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 $\pm$ 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 bio-signals. 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 $\pm$ 3 yrs, 1.76 $\pm$ 0.019 m, 83,25 $\pm$ 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

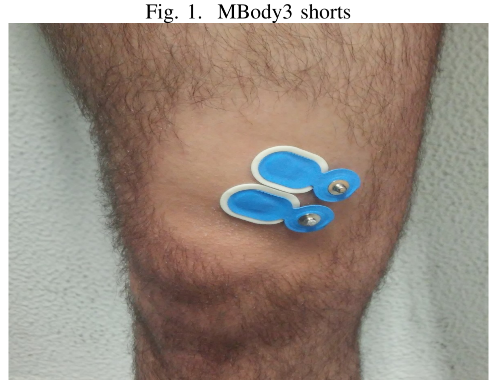


Fig. 2. BioPlux Sensors

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

[1]https://www.myontec.com/products/mbody-3/
[2]https://plux.info/12-biosignalsplux

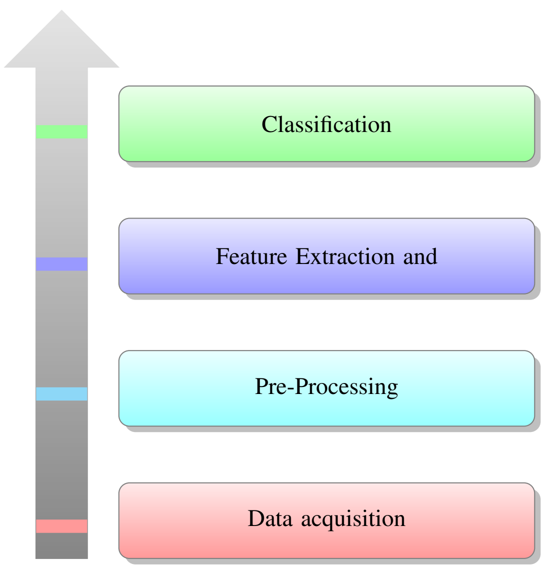
cycling exercise at 60rpm ± 2rpm at 120W (*Monark 874E, Monark Exercise AB*). Finally, the last task was a stepping exercise at the intensity of 60rpm for 5min.

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 1st APPROACH

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

TABLE II
NUMBER OF DATA SAMPLES FOR 2nd 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

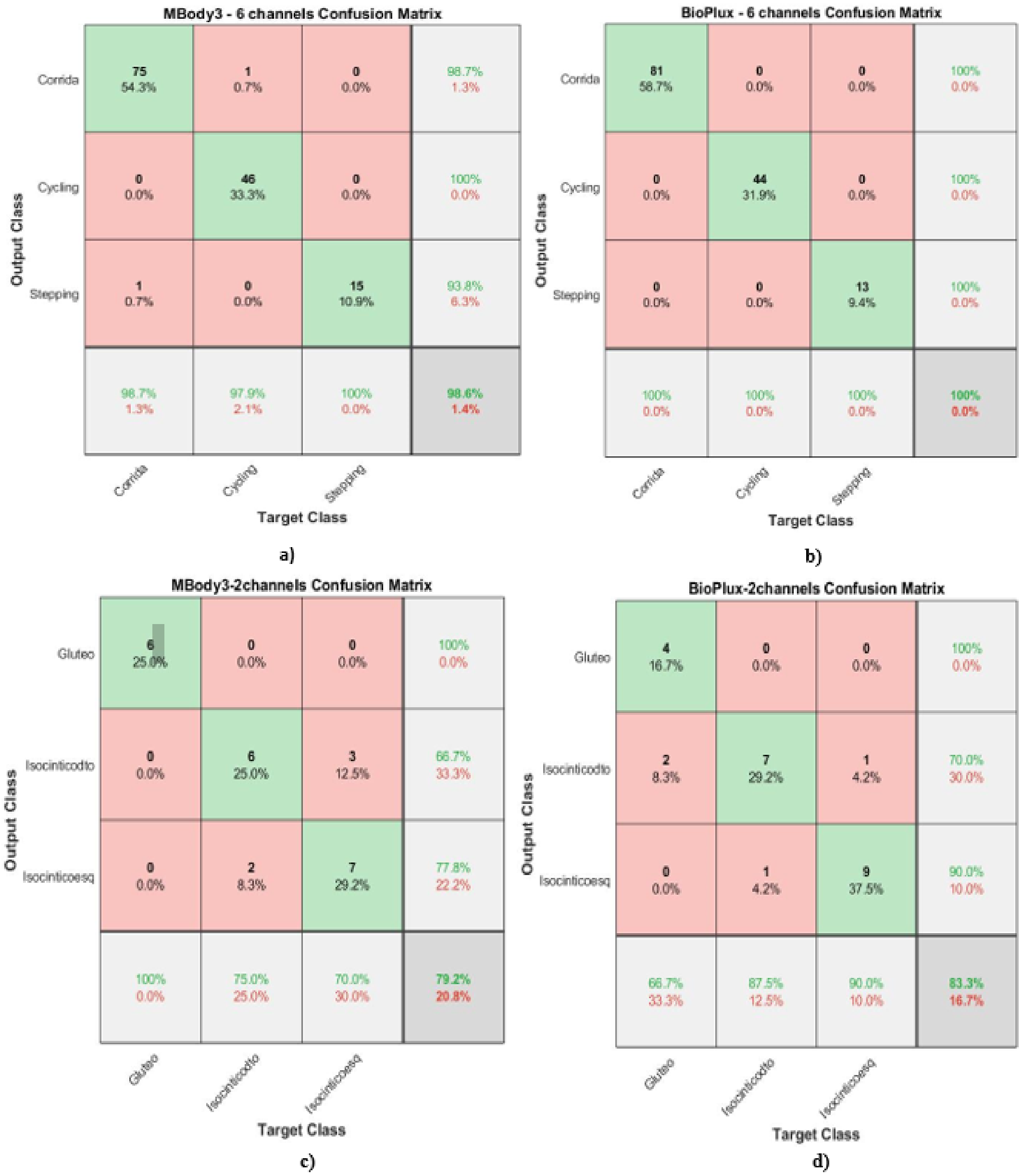


Fig. 3. Confusion matrices presented from a) to c) are the results obtained using LSTM classifier.a and b are the results obtained from the first approach; c) and d) are the results obtained from the second approach, for Mbody3 shorts and Bioplux, respectively.

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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