data, that can lead to a better knowledge of the game.

This master dissertation proposes the development of a methodology that analyses and classifies kinematic and physiological data using a type of a Recurrent Neural Network (RNN), called Long Short Term Memory Network (LSTM). To recognize a player's actions having also into consideration the position, within the field, of other team players. To do so, it was needed two wearable devices: TraXports (to collect kinematic data) and MBody3 (to collect physiological data).

With this project we hope to be able to distinguish, if either the player is jumping, running, walking (with and without the ball), shooting or passing having into consideration all players position in the field and the physiological data information of the player who wore the Mbody3 shorts.

Keywords: Technologies, wearable technologies, intelligent systems, deep learning, sports, RNN, LSTM, TraXports, Mbody3, kinematic data, physiological data

RESUMO

Nos dias de hoje, com o avanço da tecnologia *wearable*, nos sensores e nas comunicações *wireless* é possível desenvolver sistemas inteligentes capazes de monitorizar continuamente e em tempo real actividades quotidianas do ser humano.

No mundo do desporto, melhorar o desempenho do atleta, é um dos principais desafios para os treinadores, já que a variabilidade do seu desempenho, entre eventos, pode afetar o resultado final, já que o baixo desempenho de um jogador pode afetar toda a equipa. Identificar como se comportam os atletas durante treinos e jogos e como respondem às cargas de treino, prevenir lesões e prever como se irão comportar são pontos-chave para um melhor desempenho. Para esta finalidade, dispositivos *wearable* são uma mais valia na medida em que possibilitam a aquisição e análise em tempo real de dados fisiológicos, biomecânicos e de posicionamento, que podem levar a um melhor conhecimento do jogo.

Esta dissertação de mestrado propõe então o desenvolvimento de uma metodologia capaz de analisar e classificar dados, cinemáticos e fisiológicos, utilizando um tipo de Redes Neuronais Recorrentes, chamado de Rede LSTM, para fazer o reconhecimento de acções de um determinado jorgador tendo também em consideração o posicionamento dos restantes elementos da equipa. Para esse fim, será necessária a utilização de dois dispositivos *wearable*: o Traxports (para recolha de dados cinemáticos) e o MBody3 (para recolha de dados fisiológicos).

Com este projecto esperamos conseguir distinguir, se o jogador está a rematar, a fazer um passe, a andar ou a correr com e sem bola ou a saltar tendo em consideração o posicionamento de todos os jogadores em campo e os dados fisiológicos do jogador que utilizar os calções MBody3.

Keywords: Tecnologias, tecnologias *wearable*, sistemas inteligentes, *deep learning*, desporto, RNN, LSTM, TraXports, Mbody3, dados cinemáticos, dados fisiológicos

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ABBREVIATIONS AND SYMBOLS

AI- Artificial Intelligence

ANN- Artificial Neural Network

BLE- Bluetooth Low Energy

CART- Classification And Regression Tree

DAG- directed acyclic graph

EMG- Electromyography

GPS- Global Positional System

HMM- Hidden Markov Models

IMU- Inertial Measurement Unit

KNN- K-nearest Neighbour

LSTM- Long Short Term Memory

MATLAB- Matrix Laboratory

RNN- Recurrent Neural Network

RTS- Real-time location System

sEMG- Surface Electromyography

SVM- Support Vector Machine

t- Time instant t

UWB- Ultra-Wide Band

1

INTRODUCTION

Pattern recognition, in very simple words, is the science that, by observing the environment learns to distinguish patterns of interest from their background, for example it distinguishes the animals from the buildings, sky, among other things (Parasher et al., 2011).

In pattern recognition, human beings can easily recognize patterns as changes to the environment that surrounds them, such as motion, illumination, facial silhouettes and facial rotation (Samal and Iyengar, 1992; Davidenko, 2007) making the ability to recognize patterns, a reference point to define how to detect and identify information. However, when it comes to artificial recognition these tasks can be extremely challenging. Nevertheless, developments in the field of artificial intelligence made the possibility of making pattern recognition, using machines, something conceivable. This field, known as Pattern Recognition, studies the relation between machines and the environment by analysing how they are able to learn to distinguish various patterns of interest from its background and make reasonable decisions about its categorization. The whole process involves extraction of information from the sensory signals, processing it using the information stored in the brain to reach a decision that induces some action as we can see in figure 1.1.

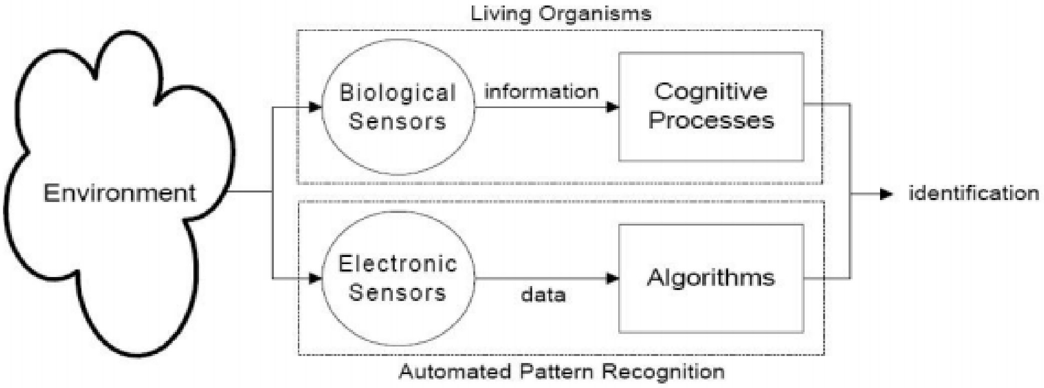

Figure 1.1: Pattern Recognition for human and Machines (Parasher et al., 2011)

All these information we work with are represented as patterns. Pattern recognition can be applied to various areas, such as speech and face recognition, classification of handwritten characters and medical diagnosis (Sharma and Kaur, 2013).

This master dissertation is a part of CORE's project witch aims to provide possibilities for coaches and technical teams, not only to analyse the team performance, which is key to achieve better results, but also to be constantly aware of potential injuries, allowing for faster interventions and a reduced cost of having a player in the bench. This is achieved by analysing physiological and kinematic data in a holistic approach through an innovative solution, thus representing a differential advantage from current alternatives available in the market that focus entirely on positional data.

The aim of this project, from now on denominated by dissertation, focuses in the creation of a wearable intelligent system, using a supervised method of deep learning, capable of recognizing a player's action during a football match having into consideration data of all players like their position in the field and physiological data from one specific player that used both systems. However, this can be challenging because there are many factors that can influence the performance of an athlete thus creating the big problem know as big data (see Section 2.2). We aim to address this problem by achieving only kinematic and physiological data to do the pattern recognition of seven actions performed by the athlete as running with and without the ball, walking with and without the ball, passing, shoting and jumping.

To do so, the analysis of the gait movement is an important step to understand the correlation between the functional activity of the gait and running pattern so they can then be distinguished later on. It is also important to prevent further injuries and to realize a greater performance (Dicharry, 2010; Brown et al., 2014; Clermont et al., 2019; Howard et al., 2018).

For a complete analysis of run pattern, it is necessary to assess both kinetics and kinematics data. The kinetics data correspond to the study of the forces that are acting on an object while the kinematics is the study of properties of body's movement. Normally, the gait patterns respect some parameters such as frequency, stride time, step time, stride length, step length, gait velocity, and cadence (Dicharry, 2010; Clermont et al., 2019; Mero et al., 1992).

In Football, athletes can run several kilometers during a game, in different types of locomotion. Straight line frontward or backward, side run and quick changes of direction in conjunction with different velocities and rhythms, reveal how football can be a challenging for pattern recognition. Those accelerations and maximal sprinting represent just less than five percent of the total distance that an athlete goes through during a game (Ishøi et al., 2018). Others factors can influence the run pattern, such as fatigue, muscle activity, poor technique and even injuries (Howard et al., 2018; Di Michele and Merni, 2014; Brown et al., 2014; Clermont et al., 2019; Ishøi et al., 2018; Svoboda et al., 2016; Steinberg et al., 2017).

The most useful skill performed by a football player is the kick, which can lead to scoring goals. It is one of the most studied movement in soccer because of the complexity and body requirement. There are many different types of kick, depending on the force generated, the main outcome, accuracy and the technique used by the player (Lees et al., 2010; Dörge et al., 2002). The movement is characterized by a rapid approach to the ball with the supporting foot beside the ball with the attempt of performing a kick with the other leg. There are two stages in the movement of the kicking leg, the backswing and the frontswing (Lees et al., 2010). To do a biomechanical analysis of the kick movement pattern, it is necessary to have into consideration the different segments, their interaction and the angular position, velocity and acceleration (Dörge et al., 2002).

According to Nunome et al. (2006), the foot-to-ball interaction on the kicking moment have a duration of 10ms. This moment of action-reaction has been studied with high velocity cameras from 1000 to 5000 Hz in order to capture:

1. the velocity of the leg before the impact,
2. the moment of impact,
3. the place where the foot makes contact with the ball and
4. the exit velocity of the ball.

This Kinematic analysis of the human movement is very important for our project since it can give us the possibility understand the complexity of human movement. Besides that variables as the position on the field, velocity, orientation and others merged with physiological data such as electromyography (EMG) and heart rate, can give us a deep analysis of many variables, transforming this large amount of data into simple and practical data, giving to the coaches, sports analysts, exercise physiologists and athletes this data in real time, augmenting the understanding of the athletes behavior during games (Couceiro et al., 2016).

In sports, predicting how an athlete is performing or the risk factor during training and matches is extremely important, wherefore they can have the best performance possible. Football is the most popular and practiced sport worldwide, injuries are still present in athletes and they are associated with player's age, training load and play category. When they practice soccer, movements like cutting, jumping, sprinting, passing, shoting, walking and running are executed. These movements, when the athletes don't have a perfect technique or are constantly repeating these, can lead to multiple injuries and limit their performance (Larson, 2014; Almeida et al., 2013; Van Beijsterveldt et al., 2013; Esteve et al., 2015).

The goal of prevention programs is to reduce injuries by increasing the ability of the tissues to absorb greater stresses (McBain et al., 2012). Prevention programs are designed to be efficient and to not occupy too much time. In these programs, the athletes train the main physical abilities like strength, resistance, coordination, flexibility, balance or agility (Barengo et al., 2014).

Eventhough we were focused on a football context, due do the difficulty of having a football team that could work with us, our strategy had to be changed slightly. Then, instead of doing the classification of the actions performed by a football athlete, we did the classification of the actions performed by an athlete in a futsal context.

1.1 Ingeniarius

The development of this master dissertation took place at Ingeniarius witch is a private company that aims for research and technological development in many fields of engineering such as robotics and automation as well as quality of life, sports and health.[1] Ingeniarius provides consulting, outsourcing and training services related to engineering.

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[1] `https://ingeniarius.pt/about-ingeniarius-store/`

Figure 1.2: Ingeniarius logo

1.2 CORE

CORE is the abbreviation for Center of Operations to Rethink Engineering and is a project that follows the activities promoted by Ingeniarius reflecting the key element of innovation and research promoted by the academic partners, Coimbra Polytechnic and University of Coimbra. This center, along with Ingeniarius, primes for the innovation and research aiming the industrial and commercial exploitation of technology knowledge such as Intelligent Systems, Robotics, Sports Engineering and Health technologies.[2]

Figure 1.3: CORE logo

1.3 Objectives

The main objectives defined for this Master dissertation project are described as follows:

1. Explore both kinematic and physiological equipment as well as choose the classification method.
2. Development an architecture that allows the integration of information from multiple sources (e.g., TraXports by Ingeniarius) in order to classify the actions performed during a game.
3. Data acquisition and pre-processing of relevant athlete's data during the match, by integrating positional and physiological information.
4. Recognition of athlete's actions: passing, shooting, running with and without the ball, walking with and without the ball and jumping.
5. Assessment of the proposed model for action classification in a sports context.

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[2] `http://core.ingeniarius.pt/`

Lastly, our goal is to contribute towards the development of CORE's project, whose research center on a mathematical modeling and wearable technologies for analysis and prediction of sport performance, by building a model capable of recognizing actions.

1.3.1 Work Plan

The work plan with the description of the tasks established for this master dissertation is the one presented in 1.1.

Table 1.1: Project's development workplan

Task	Description Task	Time									
		Jan/19	Feb/19	Mar/19	Apr/19	May/19	Jun/19	Jul/19	Aug/19	Sep/19	Oct/19
1	State Of The Art	🟦	🟦	🟦	🟦						
2	Methodology's Definition					🟦					
3	Architecture's Development					🟦	🟦	🟦			
4	Data Acquisition						🟦	🟦			
5	Data Analysis and Classification							🟦	🟦		
6	Testing and Validation							🟦	🟦		
7	Project Take OFF	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦

The "Take OFF - Building Global Technology Entrepreneurs for Advanced Material", is a program for entrepreneurs whose strategic and central objective is the creation of a coherent and integrated ecosystem that encourages the emergence of ideas and supports the acceleration of innovative start-ups in technological areas. We participated in this program with this dissertation project.

1.4 Document Structure

This Master dissertation report is divided in five Chapters and two appendices being the remainder of this document structured as follows:

Chapter Two:

In chapter two it is shown a literature review about Artificial intelligence, Big data in sports, Non-Sequential and Sequential Methods for Pattern Recognition, some related work and current technologies available in the market.

Chapter Three:

In chapter three it is described the proposed architecture for the classification of human activity including the chosen software and hardware, the pre-processing phase, feature extraction and also the adopted methodology.

Chapter Four:

In chapter four experimental results. are shown and discussed. First, we present the Experiment A where a preliminary work is described. Then comes the Experiment B as well as its experimental setup and then results are presented and discussed.

Chapter Five:

Lastly, in chapter 5, it is described the conclusions about the work developed, some contributions and future work considerations.

2

LITERATURE REVIEW

This chapter contains the literature review about Artificial Intelligence (Section 2.1), Big data in sports (Section 2.2), different Classification methods for pattern recognition (Section 2.3) as sequential (Subsection 2.3.2) and non sequential methods (Subsection 2.3.1). After that, in Section 2.4 we have a description of the wearable technologies for sports improvement that are available on the market. In Section 2.5 it is presented some of the work done in daily activity recognition and how it can give information about life style in relation to physical activity in sports, using some of the classification methods described in Section 2.3. Then, there is a Comparison of the different classification approaches (Section 2.6) and lastly it is made a Comparison of the wearable technologies (Section 2.7) previously described in Section 2.4.

2.1 Artificial Intelligence Timeline

Artificial Intelligence (AI) has been studied for decades and is still one of the most elusive subjects in Computer Science. Is an area with so many potential and with so many things to explore, which can be said that a day does not go by without a news article reporting some amazing breakthrough in artificial intelligence (Yampolskiy and Spellchecker, 2016).

The term artificial intelligence was first coined by John McCarthy in 1956 when he held the first academic conference on the subject (McCarthy et al., 1996). But the ideology behind the term arise when Turing (1950) raises the question "Can machines think?" and in the attempt to find an answer, developed the Turing test. This test is executed by two human beings and one machine with the propose of analyze the ability of a machine acquire an intelligent behaviour similar to an human behaviour. All the participants are separated and exist a conversation between the humans and the machine, in natural language. Exist an judge, which can hear the conversation and have to distinguish the machine of the others elements. If the judge cannot identify the differences, machine pass the test (Turing, 1950).

Unfortunately, at that time the capacity of the computers was to small for the Turing ambitions. Besides computing was extremely expensive, computers lacked a key prerequisite for intelligence, they couldn't store commands, only execute them. It was in the two next decades, when computers could store more information and became faster, cheaper and more accessible, that AI flourished.

With works such as Newell and Simon's *General Problem Solver* and Joseph Weizenbaum's *ELIZA* showed promise toward the goals of problem solving and the interpretation of spoken language respectively (Newell et al., 1959; Weizenbaum et al., 1966). These successes, convinced government agencies such as the Defense Advanced Research Projects Agency (DARPA) to fund AI researches at several institutions. The government was particularly interested in a machine that could transcribe and translate spoken language as well as high throughput data processing. Optimism was high and expectations were even higher (Boehm and Scherlis, 1991).

In the 1980's, John Hopfield and David Rumelhart popularized "deep learning" techniques which allowed computers to learn using experience and the therm Machine learning start being popularized. At the same decade, on the other side of the world, the Japanese government heavily funded expert systems and other artificial intelligence related endeavors as part of their *Fifth Generation Computer Project* (FGCP)[3].

During the 1990s and 2000s, many of the landmark goals of artificial intelligence had been achieved. In 1997, reigning world chess champion and grand master Gary Kasparov was defeated by IBM's Deep Blue, a chess playing computer program. This highly publicized match was the first time a reigning world chess champion loss to a computer and served as a huge step towards an artificially intelligent decision making program. In the same year, speech recognition software, developed by Dragon Systems, was implemented on Windows[4].

With the technology growing exponentially, the alliance between human and machine is even bigger, which is why we live in the age of big data. The data which a machine collects about humans are numerous, all in order to make our life easier. Sometimes this aid is so great that it leads to human discomfort. Nowadays we can have a simple coffee chat with a friend and when we gain perception, all the applications around us have something related with it. This is uncomfortable. On the other hand, one of the great comforts that AI has given us is the driving assistants who currently equip many cars, making them increasingly safe.

These are the aspects in which the future of AI and Machine Learning passes, making machines the best ally of human beings, ensuring their health and well-being, as well as the best possible efforts to perform any task. This master dissertation is itself an example of AI's future.

2.2 Big Data in Sports

Big Data Analysis has been reported to hold the promise of making effective usage of large quantities of data to estimate a wide range of quantities such as:

1. physiological variables (e.g., Heart Rate Variability, EMG)
2. technical performance (e.g., shots on goal, successful passes)
3. positional information (e.g., position of players on the field) and others

With this information it is possible to provide additional insight for decision support, improving the quality and efficiency of performance (Wu et al., 2016).

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[3] `https://www.nytimes.com/1984/11/12/business/japan-gain-reported-in-computers.html`

[4] `http://sitn.hms.harvard.edu/flash/2017/history-artificial-intelligence/`

Big data is related with the concept of quantified self (Q S): an individual engaged in the continuous self-tracking of any kind of biological, physical, behavioral, or environmental information, resulting in a fundamentally quantitative and qualitative phenomenon since it includes both the collection of objective metric data and the subjective experience (Swan, 2013).

To approach the Big Data with some ecological value in this master dissertation, first we need to understand how we should be approaching the data presented to us. We can view this information in two ways:

1. data-driven, were the user's decisions are centered and relayed on the data collected,

2. data-informed, were data is used to deeper understand what is happening on the field.

https://hackernoon.com/why-you-should-be-data-informed-and-not-data-driven-76079d187989

A data-informed approach takes into account the limitations of the data collected, uses multiple sources to make decisions, rather than just relying on data facilitating the decision making process, potentially leading to better results contrarily to data-driven where the decisions are entirely evidence-based.

From a physiological point of view, a data-informed approach can lead to better decisions and therefore performance, since there are many factors that impact performance during a match, such as technique, psychology, mentality, positioning in the field and distance between players (Couceiro et al., 2016).

As we are assessing actions made by athletes during a match using, only, physiological and positional information and since this two are the only features that will be taken into account in this master dissertation, its going to be used a data-driven approach.

2.3 Classification Methods for Pattern Recognition

2.3.1 Non-Sequential Methods

Non-sequential methods for classification in pattern recognition are characterized by independent situations in every training or testing data set.

For the use case of football, it corresponds on how the analysis is performed: a single analysis of how many times a movement is performed (e.g., how many times do a player performed a kick, or how many times the player passed/receive the ball).

2.3.1.1 Bayesian Model

Bayesian model, whose name derives from the probability calculus established by Thomas Bayes, is a probabilistic graph model known as directed acyclic graph (DAG), that represents a group of variables and its dependencies (Neapolitan et al., 2004).

This type of model is characterized by the inclusion of an evidence (provided by the observed data) to convert a prior probability (before any evidence is obtained) into a posterior probability (after any evidence is obtained) (Bishop, 2006).

Being *P(A)* and *P(B)* a prior probability of the events A and B, the conditional probability of these two events is represented by $P(A|B)$ and $P(B|A)$. So we have Bayes's theorem as:

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{2.1}$$

With this Bayes's theorem it allows us to evaluate the probability of happening the event A knowing that the event B has already occurred (Bishop, 2006).

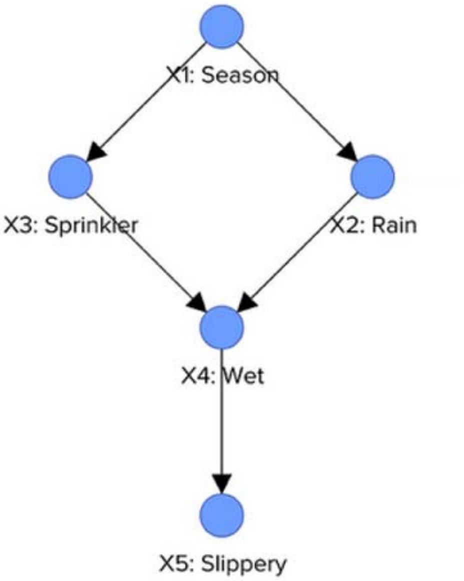

Figure 2.1: A simple Bayesian Network example[5]

As an example, in the network presented on figure 2.1 there is described the causal relationships among the seasons of the year (X1), whether it is raining (X2) or if the sprinkler is on (X3). Knowing that, is the pavement wet (X4)? And is the pavement slippery (X5)?

Here, we can tell that there is no direct consequence from the season on the slipperiness of the pavement. As we can see, the weight on that is influenced by the wetness of the floor, in other words, this network can give us the probability of a variable in study given its parents, e.g., $P(X5|X4)$ tells us the probability of the floor being slippery knowing that the floor is wet. So, the probability that can describe the example is:

$$p(X1,X2.X3,X4,X5) = p(X1)P(X2|X1)p(X3|X1)p(X4|X2,X3)p(X5|X4) \tag{2.2}$$

In conclusion, the learning process for this method goes by an estimation of each conditional probability (the sum of each variable probability given its parents) from our training set (classified data). After that, the algorithm receives an input (that did not belong to the training set), returning an output class that is more likely to be, for that sample, accordingly to the probabilistic calculations. It might be needed to add some priors to prevent overfitting and situations were we do not have enough data.

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[5] `http://www.bayesia.com/bayesian-networks-examples`

2.3.1.2 K-nearest Neighbour

In pattern recognition, K-nearest neighbour is a classification method based on the analogy, in other words this method classifies an object based on the preponderant class in between his k-nearest neighbours. This happens because it is assumed that if two objects belonging to the same data are close to each other, then they have similar characteristics (Ashari et al., 2013).

When the idea is to understand to which class a new object belongs, it is important to have into consideration the k value. This value will tell us the number of neighbours that will be considered when doing class classification. If for example k=1, it means that the object will be assigned to the class of the nearest neighbour in the training set. An assumption that can lead us to an error in classification.

Depending on the circumstances, having a large k is going to reduce the noise effect but will influence negatively the boundaries between classes. In other hand if the k value is small, comparing with the number of samples, the objects that will be considered are the nearest ones to the object that we are studying so it increases the probability of getting the true class of the object (Cover and Hart, 1967). Therefore the goal here is to find the optimal k value and that is normally done by using Euclidean metrics (depending on the type of the variables) (Weinberger and Saul, 2009).

2.3.1.3 Classification and Regression Tree

Classification and Regression Tree (CART), as its name indicates, is a model that is represented on a tree form. This method is characterized for partitioning the data space (node) in separate smaller sub-spaces followed by a simple fitting model for each one of the sub-spaces until it is find the partition that minimizes the level of impurity (Timofeev, 2004).

Impurity, in this case means that there is still traces of one class division into another. There are some reasons why this happens being one of them the tolerance of some percentage of impurity for faster performance (gini impurity). Mathematically it can be calculated through the next formula:

$$\phi(p) = \sum_{k \neq l} p_k p_l = 1 - \sum_{k \neq l} p_k^2 \tag{2.3}$$

where *p(k)* is just the probability of an item with label *k* being chosen times the probability of a mistake in categorizing that item.

To measure the impurity itself it is calculated the entropy defined as:

$$\phi(p) = -\sum_{k} p_k \log p_k \tag{2.4}$$

where *p(k)* is a fraction of examples in a given class (Safavian and Landgrebe, 1991).

2.3.1.4 Support Vector Machine

Support Vector machine (SVM) is a classical machine learning technique that can be used to solve linear or non-linear big data classification and regression problems. This type of classification method results of two stages:

1. Mapping data vectors to a N-dimensional space (bigger than the original data space);
2. Finding the best hyperplane (with the largest margin possible) that can separate the different classes of data.

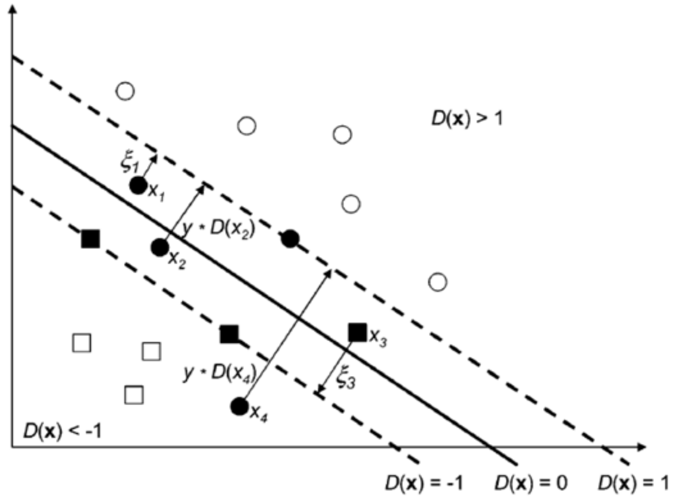

Figure 2.2: Linear SVM example with Hard-margin (Byvatov et al., 2003)

Separating the data, using the best hyperplane, into classes, allows SVM to build a model that classifies new data examples into one of the classes.

So, the goal of finding this hyperplane is to maximize the margin between the support vectors (data points of different classes near to the hyperplane) (Byvatov et al., 2003).

In the example shown on figure 2.2, the task was to separate two different type of objects (squares and circles). Circles were representing the "positive examples" (those above the decision line (D(x)=0)) and the squares the "negative examples" (those under the decision line). Support vectors are indicated by the filled objects (x2, x2, x3, x4) and ξi are slack variables for these support vectors that are not lying on the margin border (Byvatov et al., 2003).

As said before, SVM can solve linear and non-linear data classification problems. Linear SVM classification can have hard-margin (linearly separable data) and soft-margin (when data is not linearly separable); and non-linear SVM classification. However, it is not always possible to find the best hyperplane (Byvatov et al., 2003; Lorena and de Carvalho, 2007) which is the case of non-linear SVM classification as shown on figure 2.3 where a curvy boundary would be better for class splitting.

On figure 2.3 is illustrated:

a) The non-linear data;

b) The non-linear boundary for the entry data space, and

c) Linear boundary for feature space.

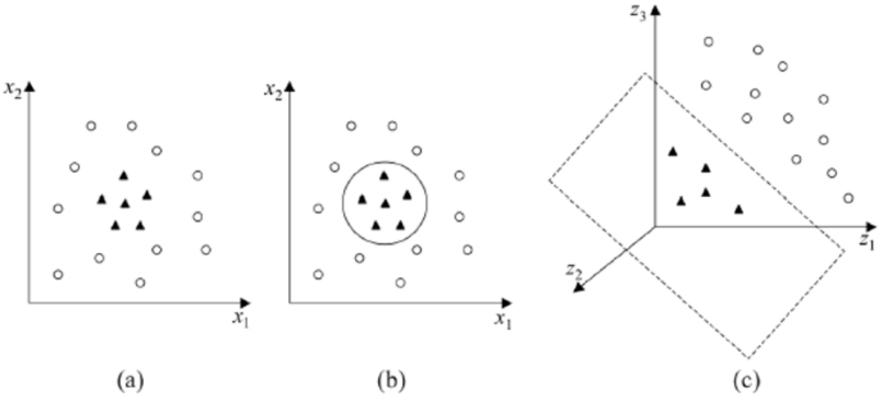

Figure 2.3: Non-Linear SVM example (Lorena and de Carvalho, 2007)

To solve the mapping problem due to its complexity it is used the Kernel trick. A Kernel is a function that has two data points as input (x,y) and computes the resulting product of those two point into the feature space.

In sum, non-linear SVMs have to map the training data X of the original space Φ (entry data) of non-linear problems to a new and bigger dimension space called feature space X (Hua and Sun, 2001) as follows:

$$\Phi : X| \rightarrow X \tag{2.5}$$

Thus, as the only important thing about mapping is the scalar product of points belonging to the feature space, we have that:

$$K(x,y) = \Phi(x) \cdot \Phi(y) \tag{2.6}$$

In practice, the most used Kernels are polynomial (or linear), Gaussian (or Radial-Basis Function) and Sigmoidal as shown on table 2.1

Most common Kernel Functions		
Kernel Types	**Function**	**Parameters**
Polynomial	$(\delta(x_i \cdot x_j) + k)^d$	δ, k, d
Gaussian	$exp(-\sigma \parallel (x_i - x_j) \parallel^2)$	σ
Sigmoidal	$tanh(\delta(x_i \cdot x_j) + k)$	δ, k

Table 2.1: Most common Kernel Functions (Lorena and de Carvalho, 2007)

2.3.1.5 Artificial Neural Network

An Artificial neural network (ANN) is a computational system that was inspired on the human brain. The purpose was to create intelligent systems that could behave as a human being. The components that are in the base of this system are (Negnevitsky, 2005):

- Neuron: basic computational unit of the network;
- Architecture: topological structure of how neurons are connected;
- Learning: is the process that occurs so the network is now capable of doing a determined task.

As we can see on figure 2.4, in this type of classification system the first layer contains the input values (neuron/hidden layer that sends data to the next neuron/hidden layer). Then there are the weight coefficients or the synapses (existing relation between neurons). Each input value is multiplied by a weight coefficient (that is going to influence the output) and then it is made a weighted sum of all the signals and then, the result of that is computed by a mathematical function which determines the activation of the neuron. So now it is possible to compute the output of the system according to the artificial neuron's data.

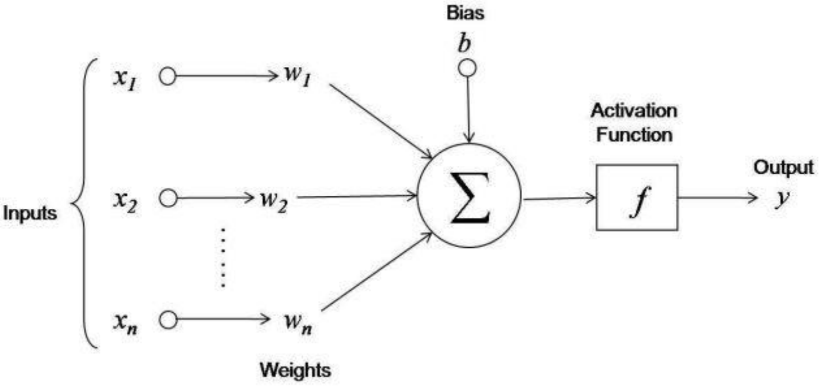

Figure 2.4: An example of an ANN activation function [6]

ANNs can be described as supervised or unsupervised learning methods. In supervised learning, the value of the weights between the neurons are constantly changing (externally) so the output is closer to the expectations. In unsupervised learning, there is no knowledge about the output data. In this case, the algorithm does a class separation by detecting similar features. The network's learning, in this case, is made by observation. In other words, here the adjust of the weighs is made by the analysis of the input data (Bishop, 2006).

Therefore, ANNs have the ability to learn from examples. A learning algorithm is a set of procedures used to adapt ANN parameters and produce an expected output. These is the reason why ANNs are so famous in robotics, recognized patterns and voice analyzes, especially using the supervised learning methods.

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[6] `https://towardsdatascience.com/statistics-is-freaking-hard-wtf-is-activation-function-df8342cdf292`

2.3.1.6 Recurrent Artificial Neural Networks

Recurrent Artificial Neural Network or RNNs are a type of Artificial Neural Network that is used for pattern recognition. In this method the connections between nodes forms a directed graph on a temporal sequence making possible the visualization of its temporal behavior predicting the next likely scenario (Agatonovic-Kustrin and Beresford, 2000).

As it happens in most cases, an Artificial Neural Network process information in a single direction (from input to output), called "feedforward", on the other hand RNN can be built to process information in a bi-directional way, in other words in two directions, that is a more elegant solution since standard RNNs have limitations as their output tending to be mostly based on previous information. (Schuster and Paliwal, 1997; Graves and Schmidhuber, 2005).

The RNN method, unlike the feedforward approach, uses feedback loops or recurrent edges that receives, besides the normal weight, input from the recurrent data point and also from hidden node values from the previous state of the network. This way it is possible to keep the memory of the previous state which allows us to perform temporal processing since the output is no longer the result of the input signals but also the value of the previous state (Lipton et al., 2015; Agatonovic-Kustrin and Beresford, 2000).

2.3.2 Sequential Methods

On patter recognition, sequential methods for data analysis are methods that takes into consideration the time factor. In other words, in football, with sequential methods it is possible of modeling time, such as video and movement analysis and recognize human activity (e.g., what action is the player performing).

This type of analysis, contrarily to non-sequential methods analysis, gives us the opportunity to have the data processed and presented to a device within a small-time window.

2.3.2.1 Markov Models

A Markov Model is a sequential machine learning method that can model time. This method uses previous knowledge to predict what is going to happen next. However, contrarily to CART (non-sequential method presented in the subsection 2.3.1.3), a Markov Model does the prediction of the next observation in a sequence using only the immediate preceding observation, being, this way, independent of all earlier observations (Bishop, 2006) as it is shown on the next equation:

$$P(x_n|x_{n-1}) \tag{2.7}$$

Having into consideration only the most recent observation is very restrictive. in order to overcome that, it is possible to move to a high-order Markov chain. This way, the probability of happening a certain observation now depends not only on the immediate preceding observation but also on the previous-but-one value. The distribution is know given by:

$$p(x_1,...,x_N) = p(x_1)p(x_2|x_1)\prod_{n=3}^{N} p(x_n|x_{n-1},x_{n-2}) \tag{2.8}$$

It gives us a more flexible method, nevertheless the number of parameters on the model is bigger than the first-order Markov chain. The bigger the order, the greater the number of parameters(Bishop, 2006).

- Hidden Markov Models

  A Hidden Markov Model (HMM) is a probabilistic system created with the objective of modelling sequences. In other words, a HMM is a machine learning method used for modelling a class sequence.

  A trained Hidden Markov Model can compute the probability of producing any new sequence. The probability value obtained can be used for discerning if the new sequence belongs to the family that was previously modelled by a HMM (Casadio et al., 2006).

2.3.2.2 Ensemble Classification

Ensemble classification methods are learning algorithms which uses the combination of a range of different classification methods with the intuit to collect the best of each one and that way, achieve the best level of the classification possible.

Inside this section of the classification methods area, exist one method which deserve an highlight - the Dynamic Bayesian Mixture Model (DBMM). This method benefits from the concept of dynamically mixing classifiers to combine the conditional probability outputs of the different classifiers assigning him different weights, resulting in more accurate and precise results. SVM and ANN, that already was been mentioned on the previous sub-sections, are part of the conjunct of the methods that are used to integrate the DBMM.

The first ensemble method developed was the Bayesian averaging, which led to the development of further algorithms (Dietterich, 2000). Some years after, emerge a DBMM architecture applied to the human activities recognition by using body motion from RGB-D images, which is designed to combine the outputs of the different conditional probabilities of the different classifiers. To do this, a weight is assigned to each of the classifiers, according to previous knowledge, by using an uncertainty measure as a confidence level, which can be updated locally during online classification. When the local weight is updated, it assigns priority to the classifier that presents more confidence along the temporal classification, since this can vary along the different frame classifications (Faria et al., 2014).

2.3.2.3 LSTM Network

Long Short Term Memory network, mostly known as LSTM, is a type of RNN (Recurrent Neural Network), introduced by Hochreiter and Schmidhuber (1997), capable of learning long-term dependencies in real time sequential data. This classification method was projected, essentially, to remember information for long periods of time as it was a pointed difficulty of RNNs model(Sak et al., 2014; Graves and Schmidhuber, 2005).

In LSTMs the first step is for the network to decide which information is going throw away from the cell state - previous cell memory (C_{t-1}) - and which one pass to the next cell. This decision is made by a sigmoid layer known as "forget gate layer" (f_t) whose result depends on h_{t-1} (previous cell output) and x_t (input vector) and its output can be a number among 0 and 1 for each number on the cell state, meaning to forget the information or to keep it, respectively.

The next step is about deciding if the information should be updated in the cell state as shown in figure 2.5 d).

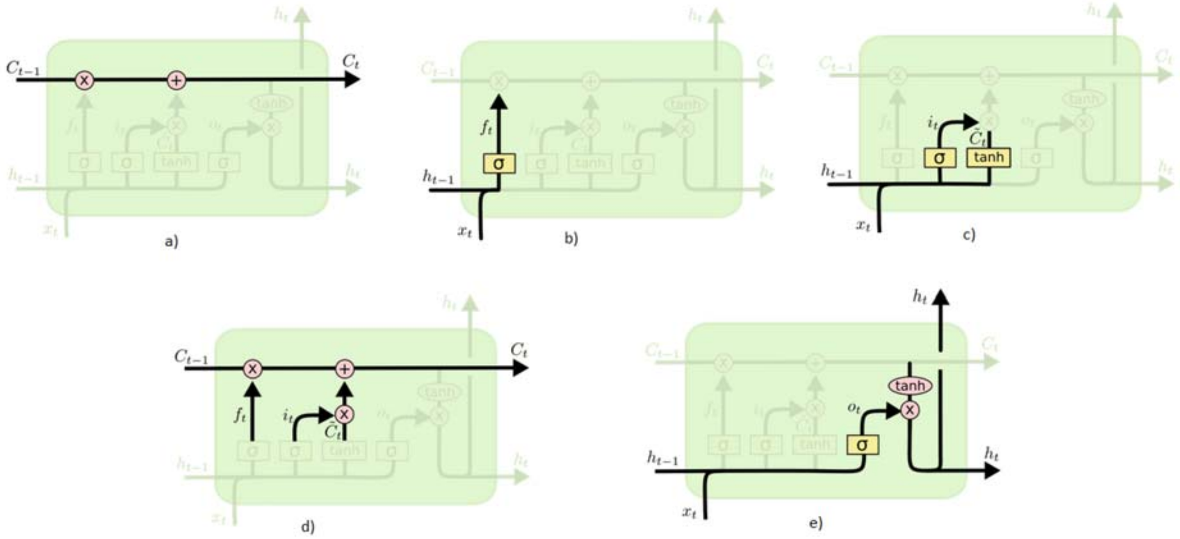

Figure 2.5: Workflow of a LSTM Network[7]where each figure represent: a) the cell state; b) the "forget gate layer"; c) Decision step: sigmoid layer known as "input gate layer" (i_t) and a tanh layer ($\tilde{C}$) that creates a vector with new values that could be added to the state; d) update the old cell state: $C_{t-1} \to C_t$; e) output of relevant information

Summing up, the cell state is a connection between all the LSTM cells. Each LSTM cell have three important gates:

- the input gate that controls whether the gate is updated:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2.9}$$

- the forget gate that controls if the memory gate is reset to zero:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2.10}$$

- the output gate that controls whether the information of the current cell state is made visible:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{2.11}$$

where W_i, W_f and W_o are weight parameters and b_i, b_f and b_o are bias parameters.

All phases (gates) of the LSTM cell have a sigmoid activation function. Apart of these gates there is another vector called $\tilde{C}$ that modifies the cell state. Each of the gates takes the hidden states and the current input x as inputs, concatenating these vectors and applying them to the sigmoid. These $\tilde{C}$ represents a new candidate values that can be applied do the cell state.

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[7] `http://colah.github.io/posts/2015-08-Understanding-LSTMs/`

Finally, remains find what will going to output. This output will be what is on the cell state, but filtered. First, the information pass in a sigmoid layer which decides what parts of the cell state going to output. Then, the cell state through tanh (to push the values to be between -1 and 1) and multiply it by the output of the sigmoid gate, so that output is only interest parts.

2.4 Wearable Technologies for Sports Improvement

To analyse human activity some kinds of sensors must be used. These sensors give us a lot of different types of information such as heart rate, eletromyography, position, velocity, among others.

This section describes some of the wearable technology with the purpose of aiding coaches and athletes that is available on the market.

2.4.1 MBody3

The MBody3 is a product that has two components: MBody 3 wearable shorts and a MCell3 (figure 2.6).

The technology integrated in Myontec Mbody3 is capable of measuring the electrical activity of the muscles (electromyography) in real-time. This device has two main operation modes: online and recording. In online mode, device sends data using Bluetooth Low Energy (BLE) to an external solution in real-time. In recording mode, this device writes data to an internal memory which can be downloaded later. With this technology it is possible to measure: sEMG, heart rate, cadence, distance, balance, stability, speed, coordination, power, warm-up and activation sequences. It is also possible to do real-time data monitoring, post-exercise analysis, automated lap analysis, report and follow-up, biofeedback training, import and export data, scale and zoom, area selection, create custom graphs, do objective muscle training monitoring, thus training load, kinesiologic analysis of movement disorders, gait and posture disturbances evaluating and muscle imbalance detection.

Figure 2.6: MBody3 wearable device by Myontec[8]

2.4.2 Athos

Athos shorts (figure 2.7) have built-in sEMG sensors that sends data to the Core (located inside of the shorts). The Core processes the data and sends it to the Athos iOS app, where

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[8] `http://www.myontec.com/products/mbody-3/`

it can be analyzed.

This instrumented garment is capable of measuring sEMG (muscles activity), heart rate, calorie expenditure and active time versus rest time. In other words, with this technology it is possible to analyze real time muscle activation, left and right balance, muscle group distribution work, muscle contribution, training load analysis and personalized calibration.

Figure 2.7: Athos wearable shorts[9]

2.4.3 Ingeniarius TraXports

TraXports (figure 2.8), is a wearable solution based on ultra-wide band (UWB) wireless technology, in which both mobile devices (tags) and stationary base stations (anchors) are IEEE standard 802.15.4-2011 UWB compliant. Multiple wireless measures are used to estimate distances between stationary stations and mobile devices, without the need of any global positioning system (GPS). These estimated distances are then used as inputs for the proposed real-time location system (RTS), by benefiting from multilateration techniques.

TraXports also encompasses an inertial measurement unit (IMU) to not only improve player's position estimation using Kalman filters, but also to provide an estimation of player's orientation in the field. Only four anchors are required to estimate player's position, thus minimizing the setup time and complexity of the overall system. Those four anchors are placed outside the field (one in each corner) and each player wears a vest that has built-in sensors such as gyroscopes, accelerometers and magnetometers. The data collected from the vests is then transmitted, through the UWB system to Ingeniarius cloud service, giving the coach the possibility to analyse, during and after the game, the positioning of the whole team or just one specific player (depending on how many players are using the vest). This combined solution is able to provide a high positional accuracy in the tens of centimeters, under both indoor and outdoor scenarios, with a frequency update of 30Hz.

2.4.4 Ingeniarius FatoXtract

FatoXtract (Figure 2.9) does not require any camera system, markers, or system infrastructure. The modular nature of FatoXtract increases the freedom of movement of the subject while reducing the preparation time and lower on-body weight of the system.

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[9] `https://www.liveathos.com/products/mens-lower-body-kit-v2`

[10] `https://store.ingeniarius.pt/TraXports/`

Figure 2.8: TraXports wearable system by Ingeniarius[10]

FatoXtract applications include biomechanics, rehabilitation, ergonomics, gaming and sports. Additionally, FatoXtract is an internet-connected product. As such, it automatically connects to the Ingeniarius Cloud, thus endowing it with real-time debugging and monitoring over the internet. All captures are made easily using web applications to store and analyse the data.

Figure 2.9: FatoXtract wearable system by Ingeniarius[11]

2.4.5 ClearSky T6

The Catapult ClearSky T6 (figure 2.10) is a technological device that has a high accurate positional tracking system for both indoors and outdoors. This technology does not use GPS system because in an indoor situation, its performance would be compromised. So, instead of using GPS system, Catapult ClearSky T6 have developed the ClearSky T6 Local Positioning system that uses stadium mounted or portable wireless base stations that are used to calculate the position of players and it can be either hard wired into the mains or work off battery power.

Figure 2.10: Catapult wearable system[12]

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[11] `https://store.ingeniarius.pt/fatoxtract/`

[12] `https://www.catapultsports.com/products/clearsky-t6`

2.5 Related Work

Over the past decade, many authors have been studying the human behaviour at the most variate contexts such as daily activities and sports. This activity recognition can offer better health care and it can as well be used to achieve optimal physical preparation of elite athletes.

According to Yang et al. (2015) most of the existing work cannot find distinguishable features to accurately classify different activities. For this reason, Yang et al. (2015) proposes a systematic feature learning method, CNN (Convolution Neural Network), to better solve Human Activity Recognition (HAR) problems. The architecture proposed employed convolution and pooling operations in order to capture signature patterns from the data collected from the sensor at different time scales. All salient patterns were unified among multiple channels and then mapped into the different classes of human activities.Yang et al. (2015) says that the strengths of the proposed method are: i) feature extraction is not performed on a hand-crafted manners; ii) extracted features have more discriminative power with respect to the classes of human activities; iii) feature extraction and classification are unified in one model so their performances are mutually enhanced. Also, they conclude that in the experiments, the proposed CNN method outperforms other state-of-the-art methods.

Regarding sports, according to Ermes et al. (2008) tracking an human being daily activity can give information about his life style in relation to his physical activity and thus promote a more healthy life style.

One important aspect about improving performance is the physiological analysis of a player, whether individual or collective. The research concerning this type of data gained a lot of interest by scientists (Joyner and Coyle, 2008). Del Boca and Park (1994), suggested a real-time approach using an ANN (artificial neural network), capable of recognizing the myoelectric data. In here, features were extracted through *Fourier* analysis and then clustered by using the *fuzzy c-means* algorithm. After that, data was automatically targeted and sent to a multilayer perceptron (MLP) type neural network. Lastly, a digital signal processor operated over the resulting set of weights, allowing the mapping of the incoming signal on-the-fly. The experimental results demonstrated that this approach produces highly accurate discrimination of the control signal over interference patterns.

Al-Mulla and Sepulveda (2010) suggested the use of LMF (method that performs both signal filtering and classification simultaneously by learning the most appropriate filters) to predict time using supervised ANN. This algorithm was composed of five training inputs and one testing input signal. To calculate the input's rate of change, the first 20% of the signal were used. In order to adjust its training weights, the ANN used time to fatigue for the five training signals, allowing it to predict it by using just 20% of the total sEMG data. The results showed an average prediction error of 9.22% for time prediction.

Modelling football data has become increasingly popular in the last few years, reason for which several models have been proposed with the purpose of estimating the characteristics that bring a team to lose or win a match or to predict the final score. The great majority of these models are based on kinematics data that many times are collected visually or with the help of cameras, such as demonstrated on the work of Montoliu et al. (2015) that applied a methodology which had the purpose of performing the team activity recognition and analysis. This methodology is the base on pattern recognition and in particular on the Bag-of Words technique. They applied these concepts in soccer video footage and, in addition to those neural networks, applied several classifiers. They showed that the used methodology was able to justify the common team patterns and the recognition of specific soccer actions like ball possession, quick attack and set piece.

In order to convert this models in an architecture more ecological and closest to the user, so as to achieve a greater accuracy, the usage of wearable technology in sports have been increasing along the time (Walter, 2018), and with FIFA wanting to introduce new technologies during games, several companies and authors published and created several works with the attempt to increase sports knowledge i.e., increasing the information about technical, tactical, physiological, kinematic and kinetic data.

Papić et al. (2009) published an article about the early identification of future successful young players with the use of a web-oriented expert system with *fuzzy module*. But this work didn't present several results or favorable outcomes. Jaspers et al. (2018) published an article about the use of neural networks to analyze the relationship between the external and internal training load in professional soccer player. They measured the external load using global positioning system technology and accelerometry. The internal load was assessed using the RPE (Rated Perceived Exertion). They applied several neural networks and LASSO (Least Absolute Shrinkage and Selection Operator) models in order to predict future RPE values for further training sessions. They concluded that both the artificial neural network and LASSO models outperformed the baseline values.

Another study found in the bibliographic research was published by Rossi et al. (2018). They studied the influence of a based GPS tracking technology and an injury forecaster in order to prevent further injuries. These new methodologies showed accuracy and interpretable results. Grunz et al. (2012) studied the artificial neural networks to recognize tactical patterns in soccer games. They use a special self-organizing maps methodology applied to several positional data collected over professional players. Comparing data from different professional players they conclude that their method can detect with relative high accuracy different tactical patterns and their variations.In an article written by Memmert and Perl (2009) a framework for creative performance analysis was developed and based on neural networks. Then, it was used to analyse creative behavior of soccer and hockey player compared to a control group. They conclude that they were able to assess greater creative behavior in the two athletes groups compared to the control group.

Concerning the combination of deep learning for action recognition and football, Baccouche et al. (2010) present a hierarchical recurrent network (LSTM) method for action classification in soccer videos. They extract from each video action at each timestep a set of features which describe both the visual content (by the mean of a BoW approach) and the dominant motion (with a key point based approach). The LSTM is then trained to classify each video sequence considering the temporal evolution of the features for each timestep. The results shows a classification rate of 92 % which is the best published result, on the date of its publication, on this dataset.

Tsunoda et al. (2017) also use LSTM for understanding team sports activity in image and location sequences. The goal in this paper was to recognize futsal plays that involve multiple players in futsal matches, using frame sequences as well as meta-information (3 dimensional locations of persons and a ball, a camera location and team ID, automatically detected). The experimental results suggest that LSTM is a good approach to activity recognition using holistic images. These results support that the object location information for futsal activity recognition is effective and the approach of recurrently integrating multiple personcentered features is more accurate than the approach of using a single person-centered feature only.

In Ordóñez and Roggen (2016) was proposed a generic deep framework for activity recognition based on convolutional and LSTM recurrent units, which: (i) is suitable for multimodal wearable sensors; (ii) can perform sensor fusion naturally; (iii) does not require expert knowledge in designing features; and (iv) explicitly models the temporal dynamics of feature activations. Was used recordings of four subjects in a daily living scenario performing morning activities, with sensors of different modalities integrated in the environment, in objects and on the body. During the drill sessions, subjects performed 20 repetitions of a predefined sorted set of 17 activities. Besides success rate is not the best, the results showed how this architecture offers better segmentation characteristics than a standard method, being capable of defining the boundaries of activities much more precisely.

With the technological development on the last decades, inertial sensors have reduced their size to the point of occupying a small space inside a smartphone. Based on this tecnhology, Hernández et al. (2019) presents a human activity recognition system that uses accelerometer and gyroscope data obtained from a smartphone as inputs to a bidirectional LSTM network. Sitting, standing, laying, walking, walking upstairs, and walking downstairs was the activities in question where an overall accuracy of 92.67 % was obtained.

During the bibliographic research, were discovered a very interesting common point in every related-work, all present some difficulties in establishing and creating the framework, due to their complexities. Taking a more positive look at the aforementioned works, it is possible to conclude that technologies are increasingly being sought to easily monitor the movement of the human body as well as monitor its physiological signals.

2.6 Comparison of Classification Approaches

In Section 2.3 it was made a brief introduction to some theoretical concepts of machine learning, ensemble and deep learning classification methods for pattern recognition. The understanding of these methods were important in order to be able perceive how to process data, separating it into classes, so it could be possible to classify human activity and possibly predict it.

It was also important to understand that, for different types of data (sequential or non-sequential) we have different types of methods where sequential data is the one that takes into consideration the time factor whereas non-sequential data is characterized by a situation in which every training or testing case is independent.

After analysing all the classification methods described, we decide to use a LSTM approach for essentially two reasons:

- The first one focuses on the fact that, in general, the use of this algorithm for time series data has shown really good results. An example of that is described in Section 2.5 where we can see that the combination of a deep learning approach for action recognition in football, until 2010, resulted in a classification rate of 92 % which was the best published result, until the moment.

- The second reason that lead us to choose LSTM approach was the fact that although using it for action recognition in football, the data used was provided by video cameras. As we searched for LSTM use cases implementations, we could see that its major implementations are in areas as handwriting recognition, text and music generation and that there was a lack of information concerning the application of this method using physiological data witch turned out to be an incentive to implement this method in our study.

2.7 Comparison of Wearable Technologies

Additionally to classification methods for pattern recognition, there are several types of technologies (described in Section 2.4), ranging from cameras to the use of sensors placed on the subject itself.

Nowadays, the use of inertial sensors is more common, having the great advantage that they can be used anywhere and have no problems with joint occlusion. In order to determine which technology is more able to complete the requisites, it was made a comparative study of some of the wearable technology on the market as it is shown in the table 2.2.

After analyzing the table 2.2, it was decided that the technologies that were going to be used were MBody3 shorts for acquiring EMG data and Ingeniarius TraXports to track athlete's position on the field. The fact that MBody3 shorts had costumers as Sporting clube de Portugal, Futbol Club Barcelona, West Ham United among others made us to choose it as our EMG collector device instead of Athos shorts. The selection of the positional system TraXports was made because it is a system created by Ingeniarius and for that, the knowledge and the level of confidence is extremely high. One of the advantages of using this system is that it can be installed indoors, what represents a huge gain when the sport in analysis is practiced in a closed environment where GPS signal is weak. Furthermore, all the data which provide from TraXports is ready to use, since the equipment using Kalman filters to improve player's position estimation.

Table 2.2: Comparative study table

Comparative study

Wearable Technologies	**Pros**	**Cons**
MBody3 shorts	1-No loose electrodes, snap connectors, or loose wires or cables; 2-Motion artefact minimized plus extremely good signal quality even during the most extreme and strenuous exercise; 3-Easy and quick preparation: "gear up and go"; 4-Sensoring bigger area offers better reproducibility (reliability, stability), especially during exercises; 5-Fully machine washable; 6-Price, simplicity, ease-of use; 7- Costumers as Sporting clube de Portugal, Football Club Barcelona, West Ham United among others	1-Bigger Sensoring area; 2-cross-talk; 3-signal cancellation
Athos shorts	1- Real Time Tracking; 2- Auto logs your sets and workout activity; 3- EMG sensors for true muscle activity analyzation	1- No bar graph view in newest App update; 2- No Android compatible app
Ingeniarius TraXports	1-Indoor and outdoor local positioning system; 2-Less susceptibility to interference; 3-Eco-friendly wearable tags; 4-Plug and play setup; 5-Extremely high knowledge and level of confidence	1- No EMG recognition data
Ingeniarius FatoXtract	1-Can be used in and outdoors; 2-Lower cost comparing with other suits; 3-Don't need camera or markers; 4-Good acquisition frequency	1-No EMG recognition data; 2-No position along time line; 3-Low ecological value
ClearSky T6	1-Compact design no bigger than a standard GPS unit; 2-Indoor and outdoor tracking to a resolution of 10-15cm; 3-High precision; 4- less susceptibility to interference	1- High cost

3

CLASSIFICATION OF HUMAN ACTIVITY ARCHITECTURE

In this chapter it is described the proposed architecture to classify human activity. In Section 3.1 we describe the MATLAB tool that was used for processing data and also for building the classification architecture. In Section 3.2 we describe specifics of the hardware that was used, TraXports and MBody3 shorts. Finally, in Section 3.3 it is described the adopted methodology witch includes, data collection (subsection 3.3.1), kinematic data pre-processing (subsection 3.3.2.2), physiological data pre-processing (subsection 3.3.2.1), feature extraction (subsection 3.3.4), the overall architecture (subsection 3.3.5) and lastly the summary (subsection 3.3.6).

3.1 Software

In order to develop the project proposed in this master dissertation, the MATLAB software was used. MATLAB is the short name for Matrix Laboratory and although at the beginning it was only a program to solve mathematical problems with matrices, nowadays it is a very flexible computational system.

One of the main reasons for the use of this software in this master dissertation was that MATLAB provides the plugins and the flexibility necessary for processing the data collected by the TraXports (kinematic data) and the MBody 3 (physiological data) as well as building the architecture to classify the data.

3.2 Hardware

3.2.1 TraXports Specifics

Our approach uses the TraXports wearable technology system for collecting data (see sections 2.4.3 and 2.7) for tracking players during matches and/or training sessions. Within Sub-subsection 3.2.1.1 it is described the database format and its specifications.

3.2.1.1 Database

The files containing the data, collected by TraXports, are exported in a CSV format which is a very simple format file used to store tabular data. The generated file look like:

```
idx , notes , posX1 , posY1 , posW1 , hr1 , action1 , ...
1 , " " , 0 , 0 , 100 , 75 , , ...
```

and contain information about:

- Pos X_n - X axis position of the n^{th} player
- Pos Y_n - Y axis position of the n^{th} player
- Pos W_n - Angular position of the n^{th} player
- hr_n - Hearth rate of the n^{th} player
- $action_n$ - An action of the n^{th} player

Although the column "action" is included on the exported file, that functionality is not implemented, yet.

That CSV file gives us a table that can be represented by:

Table 3.1: Example of TraXports CSV file

TraXports Example file							
idx	**notes**	**posX1**	**posY1**	**posW1**	**hr1**	**action1**	**...**
1	" "	0	0	100	75		...

3.2.2 MBody3 shorts Specifics

In addition to the use of TraXports, our approach also uses MBody3 shorts, wearable technology system, for collecting physiological data data (see sections 2.4.1 and 2.7). In Sub-subsection 3.2.2.1 it is described the format of MBody3 database file.

3.2.2.1 Database

The files that are generated from MBody device has two main parts: the header and the sample. The header contains information about which column corresponds to which channel and the time stamp. The sample begins right after the header and it is where we can find the data values for each channel, collected by the device.

Table 3.2: Example of Mbody3 CSV file

MBody3 Example File						
R.Quad	**L.Quad**	**R.Hams**	**L.Hams**	**R.Gluteo**	**L.Gluteo**	**Time(s)**
45	35	21	2	11	3	0.04

3.3 Methodology

The approach chosen for the development of this master dissertation includes the steps depicted in figure 3.1:

Figure 3.1: Pattern Recognition Process

3.3.1 Data Collection

The data acquisition was made during a short futsal tournament and performed by students from RobotCraft as well as interns and collaborators from Ingeniarius and had a duration of two days witch represents approximately 1 hour and 20 minutes in total. The data was collected of only one of the subjects witch was also the only one using the full equipment (Mbody3 shorts and TraXports vest).

Muscle activation of all six muscle groups was assessed using *Myontec's MBody3*, an EMG wearable shorts. The electrodes embedded in the textiles covered up three main muscle groups on both lower limbs which were the gluteal maximus muscle, quadriceps femoris muscle and the hamstrings muscle groups. The data collection was made by a wireless connection that was established via Bluetooth BLE 4.0 communication, which collected EMG data with a frequency of 25Hz and recorded it into an SD card.

TraXports was the wearable device used to collect the kinematic signals, namely pose and orientation in the field. All the players used the TraXports vests whose sensors were positioned on their backs. The data gathered were then sent to the Ingeniarius Cloud through UWB wireless technology with a frequency update of 30Hz.

3.3.2 Data Pre-Processing

Data preprocessing consists of three steps. In the first step, it was done a data extrapolation approach to compensate missing data. In the second step, a data re-sampling was done so that the number of frames per second was the same in both systems. In the third step it is presented the main objective of the data pre-processing phase, that is two synchronized systems. In the last step we described the procedure of preparing the data to feed the classification model.

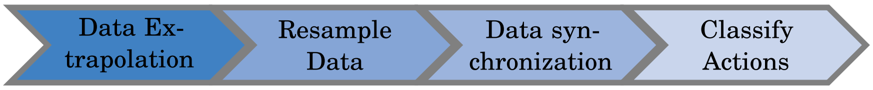


Figure 3.2: Data pre-processing flow

3.3.2.1 Data Extrapolation

Physiological Data:

Mbody3 shorts measures electrical activity of muscles, EMG, on the surface of human skin. EMG measurements requires electrodes which are in this case conductive textile material integrated to the shorts which forwards electrical activity to MCell Smart measurement device.

The physiological data given by Mbody3 shorts was designed by its manufacturer, Myontech, to give an averaged 25Hz EMG update frequency, done using a analog-to-digital converter (ADC) from 1000 Hz sampling frequency (raw data) to 25Hz witch allows us to access only the processed data. The data is filtered (rectified and smoothed) to have a digital signal since raw EMG is a bipolar analog signal. The digital signal is corrected (offset and gain), rectified and averaged and smoothing is done by averaging, which calculates the average values within frame intervals, thus reducing sample count.

Although Mbody3 shorts is equipped with a technology that intends to provide reduced power consumption and cost while maintaining a similar communication range while enabling the flexibility of the system, it has a problem, the loss of packets. Even though the data loss was minimal, in order to obtain 25 samples per second as it was expected (as it has an 25Hz output), it was needed to extrapolate the missing values by using a curve fitting technique, smoothing spline, available in Matlab R2018b.

3.3.2.2 Resample Data

Kinematic Data:

The kinematic data obtained by TraXports was designed to have an update frequency of 30Hz. Its output data is already filtered by a Kalman filter which helps to not only improve the estimation of players position but also players orientation within the field (Couceiro et al., 2016).

In addition to that, there was a need to synchronize the data collected from both equipment since they had different update frequencies 25Hz and 30Hz respectively. To do the synchronization, regarding to TraXports, it was necessary to resample its data from 30 frames per second to 25 frames per second (from 30Hz to 25Hz that is the update frequency of MBody3 shorts).

3.3.2.3 Data Synchronization

One of the most important goals of data pre-processing was to get data synchronized. This was a mandatory prerequisite to use both kinematic and physiological data. Once done all the missing data extrapolation (see 3.3.2.1) and after resampling kinematic data (see 3.3.2.2 it was time to prepare the data to feed the proposed model because now, both systems have the same number of frames per second.

3.3.2.4 Classify Actions

The last step of the pre-processing phase was the action classification phase. In here, and with the help of the videos recorded during the games, it was done the splitting of the data acquired, that is, by observation we could tell that, for example on the first two seconds of the last game the target player walked, what means that that observation has 50 frames (equipment acquires 25 frames of data per second.

3.3.3 Data Preparation

After having all our trials/observations separated, that data was introduced in a cell array and its correspondent category in a categorical array. Due to the fact that the trials had different sizes, it was then calculated the median value of the sizes of all the variables as well as its inferior (25%) and superior (75%) quantile so we could remove trials without enough data and with too much data. Subsequent to that it was noticed that if trials whose sizes were below 25% were eliminated, actions as, for example *passing* would not be in the dataset and consequently would not be possible to classify. As a result, it was decided only to divide the larger trials into other small ones thus increasing the number of trials. The dataset totaled 1076 trials including all the actions that we wanted to be able to classify as we can see in table 3.4.

3.3.4 Feature Extraction

Within this subsection it is described the features that were used in this work with the objective of better identifying an athlete's actions during a futsal game using wearable technology.

3.3.4.1 Kinematic Data

1. **Velocity Calculation**

   One of the features chosen in order to help the classifier to identify the actions carried out by the target player was his velocity. This feature was calculated by doing the module of the subtraction of its previous position to its actual position on the field as it can be seen on the equation above.

   $$v = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2} \tag{3.1}$$

   To normalize this feature, according to the literature, the maximum speed for a futsal player is between 15 $km.h^{-1}$ (4.2 $m.s^{-1}$) and 24 $km.h^{-1}$ (6.7 $m.s^{-1}$) (Naser et al., 2017) what means that it would be needed to divided velocity values with that maximum speed value. In this specific case this normalization was not done because it would not exist in 0.04 seconds any velocity value over 1.

2. **Distance to the goal**

   Another feature that was taken into consideration was the distance of the target player to the goal. This feature was calculated by doing the module of the subtraction of the opposing goalkeeper position to its actual position on the field as it can be seen on the equation above.

   $$d = \sqrt{(x_p - x_g)^2 + (y_p - y_g)^2} \tag{3.2}$$

   In order to do data normalization, in this case, it could have been done the calculus of the diagonal distance of the field (see fig 3.3), which represents the maximum distance value that a player can travel, and divide the values of the distances by this maximum distance.

   The calculus to obtain the value for the diagnonal distance was done by using pythagorean theorem so we had that:

   $$C^2 = a^2 + b^2 \tag{3.3}$$

   where C is the diagonal (hypotenuse) and a and b are the cathets. Knowing that a= 40m and b= 20m, then:

   $$C^2 = 40^2 + 20^2 \tag{3.4}$$

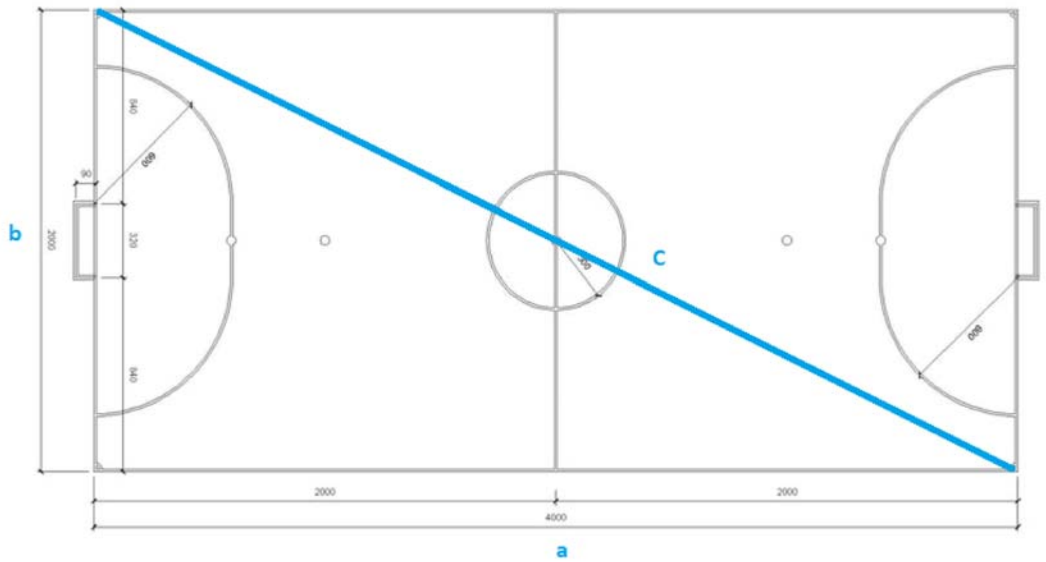


Figure 3.3: Futsal field dimensions

$$\iff C = \sqrt{2000} \iff C = 44.7m$$

3. **Orientation towards the goal**

   The last feature that was used to enable the method reasoning was the orientation towards the goal. This feature was obtained by first calculating the orientation of the player towards the goal using the formula presented below.

   $$\theta_g = atan2((y_g - y_p),(x_g - x_p)) \tag{3.5}$$

   The calculation was made by using variables as position of goal (y_g and x_g) and position of the player. Thereafter the value obtained was used to find the actual orientation of the player towards the field relatively to the first and second part of each game by subtracting to that the value of the orientation of the player within the field as it is shown in the next formula.

   $$Orientation = (\theta_g - w_p),(\theta_g - w_p) \tag{3.6}$$

   In order to do the normalization it could have been calculated de modulo of the Orientation and divide it by 180º that is the maximum rotation value.

3.3.4.2 Physiological Data

Mbody3 shorts had six channels collecting, three in each leg that corresponds to the three major muscle groups from the legs that are right and left quadriceps, hamstrings and gluteo (table 3.3).

Each of these channels represents one EMG feature for each action performed, that is, for each action we can see six different muscle activation's whereby the method can learn from.

From all the six channels we extracted six features by doing their normalization that was done by the formula:

$$norm_x = \frac{x - min(x)}{max(x)} \tag{3.7}$$

Table 3.3: Channels and muscle groups of MBody3

MBody3 features			
Channel	**Muscle Group**	**Left/Right**	**Front/Back**
1	Left Quadriceps	Left	Front
2	Right Quadriceps	Right	Front
3	Left Hamstrings	Left	Back
4	Right Hamstrings	Right	Back
5	Left Gluteus	Left	Back
6	Right Gluteus	Right	Back

3.3.5 Overall Architecture

In this subsection it presented the overall architecture which is basically the approach chosen, that is LSTM network, to classify actions automatically.

3.3.5.1 Classification Approach

As explained in section 2.6, the deep learning method implemented was LSTM. The LSTM consists in two-dimensional *input layer* with different sizes (one matrix 6xN,three matrices 7xN and one matrix 9xN) which corresponds to five tests that were made, using different features, for the same model, a *lstm layer* formed by 512 hidden layers, one *fully connected layer*, a *softmax* activation layer and one *crossentropyex* classification output layer.

After some preliminary testing, the LSTM hyperparameters are set as follows: mini batch size as 108 (approximately 10% of the total number of samples), maximum number of epoch at 1024 and learning rate at 0.01.

To evaluate the classifier performance, it was needed to stratify the data into two sets, the training set (70%) and the test set (30%) as it can be seen in table 3.4.

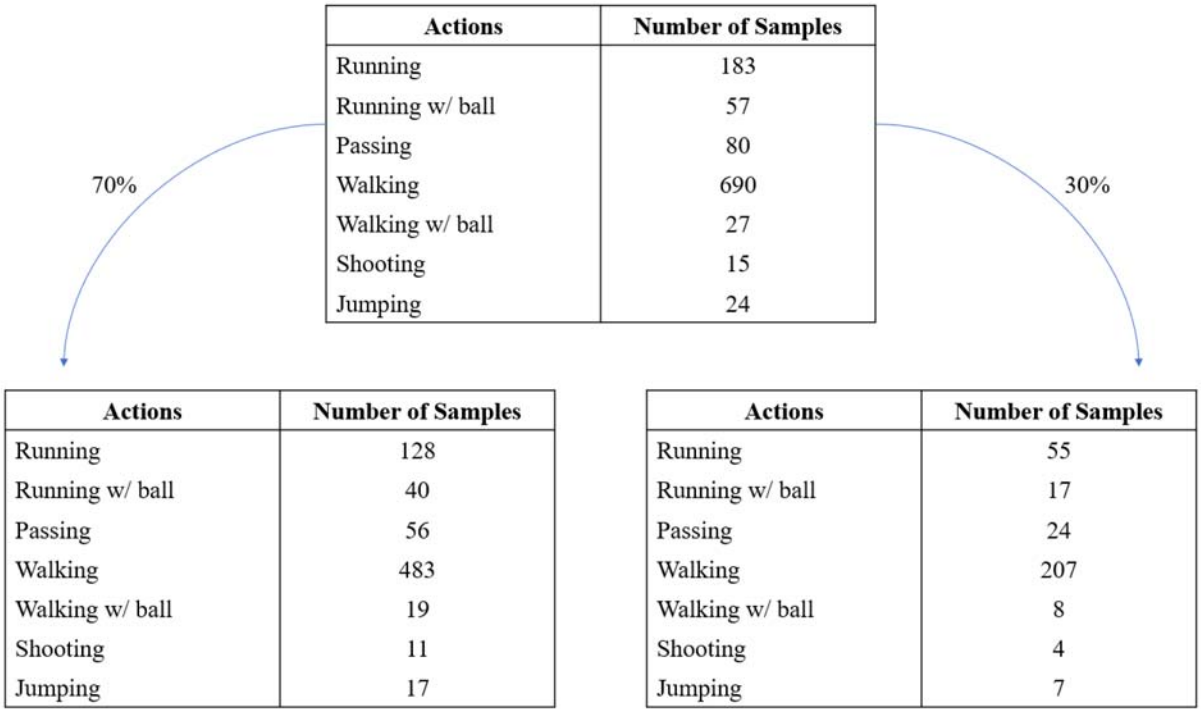
3.3.5.2 Evaluation

The evaluation phase comes after all the pre-processing and feature extraction as well as the data set preparation. Hereby the chosen classifier method is going to produce an output which is going to be used to identify the correspondent class to each trial. Once analysed the output by comparing it to the target data it is then obtained the amount of correct and incorrect data classification. To do that there are evaluation metrics that are capable of assessing the method's performance.

To visualize the algorithm performance and since it was used a supervised method, we have the confusion matrix (see table 3.5). That matrix gives us values of TP, TN, FN and FP where, TP = True Positive, TN = True Negative, FN = False Negative and FP= False Positive.

True positives corresponds to samples that were correctly classified, False positives are the ones that were incorrectly classified. Similarly, True negatives are the samples that

Table 3.4: Data set preparation



Actions	Number of Samples
Running	183
Running w/ ball	57
Passing	80
Walking	690
Walking w/ ball	27
Shooting	15
Jumping	24

Actions	Number of Samples
Running	128
Running w/ ball	40
Passing	56
Walking	483
Walking w/ ball	19
Shooting	11
Jumping	17

Actions	Number of Samples
Running	55
Running w/ ball	17
Passing	24
Walking	207
Walking w/ ball	8
Shooting	4
Jumping	7

Table 3.5: Confusion Matrix

		Output	
		Positive	Negative
Target	Positive	TP	FP
	Negative	FN	TN

were correctly classified as negatives and False negatives are the ones that were wrongly classified as negatives

In order to evaluate the performance of the proposed architecture, it was use concepts of precision, recall, f1 score and accuracy. The first one is related with reproducibility and repeatability and measures the fraction of examples classified as positive that are truly positive, that is the number of positive predictions divided by the total number of positive class values predicted. A low precision can also indicate a large number of False Positives.

$$Precision = \frac{TP}{TP + FP} \tag{3.8}$$

On the other hand, recall measures the fraction of positive examples that are correctly labeled (Davis and Goadrich, 2006), in other words recall is the number of positive predictions divided by the number of positive class values in the test data. A low recall indicates many False Negatives.

$$Recall = \frac{TP}{TP + FN} \tag{3.9}$$

Additionally, we will also use the concepts of accuracy and F1 Score, which are presented hereinafter.

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3.10}$$

Accuracy can be expressed as a proportion of correctly classified subjects ($TP + TN$) among all subjects ($TP + TN + FP + FN$) (Šimundić, 2009), and it can be expressed by the following:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.11}$$

It is important to emphasize that not only the accuracy was taken into account because accuracy can be misleading. For example, in a problem where there is a large class imbalance, a model can predict the value of the majority class for all predictions and because of that achieve higher accuracy, the problem is that this model is not useful in the problem domain. For our specific case, F1 Score is the most suitable evaluation metric as it is used in cases which data sizes are unbalanced. This metric then calculates the relation between precision and recall and we can say that if result of F1 score is high, both precision and recall of the classifier indicate good results as it normally emphasizes the lower value [13].

3.3.6 Summary

Along this chapter it has been described all the proposed architecture to classify actions using data collected during futsal matches. Beyond architecture is was also described the equipment and the software involved.

The features of interest for our case were:

1. Velocity,
2. Distance to the goal and
3. Orientation towards the goal.

The evaluation metrics were:

1. Precision,
2. Recall,
3. F1 Score and

---

[13] `https://towardsdatascience.com/accuracy-precision-recall-or-f1-331fb37c5cb9`

4. Accuracy.

4

EXPERIMENTAL RESULTS

In this chapter it is shown the experimental results and it is divided in four sections.

Within section 4.1 it is presented some preliminary study done to assess the feasibility of using MBody3 shorts to recognize actions. In section 4.2 is described the setup adopted for the development of our work, including procedure (Section 4.2.2) and sample (Section 4.2.3) descriptions, its results (4.2.4) including all the tests that were done: a baseline test (4.2.4.1, a test using features as EMG and velocity (4.2.4.2, a test using features as EMG and distance (4.2.4.3, a test using features as EMG and orientation (4.2.4.4 and lastly a test using all the features EMG, velocity, distance and orientation (4.2.4.5 . In section 4.3 is were the discussion of the results is.

4.1 Experiment A

This section presents the preliminary work witch was done mainly because we wanted to prove the feasibility of wearable technology for action recognition in a sports context comparing the results obtained using MBody3 (see 2.4.1) shorts with those obtained with a laboratory certified system, Bioplux. Here it is shown the different approaches taken as well as the data setup.

Bioplux is a *Plux* device and it is a telemetric Surface Electromyographic system recorder (Plux, Lisbon, Portugal)[14]. The raw data is acquired according to several recommendations from the International Society of Electrophysiology and Kinesiology (ISEK) (Merletti et al., 1999). This equipment has an input impedance > 100 MΩ, a common mode rejection ratio of 110 dB, amplified with a gain of 1000, a band-pass filtered (10 to 500Hz) and digitized at 1000 samples/s.

The test had two different approaches:

1. Comparing both systems, MBody3 shorts and Bioplux, using the values of all 6 channels
2. Comparing both systems, MBody3 shorts and Bioplux, using the values of only 2 channels

We wanted to assess if the data collected by MBody3 shorts was feasible so we could use it to do the recognition of the actions done by an athlete during a match. In order to do that, we designed an experiment with the purpose of validating this wearable equipment.

---

[14] `https://plux.info/12-biosignalsplux`

The experiment was designed to prove the feasibility of wearable technology for action recognition in a sports context. To do that, it was realized a study that encompassed four males (22.5±3 yrs, 1.76±0.019 m,83,25±2.63 kg). The participants included were all injury-free, and the research data assessment was carried out at the Biokinetic Laboratory, at the Faculty of Sport Sciences and Physical Education - University of Coimbra.

All participants realized the same protocol with identical exercises, intensities and resting periods between each session. Those characteristics were chosen to encompass different features both physical and physiological, in order to surround various movement conditions and patterns, and different levels of neuromuscular activation. Exercises such as walking, running, strength exercises, cycling and stepping were included in the protocol that was performed once. Thus, the participants simultaneously wear both *Myontec's MBody3* wearable EMG shorts and the traditional EMG electrodes.

Then, the participants firstly walked on a treadmill (*HP COSMOS pulsar 3p, h/p/cosmos sports & medical gmbh*) at a selected pace. Then, without resting, they reached the intensity of 9km/h, in which they run for five minutes. Afterwards, the participants realized the strength exercise which consisted of a bilateral knee flexion/extension e performed on an isokinetic dynamometer (*Biodex System 3, Medical Systems, Inc.*) regarding specific parameters and one set of 5 repetitions of a maximal isometric contract of the gluteal muscle against resistance. Then, the participants performed a 5min lower limb cycling exercise at 60rpm ± 2rpm at 120W (*Monark 874E, Monark Exercise AB*). Finally, the last task was a stepping exercise at the intensity of 60rpm for 5min.

These two approaches needed to be done because the data related to those strength exercises, extracted through Bioplux, only had 2 channels collecting data.

Muscle activation of all six muscle groups was assessed using *Myontec's MBody3*, an EMG wearable shorts, and by a traditional EMG electrodes system. The electrodes embedded in the textiles covered up three main muscle groups on both lower limbs which were the gluteal maximus muscle, quadriceps femoris muscle and the hamstrings muscle groups. The wireless connection was established via Bluetooth BLE 4.0 communication, which collected the all-ready filtered EMG data (25Hz). At the same time, a set of 6 *Plux* wireless electrodes were attached to the gluteus maximus, vastus lateralis and biceps femoris of both legs according to SENIAM (Surface EMG for Non Invasive Assessment of Muscles) Project recommendations Hermens et al. (2000).

When preparing the data, the number of samples was taken into consideration as well as the time of each sample (4 seconds each). The number of samples are indicated in table 4.1 and in table 4.2, each corresponding to first and second approaches, respectively.

Table 4.1: Number of data samples for 1st approach

Activities	***Number of samples***
Running	264
Cycling	140
Stepping	57

After preparing the data set, we proceed to training and testing the proposed framework to classify activities as running, cycling, stepping as well as strength exercises that used muscular groups as gluteal, hamstring and quadriceps, for both MBody3 shorts (see 4.1 and 4.3) and Bioplux (see 4.2 and 4.4).

Table 4.2: Number of data samples for 2^{nd} approach

Activities	***Number of samples***
Gluteo	18
Right Isokinetic	31
Left Isokinetic	32

To assess the viability of Mbody3 shorts, it was firstly tested the accuracy of the model using data that came from Bioplux which is a certified system who's output is a reliable, reason why it was used as our baseline. As it can be seen in 4.2 using Bioplux data in the first approach, the accuracy of the model was 100%, slightly bigger, than when using Mbody3 shorts data the accuracy where the accuracy was 98.6% 4.1.

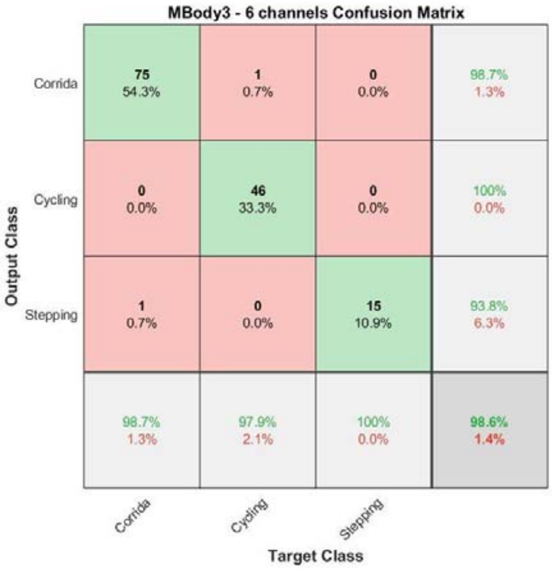


Figure 4.1: MBody3 using 6 channels

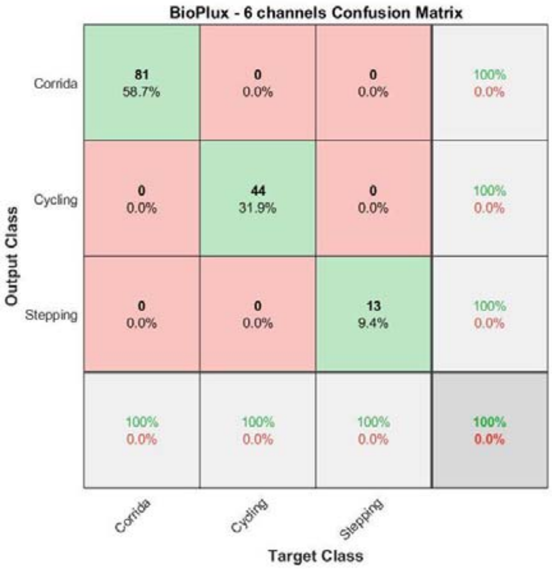


Figure 4.2: Bioplux using 6 channels

For second approach, where it was tested strength exercises, the obtained results shows that the accuracy in both cases was worst when comparing with the results from the first approach. Comparing only the two model in this approach, as it occurred in the situation before, the accuracy from Bioplux was slightly higher (83.3%) than Mbody3 shorts (79.2%) (see 4.4 and 4.3, respectively).

This preliminary work helped assess the feasibility of using a wearable system for Human Activity Recognition (HAR) in a sports context. This was an important step in the development of this dissertation since our main objective is to assess if the wearable solution that was chosen, MBody3 shorts, is also capable of correctly recognizing futsal patterns as passing, shoting, running and walking (with or without the ball) as well as jumping.

After running the four tests, two per approach, we concluded that this wearable device is as capable as a laboratory certified system with regard to recognizing activities, in other words the potential of the proposed framework is, as it can be seen by the results, good as almost all activities were correctly classified.

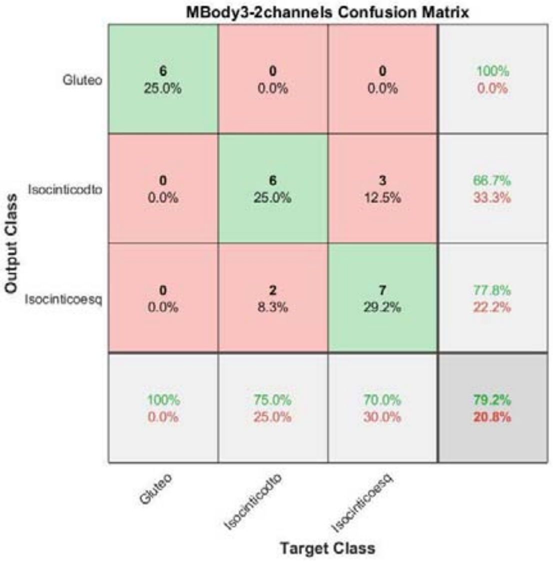


Figure 4.3: MBody3 using 2 channels

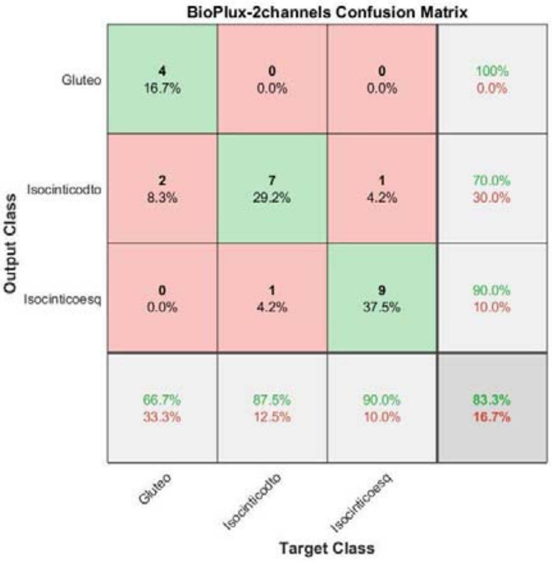


Figure 4.4: Bioplux using 2 channels

4.2 Experiment B

In section we described the experimental setup (Section 4.2.1) adopted for the development of our work, including its procedure (Section 4.2.2) and sample (Section 4.2.3) descriptions. Then, in Section 4.2.4 it is presented the experimental results that we obtained in each test that was made witch includes: a baseline test (4.2.4.1, a test using features as EMG and velocity (4.2.4.2, a test using features as EMG and distance (4.2.4.3, a test using features as EMG and orientation (4.2.4.4 and lastly a test using all the features EMG, velocity, distance and orientation (4.2.4.5).

4.2.1 Experimental Setup

Here we describe the designed setup so we could achieve our main goal, recognize and therefore classify actions that were performed by a player during futsal matches using physiological and kinematic data. As it has been already described on Chapter 3, section 3.2, the hardware used for acquiring both EMG and positional data were Mbody3 shorts and TraXports, respectively.

4.2.2 Procedure Description

We wanted to recognize some of the athlete's actions presented in table 4.3 by collect kinematic and physiological data. To do that, it was organized a mini futsal tournament of 2 days where each game had two parts and each part had a duration of 10 minutes making a total time duration of approximately 1 hour and 20 minutes. The acquisition was performed with students from RobotCraft as well as interns and collaborators from Ingeniarius.

Before starting the tournament it was needed to place all the four anchors, one in each corner of the field and turned on in a sequential order. When all anchors were synchronized it meant that the system was ready do collect as soon as the tags on the vests were turned on.

Table 4.3: Target Actions

Target Actions						
Walking	Walking with ball	Running	Running with ball	Shoting	Passing	Jumping

During matches, all players on both teams wore TraXports's vests but only one of them wore the Mbody3 shorts.

Both systems were synchronized, in other words, when the tag that belonged to the player wearing the Mbody3 shorts was turned on, the Mbody3 cell also turned on.

4.2.3 Sample Description

All the individuals that participated on this tournament encompassed twenty two males (22.2 ± 4.5 years, with max 39 years and min 19 years). All the participants were injury-free.

4.2.4 Experimental Results

The current section shows the results for the recognition of the different actions described on table 4.3 according to the five tests that were made.

First of all, it was only used EMG data in order to classify those actions which, therefore, transforms this test into our baseline test. In other words, this first test forms the base for other testing making possible the comparison of the proposed framework performance for all of the other tests.

In order to analyse the results, the proposed model has been run for 30 times and the results for each iteration were saved. For each iteration, all the five tests were analysed at the same time using the same data (that changed randomly in each iteration but keeping the same amount of data, 70% training and 30% testing).

The results presented here were brought about by the analysis of concepts as precision, recall and accuracy described in subsection 3.3.5.2.

4.2.4.1 Baseline test

The first test that have been made is the baseline test. With this, as said in section 4.2.4, we intended to make a comparative base in order to see the differences in the results when adding other kind of features.

Within table 4.4 it is shown a resumed confusion matrix with the average ± standard deviation and its total percentage. This confusion matrix quantifies the number of classification that were correctly done and the ones that weren't by the model that was proposed and implemented. When parsing table 4.4 it is possible to identify which actions were best identified.

Table 4.5 shows the mean values, in percentage, of metrics as accuracy, precision, recall and f1 score for the 30 iterations. The **Total** values represents the overall percentages obtained by doing the mean value for each evaluation metric of each action of interest.

Table 4.4: Confusion matrix of the results based only in the EMG data.

					EMG			
Target Class	Running	11,47 ± 3,5 3,561%	2,3 ± 1,51 0,714%	1,97 ± 1,25 0,611%	37,1 ± 3,43 11,522%	0,47 ± 0,67 0,145%	0,83 ± 0,73 0,259%	0,87 ± 0,88 0,269%
	Running w/ ball	4,2 ± 1,97 1,304%	1,23 ± 1,17 0,383%	0,6 ± 0,66 0,186%	9,33 ± 1,78 2,899%	0,3 ± 0,53 0,093%	0,5 ± 0,67 0,155%	0,83 ± 0,9 0,259%
	Passing	1,53 ±1,02 0,476%	1,53 ± 1,26 0,476%	11,33 ± 2,66 3,52%	2,2 ± 1,7 0,683%	1,37 ± 1,3 0,424%	3,07 ± 1,63 0,952%	2,97 ± 1,87 0,921%
	Walking	18,97 ± 4,18 5,89%	2,73 ± 1,48 0,849%	1,87 ± 0,96 0,58%	179,7 ± 4,97 55,807%	1,63 ± 1,43 0,507%	0,8 ± 0,7 0,248%	1,3 ± 1,1 0,404%
	Walking w/ ball	0,83 ± 0,86 0,259%	0,33 ± 0,54 0,104%	0,47 ± 0,76 0,145%	5,87 ± 1,12 1,822%	0,2 ± 0,4 0,062%	0,2 ± 0,4 0,062%	0,1 ± 0,3 0,031%
	Shoting	0,53 ± 0,67 0,166%	0,43 ± 0,62 0,135%	1,5 ± 0,81 0,466%	0,67 ± 0,7 0,207%	0,07 ± 0,36 0,021%	0,5 ± 0,56 0,155%	0,3 ± 0,59 0,093%
	Jumping	0,77 ± 0,76 0,238%	0,83 ± 0,9 0,259%	2,3 ± 1,07 0,714%	1,33 ± 1,07 0,414%	0,27 ± 0,44 0,083%	0,8 ± 0,75 0,248%	0,7 ± 0,82 0,217%
		Running	Running w/ ball	Passing	Walking	Walking w/ ball	Shoting	Jumping
					Output Class			

By comparing the results in both tables 4.4 and 4.5 we can notice that "Passing" and "Walking" were the actions with the best results. In terms of recall, these results showed that 92% of the times that occurred a pass, the system got it right. For the same action, and with not so good results, its precision is only 56.46% what means that only 56.46% of the times that the model said that it has occurred a pass it really did.

Analysing table 4.4, "Passing" was mostly misclassified as "Jumping" (2.3 ± 1.07 times) followed by "Running" (1,97 ± 1.87 times) and "Walking" (1,87 ± 0.96 times). For action "Walking" it is noteworthy that there is a big number of trials that were misclassified as "Running" and vice versa.

On the other hand, with the worst results we have actions as "Walking with the ball", "Shoting" and "Jumping". It should also be pointed out that these three actions were the one with the lower number of visualizations - 8, 4 and 7, respectively as it was shown in table 3.4.

At having a look in table 4.4 it is clear that these three actions were barely well classified (0.2 ± 0.4 times) . Most of the times, "Walking with the ball" was misclassified as "Walking" (1,63 ± 1.43 times) followed by "Passing" (1,37 ± 1.3 times). "Shoting" was in the most cases identified as "Passing" (3.07 ± 1.63 times).

Table 4.5: Evaluation Metrics per Test

Actions	***Accuracy***	***Precision***	***Recall***	***F1 score***
Running	57.27	29.87	65.12	40.79
Running w/ ball	53.72	12.47	54.36	19.92
Passing	76.12	**56.42**	**92.84**	69.9
Walking	72.19	**76.10**	70.67	73.27
Walking w/ ball	50.53	3.51	15.55	5.75
Shoting	53.40	7.90	43.83	13.14
Jumping	54.05	10.10	44.66	15.68
Total	59.6	28.05	55.29	34.06

In order to evaluate the overall performance of the model F1 score meets the expectations specially since the dataset that was used isn't homogeneous. This metric, as described in 3.3.5.2, represents a balance between precision and recall and for that reason it gives us a more realistic overview of the model.

In this case it is possible to see that, according to the evaluation made by F1 score, "Walking" is the action that has a higher performance as regards the correct identification of the action in question.

4.2.4.2 Test with EMG and Velocity

The second test that have been made consisted in adding one more feature, velocity described in 3.3.4, to the EMG features. With this, as said in section 4.2.4, it is expected to see some improvement in terms of recognizing and identifying correctly the actions.

As in table 4.4, table 4.6 shows the confusion matrix with the average ± standard deviation and its total percentage. When parsing table 4.6 we can see that the behavior of the method is maintained.

Table 4.6: Confusion matrix of the results based in EMG data and Velocity.

EMG + Velocity

Target Class	Running	Running w/ ball	Passing	Walking	Walking w/ ball	Shoting	Jumping
Running	11,37 ± 2,93 3,53%	2,43 ± 1,33 0,756%	1,63 ± 1,05 0,507%	37,1 ± 3,93 11,522%	0,67 ± 0,83 0,207%	1,07 ± 0,93 0,331%	0,73 ± 0,96 0,228%
Running w/ ball	4 ± 1,57 1,242%	1,4 ± 1,11 0,435%	0,5 ± 0,62 0,155%	8,93 ± 1,79 2,774%	0,3 ± 0,64 0,093%	0,87 ± 0,72 0,269%	1 ± 0,89 0,311%
Passing	1,7 ± 1,66 0,528%	0,8 ± 0,79 0,248%	11,93 ± 3,31 3,706%	2,03 ± 1,62 0,631%	0,87 ± 0,99 0,269%	3,2 ± 1,9 0,994%	3,47 ± 1,78 1,077%
Walking	18,5 ± 4,4 5,745%	2,9 ± 1,37 0,901%	1,53 ± 1,23 0,476%	180,47 ± 4,98 56,046%	1,3 ± 1,24 0,404%	1,1 ± 0,98 0,342%	1,2 ± 1,01 0,373%
Walking w/ ball	0,6 ± 0,71 0,186%	0,47 ± 0,67 0,145%	0,6 ± 0,66 0,186%	5,93 ± 1,09 1,843%	0,03 ± 0,18 0,01%	0,2 ± 0,48 0,062%	0,17 ± 0,37 0,052%
Shoting	0,37 ± 0,55 0,114%	0,37 ± 0,6 0,114%	1,43 ± 0,96 0,445%	0,57 ± 0,67 0,176%	0,03 ± 0,18 0,01%	0,53 ± 0,76 0,166%	0,7 ± 0,82 0,217%
Jumping	0,7 ± 0,69 0,217%	0,63 ± 0,71 0,197%	2,43 ± 1,05 0,756%	1,43 ± 1,02 0,445%	0,37 ± 0,66 0,114%	0,77 ± 0,76 0,238%	0,67 ± 0,75 0,207%

Output Class

"Passing" and "Walking" through all the tests continued to be the actions with the best results, having an overall F1 score of 72.62% and 73.72% as it can be seen in 4.7. Continuing in the same line of behavior, we can see that the performance of the method has thus slightly improved with the insertion of another feature. Now, as it can be seen by looking closer into "Passing" results, both precision and recall improved.

The fact that "Passing" was mostly misclassified as "Jumping" continued to happen as well as it happened with "Running" and "Walking". For "Walking" it is also noteworthy that there is a big number of trials that were misclassified as "Running" and, again, the opposite also happens.

Actions as "Walking with the ball", "Shoting" and "Jumping", respectively, continued to have the worst results.

At having a look in table 4.6 it is clear that these three actions were also misclassified. As it happened in the previous test, "Walking with the ball" was mostly misclassified as "Walking" followed by "Passing". "Shoting" was in the most cases identified as "Passing". It is noteworthy that there were a small improvement between differentiating "Running" and "Walking" when adding the feature velocity.

As it was done in subsection 4.2.4.1, in order to evaluate the overall performance of the model we looked with attention to F1 score. In this case it is possible to see that, according to the evaluation made by F1 score, "Walking" continued to be the action that has a higher performance as regards the correct identification of the action in question.

Table 4.7: Evaluation Metrics teste2

Actions	***Accuracy***	***Precision***	***Recall***	***F1 score***
Running	57.27	30.46	66.04	41.59
Running w/ ball	54.98	14.95	57.61	23.34
Passing	77.94	59.86	93.51	**72.62**
Walking	72.75	**76.36**	**71.28**	**73.72**
Walking w/ ball	52.01	—	3.00	1.09
Shoting	52.71	6.51	34.77	10.80
Jumping	53.25	8.51	44.28	13.80
Total	60.13	28.09	52.93	33.85

4.2.4.3 Test with EMG and Distance to the goal

The third test made consisted in adding once again another feature, distance to the goal described in 3.3.4, to the EMG features. With this, as said in section 4.2.4, it is expected to see some improvement in terms of recognizing and identifying correctly the actions by comparing it to the results obtained when using only features from EMG.

Table 4.8 shows the confusion matrix with the average ± standard deviation and its total percentage. When parsing this table we can see that the behavior of the method is maintained.

Table 4.8: Confusion matrix of the results based in EMG data and Distance to the goal.

		EMG + Distance to the goal						
Target Class	Running	10,9 ± 3,37 3,385%	2,3 ± 1,42 0,714%	1,63 ± 0,91 0,507%	38 ± 3,86 11,801%	0,47 ± 0,85 0,145%	0,67 ± 0,7 0,207%	1,03 ± 1,08 0,321%
	Running w/ ball	4,23 ± 1,5 1,315%	1,27 ± 1,24 0,393%	0,5 ± 0,67 0,155%	9,03 ± 1,7 2,805%	0,23 ± 0,42 0,072%	0,73 ± 0,89 0,228%	1 ± 1,24 0,311%
	Passing	2,1 ± 1,83 0,652%	1,4 ± 1,05 0,435%	10,7 ± 2,73 3,323%	1,8 ± 1,62 0,559%	1,5 ± 1,31 0,466%	2,6 ± 1,5 0,807%	3,9 ± 2,66 1,211%
	Walking	19,17 ± 4,6 5,952%	2,6 ± 1,52 0,807%	1,77 ± 1,31 0,549%	180,57 ± 4,64 56,077%	0,93 ± 0,93 0,29%	0,7 ± 0,74 0,217%	1,27 ± 1,12 0,393%
	Walking w/ ball	0,73 ± 0,68 0,228%	0,63 ± 0,71 0,197%	0,53 ± 0,67 0,166%	5,53 ± 0,99 1,718%	0,17 ± 0,37 0,052%	0,07 ± 0,25 0,021%	0,33 ± 0,6 0,104%
	Shoting	0,3 ± 0,46 0,093%	0,4 ± 0,61 0,124%	1,13 ± 0,85 0,352%	0,33 ± 0,47 0,104%	0,33 ± 0,47 0,104%	0,73 ± 0,73 0,228%	0,77 ± 1,02 0,238%
	Jumping	0,57 ± 0,8 0,176%	0,4 ± 0,49 0,124%	2 ± 1,13 0,621%	1,43 ± 1,28 0,445%	0,3 ± 0,53 0,093%	0,97 ± 0,87 0,3%	1,33 ± 1,04 0,414%
		Running	Running w/ ball	Passing	Walking	Walking w/ ball	Shoting	Jumping
		Output Class						

"Passing" and "Walking" continued to be the actions with the best results, having an overall F1 score of 71.74% and 73.69% as it can be seen in 4.9. Continuing in the same line of behavior, we can see that the performance of the method has thus slightly improved with the insertion of another feature. Now, as it can be seen by looking closer into "Passing" results, as it was done with feature velocity, both precision and recall improved.

The fact that "Passing" was mostly misclassified as "Jumping" continued to happen as well as it happened with "Walking" and "Running". For "Walking" it is also noteworthy that there is a big number of trials that were misclassified as "Running" and, again, the opposite also happened.

Actions as "Walking with the ball", "Shoting" and jumping, respectively, continued to have the worst results.

At having a look in table 4.8 it is clear that these three actions were also misclassified. As it happened in the two previous tests, "Walking with the ball" was mostly misclassified as "Passing" followed by "Walking". "Shoting" was in the most cases identified as "Passing".

Table 4.9: Evaluation Metrics teste3

Actions	***Accuracy***	***Precision***	***Recall***	***F1 score***
Running	56.53	28.57	64.07	39.40
Running w/ ball	54.43	13.88	55.23	21.47
Passing	77.22	58.80	92.90	**71.74**
Walking	72.73	**76.32**	**71.27**	**73.69**
Walking w/ ball	52.01	—	14.79	5.21
Shoting	55.40	11.83	56.73	19.05
Jumping	56.37	14.55	65.78	23.16
Total	60.67	29.14	60.11	36.25

As it was done in subsection 4.2.4.1, in order to evaluate the overall performance of the model we looked with attention to F1 score. In this case it is possible to see that according to the evaluation made by F1 score that "Walking" continued to be the action that has a higher performance as regards the correct identification of the action in question.

4.2.4.4 Test with EMG and orientation towards the goal

The fourth test that have been made consisted in adding the feature orientation towards the goal described in 3.3.4, to the EMG features. With this, as said in section 4.2.4, it is expected to see some improvement, as it has happened in the other tests, in terms of recognizing and identifying correctly the actions.

As in table 4.4, table 4.10 shows the confusion matrix with the average ± standard deviation and its total percentage. When parsing table 4.10 we can see that the behavior of the method is maintained.

Table 4.10: Confusion matrix of the results based in EMG data and Orientation.

EMG + Orientation

Target Class	Running	Running w/ ball	Passing	Walking	Walking w/ ball	Shoting	Jumping
Running	10,83 ± 3,3 3,364%	1,37 ± 0,87 0,424%	2 ± 1,18 0,621%	38,93 ± 3,04 12,091%	0,57 ± 0,67 0,176%	0,77 ± 0,88 0,238%	0,53 ± 0,67 0,166%
Running w/ ball	2,97 ± 1,43 0,921%	0,9 ± 0,94 0,28%	0,6 ± 0,66 0,186%	10,1 ± 1,47 3,137%	0,37 ± 0,48 0,114%	1,37 ± 1,05 0,424%	0,7 ± 0,69 0,217%
Passing	2,4 ± 1,72 0,745%	1,5 ± 1,45 0,466%	10,07 ± 2,29 3,126%	1,6 ± 1,6 0,497%	1,97 ± 1,7 0,611%	3,23 ± 1,58 1,004%	3,23 ± 1,8 1,004%
Walking	17,87 ± 3,71 5,549%	2,27 ± 1,69 0,704%	1,53 ± 1,23 0,476%	181,9 ± 4,49 56,491%	1,43 ± 1,02 0,445%	0,67 ± 0,87 0,207%	1,33 ± 1,16 0,414%
Walking w/ ball	0,63 ± 0,66 0,197%	0,3 ± 0,46 0,093%	0,4 ± 0,55 0,124%	6 ± 1,15 1,863%	0,07 ± 0,25 0,021%	0,13 ± 0,34 0,041%	0,47 ± 0,56 0,145%
Shoting	0,4 ± 0,61 0,124%	0,6 ± 0,66 0,186%	1,53 ± 0,88 0,476%	0,17 ± 0,37 0,052%	0,27 ± 0,57 0,083%	0,5 ± 0,62 0,155%	0,53 ± 0,62 0,166%
Jumping	0,63 ± 0,8 0,197%	0,97 ± 0,98 0,3%	1,6 ± 0,8 0,497%	1,43 ± 1,09 0,445%	0,47 ± 0,76 0,145%	0,67 ± 0,7 0,207%	1,23 ± 0,84 0,383%

Output Class

"Passing" and "Walking" continued to be the actions with the best results, having an overall F1 score of 70.85% and 73.49% as it can be seen in 4.11. Continuing in the same line of behavior, we can see that the performance of the method has thus slightly improved with the insertion of another feature. Now, as it can be seen by looking closer into "Passing" results, precision slightly improved and recall is a bit lower.

The great difficulty that can be seen in this results as it has been happening in all tests done until now, is to differentiate "Walking" from "Running" and vice versa, "Jumping" and "Shoting" from "Passing" and vice versa.

Actions as "Walking with the ball", "Shoting" and "Jumping", respectively, continued to have the worst results. Both "Walking with the ball" and "Running with the ball" are misclassified as "Running", "Walking" and "Passing".

Table 4.11: Evaluation Metrics

Actions	***Accuracy***	***Precision***	***Recall***	***F1 score***
Running	57.31	30.04	65.22	41.00
Running w/ ball	52.84	10.80	43.01	16.83
Passing	76.66	57.89	92.47	**70.85**
Walking	72.63	**75.76**	**71.38**	**73.49**
Walking w/ ball	49.16	0.83	5.66	1.45
Shoting	52.38	5.88	40.18	10.09
Jumping	57.69	17.22	72.58	27.08
Total	59.81	28.35	55.79	34.40

As it was done in subsection 4.2.4.1 and with the other test, in order to evaluate the overall performance of the model we looked with attention to F1 score. In this case it is possible to see that according to the evaluation made by F1 score that "Walking" continued to be the action that has a higher performance and "Walking with the ball" is the one with lower performance as regards the correct identification of the action in question.

4.2.4.5 Test with All Features

The last test that have been made consisted in testing with all features, EMG, velocity, distance to the goal and orientation towards the goal. This final test is expected to give better results than the others as it has more features to learn from thus improving the method's performance in terms of recognizing and identifying correctly the actions.

As in all the previous confusion matrices, table 4.12 shows the confusion matrix with the average ± standard deviation and its total percentage for this final test gathering all the features in study. When parsing table 4.12 we can see that the behavior of the method is maintained but with a few slight improvements. This test has the higher true positive (TP) value obtained over the five tests corresponding to action "Walking"

"Passing" and "Walking" continued to be the actions with the best results, having an overall F1 score of 71.89% and 73.80% as it can be seen in 4.13. According to the overall results and analysing the mean of accuracy, precision, recall and F1 score this test was the one that showed better results. Doing an individual analysis, "Walking with the ball" had the worst values of all tests with a F1 score value lower than 1 (0.82).

"Passing" was mostly misclassified as "Running" continued to happen as well as it happened with "Jumping" and "Walking". For "Walking" it is also noteworthy that there is a big number of trials that were misclassified as "Running" and, again, the opposite also happens. "Running" with ball was normally mistaken with "Running" and "Passing".

Table 4.12: Confusion matrix of the results based in all features.

All Features

Target Class	Running	Running w/ ball	Passing	Walking	Walking w/ ball	Shoting	Jumping
Running	11,07 ± 2,76 3,437%	2,03 ± 1,43 0,631%	1,8 ± 0,98 0,559%	38,2 ± 3,15 11,863%	0,57 ± 0,62 0,176%	0,7 ± 0,82 0,217%	0,63 ± 0,87 0,197%
Running w/ ball	3,07 ± 1,41 0,952%	1,43 ± 1,05 0,445%	0,6 ± 0,71 0,186%	9,87 ± 1,84 3,064%	0,43 ± 0,72 0,135%	1,1 ± 1,11 0,342%	0,5 ± 0,67 0,155%
Passing	2,43 ± 1,36 0,756%	1,63 ± 1,35 0,507%	10,93 ± 2,53 3,395%	1,83 ± 1,75 0,569%	1,73 ± 1,36 0,538%	3,4 ± 1,4 1,056%	2,03 ± 1,11 0,631%
Walking	18,17 ± 3,85 5,642%	2,4 ± 1,7 0,745%	1,6 ± 1,17 0,497%	182,2 ± 4,97 56,584%	1 ± 1,21 0,311%	0,83 ± 0,97 0,259%	0,8 ± 0,79 0,248%
Walking w/ ball	0,73 ± 0,93 0,228%	0,33 ± 0,47 0,104%	0,57 ± 0,72 0,176%	5,77 ± 1,05 1,791%	0,03 ± 0,18 0,01%	0,43 ± 0,5 0,135%	0,13 ± 0,34 0,041%
Shoting	0,43 ± 0,5 0,135%	0,83 ± 0,86 0,259%	1,4 ± 0,84 0,435%	0,33 ± 0,65 0,104%	0,17 ± 0,37 0,052%	0,5 ± 0,56 0,155%	0,33 ± 0,47 0,104%
Jumping	0,77 ± 0,8 0,238%	0,8 ± 0,83 0,248%	1,6 ± 1,11 0,497%	1,67 ± 1,11 0,518%	0,33 ± 0,6 0,104%	0,83 ± 0,9 0,259%	1 ± 0,77 0,311%

Output Class

Actions as "Walking with the ball", "Shoting" and "Jumping", respectively, continued to have the worst results.

Having a look in table 4.12 it is possible to see that, as it happened in the previous test, "Walking with the ball" was mostly misclassified as "Passing" followed by "Walking". "Shoting" and "Jumping" were in the most cases identified as "Passing".

Table 4.13: Evaluation Metrics

Actions	***Accuracy***	***Precision***	***Recall***	***F1 score***
Running	57.45	30.30	65.62	41.31
Running w/ ball	55.07	15.11	58.91	23.41
Passing	77.28	58.86	93.01	**71.89**
Walking	72.99	**76**	**71.78**	**73.80**
Walking w/ ball	50.61	—	2.88	**0.82**
Shoting	53.42	7.95	43.30	12.56
Jumping	59.59	21.01	67.74	30.38
Total	60.92	29.89	57.61	36.31

In this case it is possible to see that according to the evaluation made by f1 score that "Walking" continued to be the action that has a higher performance and "Walking with the ball" the lower performance as regards the correct identification of the action in question.

4.3 Discussion

Throughout this master dissertation it is presented the supervised method approach that was chosen in order to recognize actions from athletes. To do that it was used EMG and positional data obtained from Mbody3 shorts and TraXports, respectively. During all the acquisitions, both systems were collecting data and recording it so it would be possible to analyze in offline mode. Mbody3 shorts had six channels collecting, three in each leg that corresponds to the three major muscle groups from the legs that are right and left quadriceps, hamstrings and gluteo while TraXports collected positional data, that is the position of the players within the field as well as its orientation (x, y, θ).

Independently of the type of actions that the athlete was performing there were always the same number of channels collecting, thus the same amount of data. As a result of that and adding the fact that they were some similar actions, not all actions were well classified. Another reason why some of the target actions were not correctly classified was the fact that they were a minority in the dataset as it can be seen on figure 4.5.

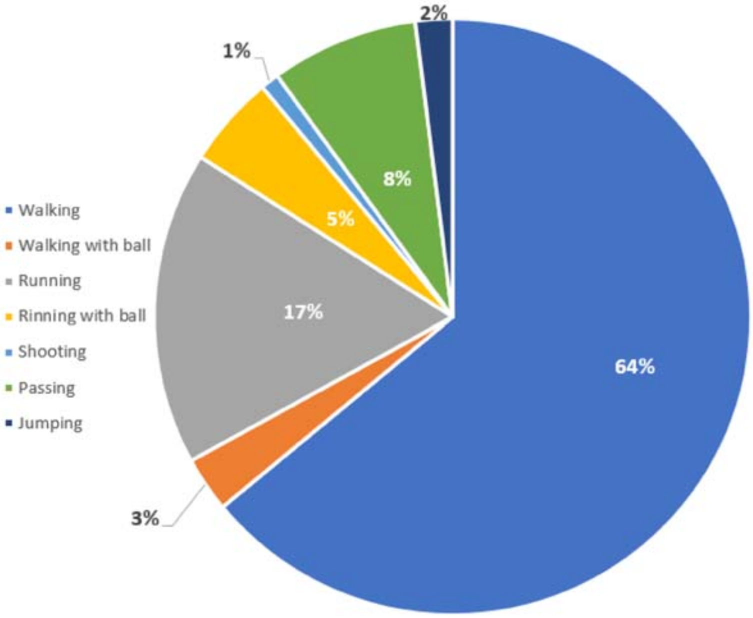


Figure 4.5: Class distribution

During the games, the player that wore the Mbody3 shorts did not perform many "Shots" (only 1% of the data), "Jumps" (2% of the data) and "Walking with the ball" (3% of the data). "Running with the ball" and "Passing" were also actions with lower occurrences, 5% and 8% of the dataset respectively. On the other hand "Walking" and "Running" were the ones that happened more frequently representing 64% and 17% of the acquired data, respectively.

Because of the similarity between some of the actions, it was needed to find some features that would help differentiating them. The first test that was made was the baseline test, that in other words is the method tested using only EMG data where its results were then used to compare with the performance of the same method adding more features. The second, third and fourth test were made by using EMG data plus another feature (velocity, distance do to goal and orientation towards the goal respectively) and the fifth and last test used EMG data plus all the other three features in which the best results were obtained.

One of the objectives of this work was to assess if it was possible to identify when the player had the ball whether running or walking. After analyzing the results it was noticed that the model barely identified these action misclassifying them as just "Running" or "Walking". Some of the times it was also misinterpreted as "Passing".

Even though, "Walking" was the trial with numerical superiority, the model was not perfect identifying it. A fraction of the data was consistently classified as "Running" and vice versa. This confusion improved after adding the feature velocity but not enough to totally distinguish them. This is also caused by the fact that the player that were tracked didn't run much and when he did it was not really that different from walking likewise "Shoting" and "Jumping" that were majorly classified as "Passing".

On the other hand, "Passing" was the action with the best value of recall, that is whenever a pass was made the method identified it correctly as a pass, followed by "Walking", "Running", "Jumping", "Running" with the ball, "Shoting" and with the worst classification for this metric it is walking with the ball (see table 4.14).

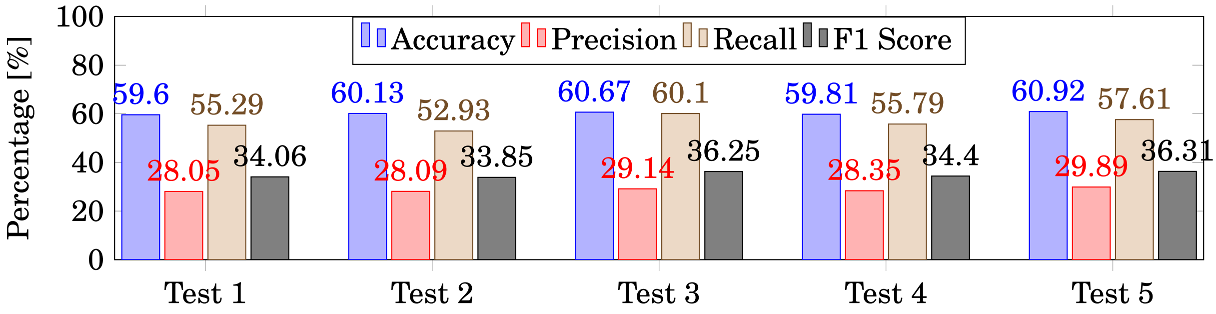
Table 4.14: Evaluation Metrics for each action

Actions	***Accuracy***	***Precision***	***Recall***	***F1 score***
Running	57.23	29.85	65.21	40.82
Running w/ ball	54.21	13.44	53.82	20.99
Passing	77.04	58.37	92.94	71.40
Walking	72.66	76.11	71.28	73.59
Walking w/ ball	51.25	—	8.78	2.86
Shoting	53.46	8.01	43.76	13.13
Jumping	56.19	14.29	59.01	22.02
Total	60.30	28.58	56.4	33.26

In terms of accuracy it is possible to see in table 4.14 that the action with the best result was "Passing" and then "Walking". "Walking with the ball" was the one with the lower value. By analyzing precision and F1 score, "Walking" was the one with the best results followed by "Passing".

Having a closer look to the graphic below where it is presented the evaluation metrics obtained for each test is is clear that there was an improvement in some evaluation metrics, even though it was small, for each test.

Comparing test 1, that is our baseline test, with all the others we can see that in test 2 where the feature velocity was added to EMG features, both accuracy and precision slightly improved. In test 3, using the distance of the player to the opponent goal, test 4 using the orientation towards the opponent goal and test 5 using all features, all metrics showed better results. Between tests it can be seen that when using all features the overall evaluation is better. As said before, F1 score is a metric that gives a balance between precision and recall being mostly used for datasets that are unbalanced, which is the case. Considering that, we can conclude that the test with a more realistic overview is the test that uses all features, test 5.



We can thus conclude the model is not the best identifying all the actions that were proposed but for walking and passing the method had an averaged behavior.

5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

One of the main challenges for coaches is to improve his athletes's performance specially due its variability. This performance variability along with an inadequate decision-making can lead to under-performing players, which can affect the whole team. Understanding how athletes behave during training and matches are key points to achieve an overall better collective performance, and, as consequence, better results. With this motivation in mind, the main aim of this project focuses in the creation of a wearable intelligent system capable of recognizing actions performed by an athlete during a futsal match. To do that it was needed to carry out the following steps (Section 1.3), in the first place we explore both kinematic and physiological equipment as well as choose the classification method. Then it came the development of the architecture that allowed the integration of the data collected from multiple sources, TraXports and MBody3 shorts, to classify those actions. After that we entered the phase of acquiring data as well as its pre-processing. With all of these steps done we trained and test the designed architecture for recognizing actions as passing, shoting, running with and without the ball, walking with and without the ball and jumping.

Concerning the initial phase, we did a research of the equipment available in the market (2.4) for acquiring bio-signals, more specifically eletromyography, and also positional information. After studied and compared all the solutions found we decided that the most suitable choices were TraXports, to collect positional information of the players, and MBody3 shorts to collect physiological information (Section 2.7).

Then, in Section 2.3 it was described both sequential and non-sequential classification methods. As our project focuses on the use of sequential data we decided to go with a supervised sequential method classifier based on a type of Recurrent Neural Network known as LSTM (Section 2.6.

After choosing the equipment and the method, in Chapter 3 development of the architecture that allowed the integration of the data collected from TraXports and MBody3 shorts where we established the overall methodology for the proposed architecture, witch includes the software that was going to be used (MATLAB), some of the equipment specifications, the process of data collection, where it is explained the signal pre-processing phase and also the choice of the features. Besides that, it also includes the classification approach as well as the metrics for evaluating the performance of the method.

For acquiring data (Section 3.3.1), it was organized a mini futsal tournament of 2 days where each game had two parts and each part had a duration of 10 minutes making a total time duration of approximately 1 hour and 20 minutes. Both systems were collecting data and recording it so we could analyze it in offline mode. Mbody3 shorts had six channels collecting, three in each leg that corresponds to the three major muscle groups from the legs that are right and left quadriceps, hamstrings and gluteo (Section 3.2.2) while TraXports collected positional data, that is the position of the players within the field as well as its orientation (x, y, θ) (Section3.2.1).

Subsequently, we did the data pre-processing (Section 3.3.2) witch was an important step to have the data synchronized, in other words, to have the same number of samples per second.

In order to find distinctive patterns within each actions we proceed to the choice of some features of both kinematic and physiological data to better identifying those actions. For kinematic data, we decided to extract features as velocity of the player, distance to the opposing goalkeeper and the player's orientation towards the opponent goalkeeper (using both positional information). With regard to EMG data we did the normalization of the data obtained from the six channels.

Before testing and training our model we did an experience, namely Experiment A witch can be seen in Section 4.1 where we presented a deep learning method, LSTM, architecture for assessing the capability of using MBody3 to classify human activities, in a controlled environment, using the EMG data collected from two different systems Mbody3 shorts and Bioplux that uses a traditional methodology of collecting physiological data. At the end of this experiment we concluded that the Mbody3 shorts was capable to recognize activities.

Having the good results of Experiment A, we then moved on to the Experiment B that is the experiment where we did the testing and training of our model relatively to the recognition of actions performed by an athlete using as input the features presented in Section 3.3.4.

The feature selection along with the classification method proposed didn't fulfill the overall expectations in so far as it was not possible to identify all the actions performed. The best results were obtained when using all features, EMG plus velocity, distance and orientation towards the opponent goalkeeper with a overall accuracy of 60.92%, precision of 29.89%, recall of 57.61% and a balance between precision and recall (F1 score) of 36.31%. Although there is still margin for improvement, these results are better than when we only analyze physiological data where the overall accuracy was about 59.6%, precision 28.05%, recall 55.29% and a balance between precision and recall (F1 score) 34.06% which leads us to conclude that these features and perhaps the parameterization were not perfect but enough to improve the method's performance. One of the reasons that may be behind these less good results is the fact that the the synchronization of data collected from both systems was "handmade", there is a possibility that it wasn't correctly done so the data were not fully synchronised. If this is really happening then it is understandable why we didn't get better results inasmuch as the splitting of the data is then compromised.

Another reason might be the fact that the player that was tracked is an amateur within this sport what resulted in a low number of visualizations of the pretended actions. As we can see in table 3.4, we had an unbalanced number of visualizations between the actions what could have influenced the results.

Despite of the not being the best results, we could see that when adding features of kinematic data the performance of the method improved so we can say that its introduction is proven to be helpful in the task of identifying actions as it helps to find differential features among the signal.

5.2 Contributions

During the development of this master dissertation the opportunity arose to participate in an international conference named "AmiEs- International Symposium on Ambient Intelligence and Embedded Systems". There we presented a paper (see appendix A) that investigates, in comparison with a validated and reliable surface Electromyographic laboratory equipment, the viability of using wearable textiles electrodes in sports, to recognize activities taking into consideration subject's bio-signals. The assessment of the proposed set of features was done by employing a type of Recurrent Neural Network (RNN) known as Long Short Term Memory Network (LSTM).

I've participated in a poster session (see appendix B) during the Biomedical Engineering Days held at ISEC with the purpose of showing our project to the community.

Besides that, we develop a business model when participating in a so-called "TAKE-OFF" entrepreneurship program witch lead us to do an international pitch in Italy (Como di lago).

5.3 Future Work

In order to improve the performance of the model, for further work, it should be done more intensive testing with regard to the synchronization of the two systems as it represents one of the more important factors to perform the task of identifying a player's action. Another thing that would be interesting to do is testing the proposed approach with professional or semi-professional players as it is expected that their techniques would be better. For improving the performance of the classifier it could be also asked to the player to be more active during the acquisitions thus performing more of the actions that it is aimed to identify. Doing that and augmenting the collection time by, for example, organizing more games, would provide more trials. Regarding the choice of the classification method, it should be made adjustments to the model's parameters used in this project as well as it could be done more tests using other methods capable of dealing with sequential data in order to assess their feasibility and with that do the benchmark between the different classification approaches.

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APPENDIX A

The paper **Rodrigues, A., Afonso, J., Marouvo,J., Coutinho,F., Barreiros,J., and Couceiro, M.(2019).Validation study of Wearable Technology for action recognition in a sport context. 11-14September-AmiEs-International Symposium on Ambient Intelligence and Embedded Systems.** was presented at the Internacional Symposium on Ambient Intelligence and Embedded Systems 11 to 14 of September of 2019 in Coimbra at ISEC.

Validation study of Wearable Technology for action recognition in a sport context

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***Abstract*—Nowadays, with the advancements in areas as sensing, wearable and wireless communication technologies, it is possible to develop intelligent systems to monitor continuous human activities, in real-time, from a wide range of fields, including sports. This paper investigates the viability of using wearable textiles electrodes to recognize sports-related activities taking into consideration subject's bio-signals. Four healthy, injury-free active males (22.5 ± 3 yrs) were included in this study. To determine if the accuracy of the wearable technology allowed us to recognize movement patterns, subjects realized one single protocol session, comprising walking, running, strength, cycling and stepping tasks. Athletes simultaneously wore the wearable surface electromyographic (EMG) solution and a validated and reliable EMG laboratory equipment, measuring the quadriceps, hamstrings and gluteal muscles myoelectrical activity of both legs. To provide average rectified EMG, the data from both devices was identically processed. The deep learning method Long Short-Term Memory (LSTM) is used to process the entire sequences of data coming from both devices, which allowed to determine that the wearable system and the laboratory instrument had an accuracy of 98.6% and 100%, respectively, for activities that used all six channels (cycling, running and stepping), and 79.2% and 83.3%, respectively, for activities that used only two channels (strength exercises).**

***Index Terms*—LSTM, Electromyography, Pattern recognition, textile electrodes**

I. INTRODUCTION

On a daily basis, a human being can easily recognize patterns as well as changes in the surrounding environment, such as motion, illumination, facial silhouettes, and others, making this a good starting point to determine how to detect, identify and contextualize information [3], [17]. In the last few years, the advances in sensing, wearable and wireless communication technologies, combined with the growing interest in neural computing, resulted in a wide range of applications; many concerned with pattern recognition [2]. Because of that, it is now possible, under specific conditions, to develop intelligent systems capable of recognizing and monitoring continuous human activities in real-time. One of the most challenging contexts to deploy such systems is in sports-related activities, where a panoply of data should be analysed during training and competition, such as core temperature, heart rate variability, hydration and muscle activation. Nonetheless, the majority of the available tools capable of reliably extracting these data are laboratory instruments, which dampens their deployment and ecological validity under real-world situations, namely during training and competition. In order to overcome this limitation, an increasing wider range of wearable solutions has been making its way to the market. Wearable technology has, by far, the greatest potential to provide the most accurate information, in real-time, for coaches and sport scientists [5], allowing the collection of a wider range of data necessary for understanding the overall dynamics of the athlete. Contrary to the main alternative technologies, as laboratory instruments, ecologically validated wearable solutions can be deployed during training and competition, having the potential to provide real-time data concerning each players physiological and kinematic data that cannot be retrieved otherwise. However, wearable technologies remain mostly unused within real sports training and competition. One reason for this is that most of the sensing modalities found in present wearables, including surface electromyography (sEMG), are non-specific, noisy and offer a decreased performance over use. Furthermore, most wearables still rely on techniques that have been available for decades, without exploring advanced approaches, namely based on deep learning, to mitigate their limitations when compared with laboratory instruments. It is therefore necessary to further compare available wearable solutions with laboratory instruments by using advanced state-of-the-art approaches. This will allow to clearly understand the fundamental challenges faced by these technologies, paving the way towards the development of their next generation, side-by-side with novel scientific breakthroughs in data analysis.

A. Contribution and paper structure

This paper investigates, in comparison with a validated and reliable surface Electromyographic laboratory equipment, the viability of using wearable textiles electrodes in sports, to recognize activities taking into consideration subject's biosignals. The assessment of the proposed set of features is done by employing a type of Recurrent Neural Network (RNN) know as Long Short Term Memory Network (LSTM). This paper is divided as follows: Section II presents the literature review on daily life and sports activities recognition, where it is exposed some of the work that has been done over the past years towards the introduction of wearable devices and its ecological value into areas such as sports. The proposed methodology is presented in Section III where the protocol includes the participants, the equipment, all the procedures, as well as data collection and processing is described. Section IV presents the experimental setup. It is shown the different approaches that have been adopted as well as the data setup which is then considered in Section V. At the end of this paper there is Section VI that presents the final remarks about this validity setup and its results.

II. BACKGROUND

Over the past decade, many authors have been studying the human behaviour at the most diverse contexts such as daily activities and sports. This activity recognition has applications in health care and can be used to achieve optimal physical preparation of elite athletes.

According to *Yang et al.* [19] most of the existing work cannot find distinguishable features to accurately classify different activities. For this reason, *Yang et al.* proposes a systematic feature learning method, CNN (Convolution Neural Network), to better solve Human Activity Recognition (HAR) problems. The architecture proposed employed convolution and pooling operations in order to capture signature patterns from the data collected from the sensor at different time scales. All salient patterns were unified among multiple channels and then mapped into the different classes of human activities. According to [19] the strengths of the proposed method are: i)feature extraction is not performed on a hand-crafted manners; ii)extracted features have more discriminative power with respect to the classes of human activities; iii) feature extraction and classification are unified in one model so their performances are mutually enhanced. Also, they conclude that in the experiments, the proposed CNN method outperforms other state-of-the-art methods.

Regarding sports, according to *Ermes, et al.* [6] tracking an human being daily activity can give information about its life style in relation to its physical activity and thus promote a more healthy life style. One important aspect about improving performance is the physiological analysis of a player, whether individual or collective. The research concerning this type of data gained a lot of interest by scientists [11]. *Boca and Park* [4], suggested a real-time approach using an ANN (artificial neural network), capable of recognizing the myoelectric data. In here, features were extracted through *Fourier* analysis and then clustered by using the *fuzzy c-means* algorithm. After that, data was automatically targeted and sent to a multilayer perceptron (MLP) type neural network. Lastly, a digital signal processor operated over the resulting set of weights, allowing the mapping of the incoming signal on-the-fly. The experimental results demonstrated that this approach produces highly accurate discrimination of the control signal over interference patterns.

Al-Mulla and Sepulveda [1] suggested the use of LMF (method that performs both signal filtering and classification simultaneously by learning the most appropriate filters) to predict time using supervised ANN. This algorithm was composed of five training inputs and one testing input signal. To calculate the input's rate of change, the first 20% of the signal were used. In order to adjust its training weights, the ANN used time to fatigue for the five training signals, allowing it to predict it by using just 20% of the total sEMG data. The results showed an average prediction error of 9.22% for time prediction.

Modelling football data has become increasingly popular in the last few years, reason for which several models have been proposed with the purpose of estimating the characteristics that cause a team to lose or win a match or to predict the final score. The great majority of these models are based on kinematics data that many times are collected visually or with the help of cameras, such as demonstrated on the work of *Montoliu et al.* [14] that applied a methodology which had the purpose of performing the team activity recognition and analysis. This methodology is the base on pattern recognition and in particular on the Bag-of Words technique. They applied these concepts in soccer video footage and, in addition to those neural networks, applied several classifiers. They showed that the used methodology was able to justify the common team patterns and the recognition of specific soccer actions like ball possession, quick attack and set piece.

In order to convert this models in an architecture more ecological and closest to the user, so as to achieve a greater accuracy, the usage of wearable technology in sports have been increasing along the time [18], and with FIFA wanting to introduce new technologies during games, several companies and authors published and created several works with the attempt to increase sports knowledge i.e., increasing the information about technical, tactical, physiological, kinematic and kinetic data.

Papic et al. [15] published an article about the early identification of future successful young players with the use of a web-oriented expert system with *fuzzy module*. But this work didn't present several results or favorable outcomes. *Jaspers et al.* [10] published an article about the use of neural networks to analyze the relationship between the external and internal training load in professional soccer player. They measured the external load using global positioning system technology and accelerometry. The internal load was assessed using the RPE (Rated Perceived Exertion). They applied several neural networks and LASSO (Least Absolute Shrinkage and Selection Operator) models in order to predict future RPE values for further training sessions. They concluded that both the artificial neural network and LASSO models outperformed the baseline values.

Another study found in our bibliographic research was published by *Rossi et al.* [16]. They studied the influence of a based GPS tracking technology and an injury forecaster in order to prevent further injuries. These new methodologies showed accuracy and interpretable results. *Grunz et al.* [7] studied the artificial neural networks to recognize tactical patterns in soccer games. They use a special self-organizing maps methodology applied to several positional data collected over professional players. Comparing data from different professional players they conclude that their method can detect with relative high accuracy different tactical patterns and their variations.

In an article written by *Memmert et al.* [12] a framework for creative performance analysis was developed and based on neural networks. Then, it was used to analyse creative behavior of soccer and hockey player compared to a control group. They conclude that they were able to assess greater creative behavior in the two athletes groups compared to the control group. We can conclude that during our bibliographic research, we found a very interesting common point in every related-work. All present some difficulties in establishing and creating the framework, due to their complexities.

III. METHODOLOGY

A. Participants

In order to prove the feasibility of wearable technology for action recognition in a sports context, it was realized a study that encompassed four males (22.5 ± 3 yrs, 1.76 ± 0.019 m, 83,25 ± 2.63 kg). The participants included were all injury-free, and the research data assessment was carried out at the Biokinetic Laboratory, at the Faculty of Sport Sciences and Physical Education - University of Coimbra.

B. Equipment

1) The *Myontec's MBody3* shorts is a constituted by two components: *MBody 3* Surface Electromyographic wearable shorts and *MCell3* (Myonear Pro,Myontec, Finland)[1]. This device can operate in online mode or in recording mode. In online mode, device sends data using a wireless connection establish communication to an external solution in real-time via Bluetooth Low Energy 4.0 (BLE). In recording mode, the device extract neuromuscular activity form lower limbs muscles group, making the recording in an internal memory which can be downloaded and used later.

2) The *Plux* device is a telemetric Surface Electromyographic system recorder (Plux, Lisbon, Portugal)[2]. The raw data is acquired according to several recommendations from the International Society of Electrophysiology and Kinesiology (ISEK) [13]: an input impedance $>$ 100 M, a common mode rejection ratio of 110 dB, amplified with a gain of 1000, a band-pass filtered (10 to 500Hz) and digitized at 1000 samples/s.

Fig. 1. MBody3 shorts

Fig. 2. BioPlux Sensors

C. Procedures

All participants realized the same protocol with identical exercises, intensities and resting periods between each session. Those characteristics were chosen to encompass different features both physical and physiological, in order to surround various movement conditions and patterns, and different levels of neuromuscular activation. Exercises such as walking, running, strength exercises, cycling and stepping were included in the protocol that was performed once. Thus, the participants simultaneously wear both *Myontec's MBody3* wearable EMG shorts and the traditional EMG electrodes as shown in Figs.1 and 2. The neuromuscular activity data was acquired using the telemetric *BioPlux* system.

Then, the participants firstly walked on a treadmill (*HP COSMOS pulsar 3p, h/p/cosmos sports & medical gmbh*) at a selected pace. Then, without resting, they reached the intensity of 9km/h, in which they run for five minutes. Afterwards, the participants realized the strength exercise which consisted of a bilateral knee flexion/extension e performed on an isokinetic dynamometer (*Biodex System 3, Medical Systems, Inc.*) regarding specific parameters and one set of 5 repetitions of a maximal isometric contract of the gluteal muscle against resistance. Then, the participants performed a 5min lower limb

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[1] https://www.myontec.com/products/mbody-3/

[2] https://plux.info/12-biosignalsplux

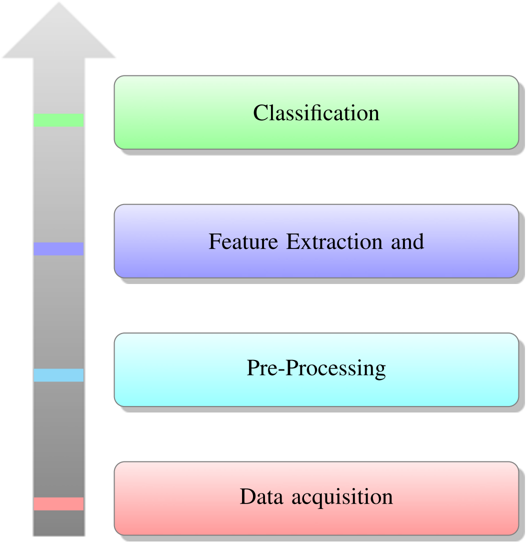
cycling exercise at 60rpm ± 2rpm at 120W (*Monark 874E, Monark Exercise AB*). Finally, the last task was a stepping exercise at the intensity of 60rpm for 5min.

D. EMG data collection

Muscle activation of all six muscle groups was assessed using *Myontec's MBody3*, an EMG wearable shorts, and by a traditional EMG electrodes system. The electrodes embedded in the textiles covered up three main muscle groups on both lower limbs which were the gluteal maximus muscle, quadriceps femoris muscle and the hamstrings muscle groups. The wireless connection was established via Bluetooth BLE 4.0 communication, which collected the all-ready filtered EMG data (25Hz). At the same time, a set of 6 *Plux* wireless electrodes were attached to the gluteus maximus, vastus lateralis and biceps femoris of both legs according to SENIAM (Surface EMG for Non Invasive Assessment of Muscles) Project recommendations [8].

E. EMG data processing

Relatively to EMG data processing, briefly, pattern recognition requires four stages [9]:



After that and considering a supervised classification approach, the process to classify patterns compromises other two stages:

1) Training - This phase encompasses using a set of time series of EMG data from participants performing each activity, being divided into time windows and afterwards manually labeled.
2) Testing - This phase is going to evaluate the accuracy of the model by giving a test dataset as the input, i.e., feeding the trained model with data that has not been used for training purposes.

The test and training data sets are created by splitting the data set, containing all the visualizations, randomly 30% for testing data set and 70% for training data set. Both data was processed and also tested with the Long short-term memory (LSTM) network using *MATLAB R2018b* software. Firstly, the surface EMG data that was recorded by the *Myontec's MBody3* shorts was automatically processed and exported to a laptop. The exported data was already filtered (rectified and smoothed) to give an average 25Hz EMG output. Smoothing was done by averaging, which calculates the average values within frame intervals, thus reducing sample count. In order to be able to compare data from both systems, the surface EMG data recorded with the *Plux* had also to be filtered and processed. To do so, the extracted raw data was processed with a second *Butterworth* band-pass filter (20-300 Hz) and down-sampled at 25Hz filtered signal.

IV. EXPERIMENTAL SETUP

The present section presents the experimental setup. Here it is shown the different approaches taken as well as the data setup. The test had two different approaches:

1) Comparing both systems using the values of all 6 channels
2) Comparing both systems using the values of only 2 channels

These two approaches needed to be done because the data related to strength exercises, extracted through BioPlux, only had 2 channels collecting data.

When preparing the data, the number of samples was taken into consideration as well as the time of each sample (approximately 4 seconds each). The number of samples are indicated in the I and in the II, each corresponding to first and second approaches, respectively.

TABLE I
NUMBER OF DATA SAMPLES FOR 1^{st} APPROACH

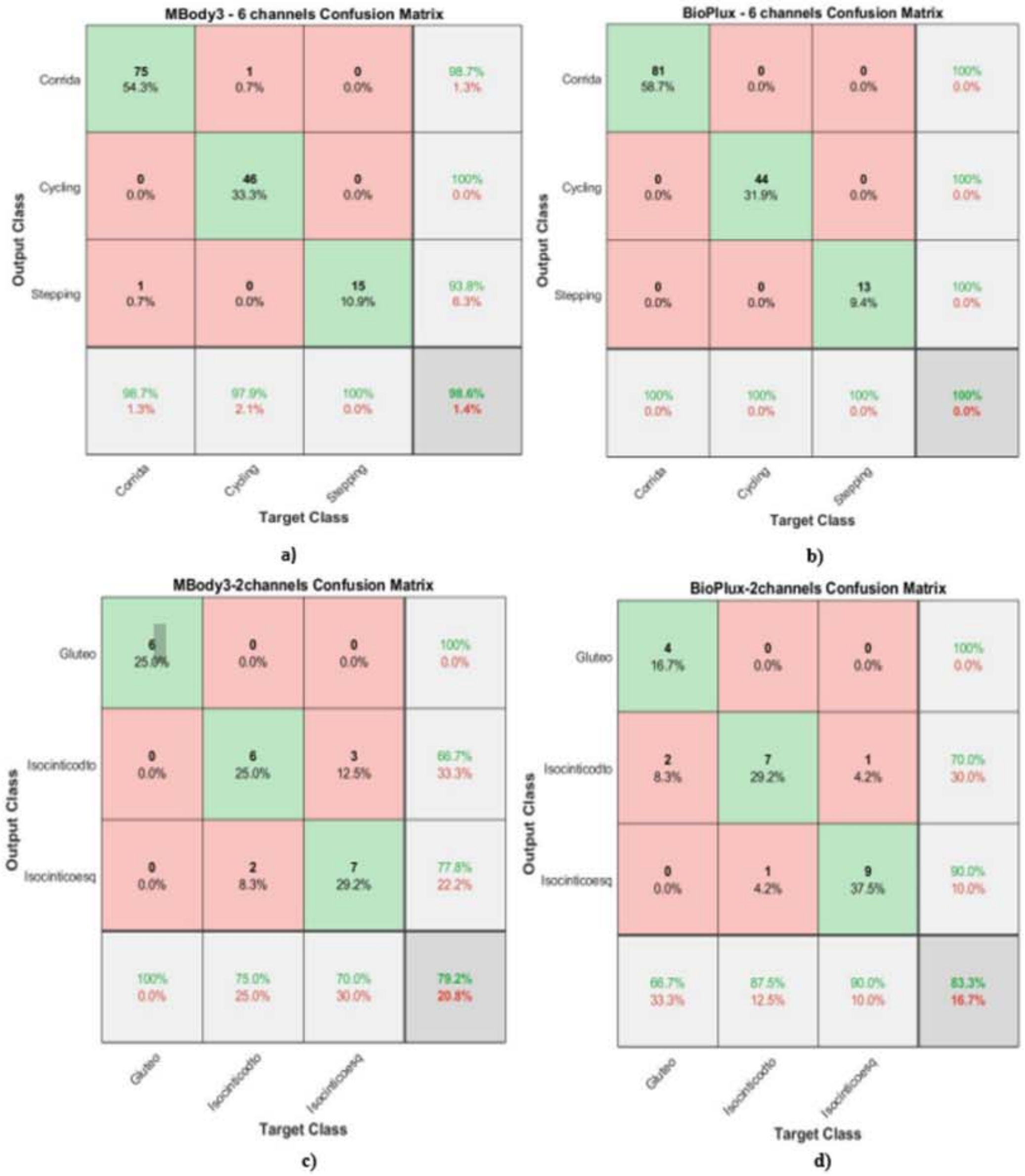
Activities	*Number of samples*
Running	256
Cycling	140
Stepping	57

TABLE II
NUMBER OF DATA SAMPLES FOR 2^{nd} APPROACH

Activities	*Number of samples*
Gluteo	18
Right Isokinetic	31
Left Isokinetic	32

V. EXPERIMENTAL RESULTS

The current section presents the accuracy results obtained by the framework approach that was chosen in order to classify activities as running, cycling, stepping as well as strength exercises that used muscular groups as gluteal, hamstring and quadriceps, for both *MBody3* shorts (see a) and c) from Fig. 3 and *Bioplux* (see b) and d) from Fig.3 systems. In order to assess the viability of Mbody3 shorts it was firstly tested the accuracy of the model using data that came from Bioplux which is a certified system who's output is a reliable, reason why it was used as our baseline. As it can be seen in Fig.3 for



	Corrida	Cycling	Stepping	
Corrida	75 54.3%	1 0.7%	0 0.0%	98.7% 1.3%
Cycling	0 0.0%	46 33.3%	0 0.0%	100% 0.0%
Stepping	1 0.7%	0 0.0%	15 10.9%	93.8% 6.3%
	98.7% 1.3%	97.9% 2.1%	100% 0.0%	98.6% 1.4%

a)

	Corrida	Cycling	Stepping	
Corrida	81 58.7%	0 0.0%	0 0.0%	100% 0.0%
Cycling	0 0.0%	44 31.9%	0 0.0%	100% 0.0%
Stepping	0 0.0%	0 0.0%	13 9.4%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%

b)

	Gluteo	Isocinticodto	Isocinticoesq	
Gluteo	6 25.0%	0 0.0%	0 0.0%	100% 0.0%
Isocinticodto	0 0.0%	6 25.0%	3 12.5%	66.7% 33.3%
Isocinticoesq	0 0.0%	2 8.3%	7 29.2%	77.8% 22.2%
	100% 0.0%	75.0% 25.0%	70.0% 30.0%	79.2% 20.8%

c)

	Gluteo	Isocinticodto	Isocinticoesq	
Gluteo	4 16.7%	0 0.0%	0 0.0%	100% 0.0%
Isocinticodto	2 8.3%	7 29.2%	1 4.2%	70.0% 30.0%
Isocinticoesq	0 0.0%	1 4.2%	9 37.5%	90.0% 10.0%
	66.7% 33.3%	87.5% 12.5%	90.0% 10.0%	83.3% 16.7%

d)

Fig. 3. Confusion matrices presented from a) to c) are the results obtained using LSTM classifier.a and b are the results obtained from the first approach; c) and d) are the results obtained from the second approach, for Mbody3 shorts and Bioplux, respectively.

the first approach, when the purpose was to identify running, cycling and stepping, the accuracy of the model for Bioplux data was 100% Fig. 3 b), slightly bigger than the accuracy when using Mbody3 shorts data (98.6%) Fig. 3 a). For the second approach, as described on section IV, where was tested strength exercises, the obtained results shows that the accuracy in both cases was worst when comparing with the results from the first approach. Comparing only the two model in this approach, as it occurred in the situation before, the accuracy from Bioplux was slightly higher (83.3%) than Mbody3 shorts (79.2%) (see Fig.3 d) and c), respectively.

VI. DISCUSSION

In this paper, we presented a deep learning method know a *LSTM* network architecture for classification of human activities using EMG data collected from two different systems *Mbody3* shorts and *Bioplux* . The aim of this work was to assess the capability of identifying activities using a wearable solution. Comparatively to a laboratory certified equipment as is *Bioplux*, as it was already expected, the results were better when testing with *Bioplux* data. Nevertheless, the difference between the accuracy that was obtained with these two systems is not high, 1.4% in the first approach and 4.1% in the second. The biggest difference between these two approaches, besides the type of activity, is that in the first one all six channels (3 muscle groups per leg) were used what means that the data was composed of six different features contrarily to the second approach that only had 2 channels collecting data, that is, 2 features per exercise.

VII. CONCLUSION

This research assess the feasibility of using a wearable system for Human Activity Recognition. After running the four tests, two per approach, we concluded that this wearable device is as capable as a laboratory certified system with regard to recognizing activities, in other words the potential of the proposed framework is, as it can be seen by the results, good as almost all activities were correctly classified.

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[3] http://core.ingeniarius.pt/

APPENDIX B

The poster **Rodrigues, A., Coutinho,F., Barreiros,J., and Couceiro, M.(2019).Towards Wearable Intelligent System for Human Activity Recognition and Prediction."Jornadas de Engenharia Biomédica"** was presented at "Jornadas de Engenharia Biomédica" event, organized by ISEC on the 17 of May of the present year.

Jornadas de Engenharia Biomédica
17 de maio de 2019

Towards Wearable Intelligent System for Human Activity Recognition and Prediction

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INTRODUCTION

- Nowadays, with the advancement in areas as sensing technologies, wearable technologies and wireless communication technologies and its fusion with techniques as machine learning, it is possible to develop intelligent systems to monitor continuous activities in real-time.
- Using tradicional methods for the recognition of football player's actions as passing or shooting can be difficult due to its similarities.
- As such, we propose the development of an architecture capable of recognizing this type of actions using, not only, athlete's physiological data but also its team mates position and orientation in the field during a match [1].

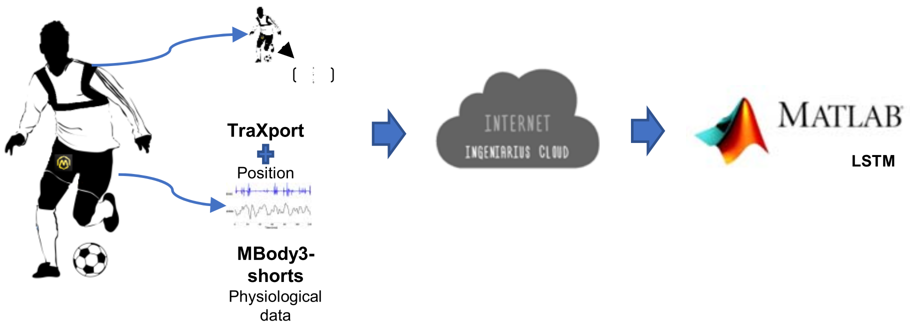
OBJECTIVES

The goal of this Master dissertation is to develop an architecture that can integrate data from different sources like TraXports by Ingeniarius, which gives us positional information, and the MBody3 shorts, that gives us physiological information, that will allow:

1. Acquiring positional and physiological information of players during the match;
2. Recognizing a player's actions such as: *passing* or *shooting*;

METHODOLOGY

- The development of the activity identificatio framework depends on many steps: data collection using TraXports and Mbody3-shorts; sending the data collected, in real-time, to the cloud; and using software MATLAB to process the data collected.
- In MATLAB, the method for pattern recognition that is going to be used is Long Short Term Memory Network (LSTM), that is a type of Recurrent Neural Network.
- This classification method was projected, essentially, to remember information for long periods of time [2][3].



TraXport
Position

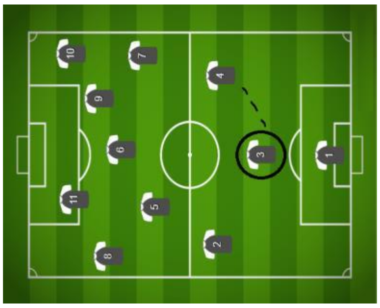
MBody3-shorts
Physiological data

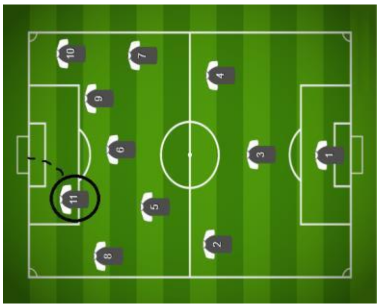
LSTM

- To distinguish if the player is passing or shooting, we can rely on the position of the player, considering other players, as well as merging this with physiological data like EMG.

1. **First Case**: The player with the ball passes the ball to his team mate.

2. **Second Case**: The player with the ball shoots the ball in order to score.





Taking into consideration the EMG from player number 3, his position and the position of his team mate ,player number 4, we would be able to identify the action taken by player number 3 as a *"passing"* (rather than *"kicking"*).

Taking into consideration the EMG from player number 11 and his position on the field and the position of his team mates, we would be able to confidently identify that he's taking the *"shooting"* action.

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