Real-Time Gesture Classification for Monitoring Elderly Physical Activity Using a Wireless Wearable Device

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***Abstract*—Gestures are part of communication between humans, however, they can also have an important role to play for improving human-machine interaction. Moreover, gesture recognition can have relevant applications for activity monitoring in older adults. This paper proposes the use of the Pandlet (a wearable wireless device that features a 3-axis accelerometer, gyroscope and magnetometer) for the recognition of two distinct throwing movements performed in the Boccia game. The results from this paper will be inserted into the iBoccia framework, created with the aim of monitoring and promoting physical activity on the elderly by playing the game of Boccia. The recognition of throwing gestures shall allow a caregiver to follow the performance of the elder throughout the game and the force associated with each throw, which can be important for identifying muscular diseases. Furthermore, it can be used for the elders to interact with a user interface that displays the current game score. To achieve the goal proposed by this paper, a Support Vector Machine (SVM) was trained with data extracted from eight subjects regarding two types of throws used in the Boccia game and movements performed when the player is not playing. The trained model was afterwards implemented for real-time classification and tested on four subjects. Overall, the average test accuracy was of 75±8%. These results show that the model is able to successfully recognize different throwing gestures and encourages its use on the iBoccia framework.**

Keywords-Gesture Recognition; Activity Monitoring; SVM; Boccia

I. INTRODUCTION

Gestures are an essential part of general human interaction. Whether it involves physical movements of the fingers, hands, arms, head or any other part of the body, gestures are usually performed with the intent of conveying important information to the interlocutor or interacting with the surrounding environment [1].

Gesture recognition can also be used for further improving human-machine interaction. The current trend of applications based on virtual reality demands a more suitable type of interaction that traditional devices, such as mouse and keyboard, cannot cope with [2]. Moreover, it can have an important role to play in a wide range of applications, such as sign language recognition [3], improve airport security [4] and various health applications, such as physical rehabilitation in individuals with motor disabilities [5] or the diagnosis of neurological disorders [6]. However, the focus of this paper will fall on elderly activity monitoring.

The work described by this paper is based on the exploitation of machine learning algorithms for detecting, in real-time, different types of ball-throwing movements performed by elders during a Boccia game. This is intended to be the follow up of previous work [7] and the obtained algorithm will be posteriorly annexed to the iBoccia framework [8][9]. This framework was created with the purpose of monitoring the bio-signals of the elders while they play Boccia, simultaneously motivating them to practice physical activity by enhancing the overall game experience. It comprehends an User Interface (UI) that displays, to the elders, the score of the game in real-time through the use of a computer vision algorithm [10][11] and an UI designed for the caregivers. In the latter, it is possible to keep track of information related with the heartbeat, stress levels and game performance from each of the players throughout several games. The data necessary is acquired using various sensors non-wearable and wearable sensors, including the Pandlet [12], a wireless wearable device developed by Fraunhofer.

In the present paper, this device was used to extract inertial data from various subjects and train a multiclass Support Vector Machine (SVM) model. The trained model was afterwards used for classifying data obtained from the Pandlet in real-time. For this task, three distinct classes were considered: underarm throw, overarm throw and a class dedicated to all the movements performed by the player different from the latter.

Considering the aforementioned remarks, recognizing the players' throwing movements would make possible for the caregiver to identify what type of throws the elder executed throughout the game, along with the force applied in each throw, which is easily computed from the accelerometer data. Most importantly, posterior analysis of this data could allow the caregiver to observe the evolution of the throwing force over time, which could help identifying potential muscular diseases that often occur at an old age.

This paper is structured as follows. Section II presents a brief literature review regarding gesture recognition and activity monitoring in old adults. Section III describes the used methodology for training and testing the SVM model and section IV displays the attained results. Finally, Section V addresses the final remarks and future work.

II. LITERATURE REVIEW

Currently there are three main approaches for gesture recognition: vision based without markers [13][14], using coloured markers [15][16] and using wireless devices integrating inertial sensors, such as the Pandlet. Considering the latter, Hidden Markov Models (HMM) have been frequently used in various works related with gesture recognition. Positive outcomes have been obtained using this model. For instance, Schlömer *et al*. [17] employed a Wii-controller for the recognition of five gestures. The average accuracy was of 90%. On the other hand, Wilson *et al*. [18], compared HMM with Linear Time Warping (LTW) and Dynamic Time Warping methods (DTW), by means of accuracy, for evaluating the classification of seven gestures using a wireless device with inertial sensors. The results showed that HMM proved to be the best approach, achieving an accuracy of 90.43%. Despite HMM's popularity in this type of applications, various other approaches have been explored regarding classification strategies including the use of Artificial Neural Networks (ANN) [19] and SVM [20], which also produced accurate results. Previous work [7] included the use of the latter with a DTW kernel for the offline classification of the overarm and underarm Boccia throwing movements. The accuracies obtained with the data extracted from the Pandlet were, however, shadowed by the accuracies obtained using the Kinect (66.7% and 80%, respectively).

There are five main groups of activity monitoring technology in the elderly [21]: passive infrared sensors, body-worn sensors, video monitoring, sound recognition and multicomponent approaches. Regarding body-worn sensors, the works found in the literature mainly focus on recognizing daily activities performed by the elderly in order to assess their health status [22], based on the premise that mobility is a good health indicator. Najafi *et al*. [23] used a kinematic sensor attached to the chest to detect sitting, standing and lying body positions, along with periods of walking and postural transitions.

Due to the decline of muscular strength, which is characteristic of old age, it is also essential to detect falls, which can be also found abundantly in the literature [24], [25]. For instance, Kang *et al*. [26] used a single 3-axis accelerometer placed on the subject's waist to recognize, besides daily activities as seen in Najafi *et al*., an emergency state such as a falling situation. This system was tested on five healthy young subjects and the attained detection rate was of 96%.

To the best of the authors' knowledge, no other works regarding the use of gesture recognition applied to Boccia were found in the literature. However, some studies were performed regarding the kinematic analysis of the throwing movement in individuals with cerebral palsy [27][28].

III. METHODS

This section addresses the used methodology for acquiring data with the Pandlet, along with a brief description about this device. This is followed by the strategies used for feature selection and training of an SVM. Finally, the used approach for testing the model is described.

A. The Pandlet

As stated in Section 1 of this paper, the Pandlet is a wireless wearable device developed by Fraunhofer. It can be placed on the individual's wrist as an armbrace and embodies a 3-axis accelerometer, gyroscope and magnetometer, enabling the tracking of the user's movements. It also features an Application Programming Interface (API), which allows the communication via Bluetooth with Windows, Linux and Android platforms.

For the purpose of this paper, a 50 Hz sampling was enabled. Furthermore, a total of sixteen attributes were extracted in each acquisition: the orientation, in Euler angles (pitch, yaw and roll) and quaternions, along with the values from the accelerometer, gyroscope and magnetometer for each axis.

B. Data Acquisition

Two throwing gestures were considered, the overarm throw and the underarm throw, which are both depicted in Fig. 1. During a game of Boccia, these gestures are typically used by the player with the intention of hitting the target ball, which is called the *jack* [29].

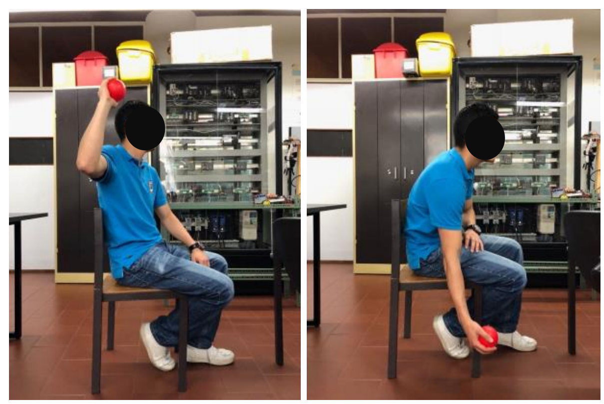

Figure 1. On the left: the overarm throw; On the right: the underarm throw

Eight subjects with 24±1 years of age were selected for the task at hand. Since the elders from the nursing home where the final system will be tested play while sitting, the subjects were asked to sit in a chair. The Pandlet was afterwards placed in the subject's right wrist.

A ball, used to act as the *jack*, was placed about 8 meters away from the sitting subject. The subject was then asked to throw the ball using the underarm throw fifty times and using the overhand throw another fifty times, always with the intent of hitting the *jack* and using the right arm. Every throwing movement was recorded for 2 seconds, immediately after the subject was given a signal to start. Thus, fifty recordings of each movement were obtained for each of the subjects. Moreover, in between the execution of the throws, the natural movements of the player would be recorded. Much like the other classes, fifty recordings of 2

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seconds were performed. This was done so that the algorithm could recognize when the user is not currently playing. Overall, a total of 1200 recordings were performed.

C. *Training the Model*

Regarding the training of the model, ten of the attributes were considered: the orientation in quaternions, plus the acceleration and angular speed for each axis. The 1200 data windows with 2 seconds of length were afterwards used to train, without any further feature extraction, a multi-class SVM with a linear Kernel and Sequential Minimal Optimization (SMO) learning. The decision of using an SVM was based on previous work [7]. Besides, according to the literature, good results have been obtained using an SVM for gesture recognition with wireless devices [30][31][32].

The training of the SVM and its subsequent real-time implementation were performed by using the Accord.NET framework [33]. This framework offers multiple applications for scientific computing in .NET, such as statistical data processing, machine learning and pattern recognition. Moreover, it features a wide selection of classifiers, kernel functions, performance measuring techniques and hypothesis tests.

D. *Testing the Model*

The training of the model was followed by its real-time implementation. For classification purposes, windows with 2 seconds of length were used with no overlapping.

Testing protocol was similar to what was described in subsection B. In total, four subjects with 24.5±1.0 years of age participated in the test. The subjects selected for testing were different from the ones selected for data acquisition. This was done to test the system's robustness and avoid influence from overfitting.

The subject was invited to sit on a chair and the Pandlet was placed on his/her right wrist. Afterwards he/she was told to execute all throwing movements with the right arm.

Twenty balls were given to the subject and the *jack* was placed about 8 meters in front of him/her. The subject was then asked to throw ten of the twenty balls using the overarm throw movement and the remaining ten using the underarm throw movement, always with intent of hitting the jack. The obtained results are presented in the following section.

IV. RESULTS

Table I presents the average recognition accuracy confusion matrix, considering the computed results from all the subjects during testing. Class A refers to the underarm throw, B to the overarm throw and C to any movement that differs from a throw. All percentages refer to accuracy.

TABLE I. AVERAGE RECOGNITION ACCURACY CONFUSION MATRIX

		Predicted Classes		
		A	***B***	***C***
Actual Classes	***A***	80%	-	20%
	B	-	70%	30%

For evaluation purposes, the classifier's output was only considered when throwing movements were executed by the subject. Thus, each time the subject performed a throw, the output label was noted.

As it can be observed in Table I, during testing, the model did not mislabel any underarm throw as an overarm throw or vice-versa. Instead, when a throwing movement was mislabelled, it was always classified as class C (non-throwing movement).

The obtained average accuracies for each subject can also be observed in Table II.

TABLE II. AVERAGE ACCURACIES OF EACH SUCBJECT

Subject	Accuracy (%)
1	65
2	75
3	85
4	75

Overall, the total average accuracy for throwing gestures recognition was of 75±8%.

V. FINAL REMARKS

The work described in this paper focused on the training of a linear SVM and subsequent implementation for real-time classification. The model, trained with data acquired from eight subjects, was used for the recognition of two throwing movements used in the game of Boccia: the overarm and the underarm throw. Furthermore, it was also used to recognize when the player is idle, i.e., any movement performed by the used that differs from a throw. Thus, this classification problem comprised three classes which, in this paper, were identified as classes A, B or C.

The results from the real-time testing phase showed that classification achieved an average accuracy of 75±8%, showing that the system successfully recognizes and differentiates between the two throwing gestures and other movements performed by the player while "idle".

The system recognized the underarm throw more efficiently, obtaining an 80% accuracy, comparing to the 70% obtained for the overarm throw. This difference could be justified by the fact that, during data acquisition for training, subjects performed the underarm throw more similarly amongst themselves, oppositely to the overarm movement, in which the execution varied from subject to subject.

Another positive aspect is that the classifier did not misclassify class A as class B and vice-versa, which appears to mean that the data from both throws differs sufficiently for the algorithm to not misclassify one for another.

However, the accuracy considerably varies between some of the subjects, which is one of the downsides of the proposed system. This shows that each subject has a different method of throwing, which might differ substantially from the recorded gestures contained in the data set used for training. This might be a constraint for testing the system during a real Boccia game situation, due to the probability of the elders having very different throwing techniques amongst

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themselves, therefore, it is imperative to have a robust model. Having this into account, the usage of other classification techniques should be used for further improving of the results, such as feature extraction, enable overlapped windows for real-time classification or even using other kernels and classifiers. Furthermore, more data should be acquired from different subjects in order to have a more extensive and variable training set, thus increasing the model's robustness.

Regarding future work, it is intended to implement this system in the iBoccia framework for gesture recognition. As stated in Section I from this paper, this framework comprises two UIs, one for the caregiver to monitor the elder's physical activity and another which displays the game score, in real-time, for the elders. The implemented algorithm for gesture recognition will allow the caregiver to keep track of the different throwing movements performed in each game by the elders. Thanks to the accelerometer data and knowledge of the approximate weight of a Boccia ball (0.275 kg) it is also possible to compute the approximate force applied by the player during the throw and plot this data for later consultation, thus allowing the caregiver to detect decreases in the elder's strength and identify muscular diseases characteristic of old age.

On the other hand, the results from the work described in this paper will be also useful for the elders to interact indirectly with the UI that displays the current game score. By using gesture recognition, it can be possible for the system to automatically detect when a player's turn is over and notify the next player that his/her turn has started by showing the respective elder's photo and name on the screen. This can further motivate the elders to play Boccia by enhancing the game experience.

In addition, the proposed system is predicted to be tested during a Boccia match played in a nursing home. Bearing this in mind, it is pertinent to use data acquired from the elders during the match for adding to the data set used to train the model. The results, as seen in this paper, will be evaluated using accuracy as performance metric.

Overall, the results obtained with the proposed system are encouraging and allow the further development of innovative solutions for monitoring and motivating elder physical activity.

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