iBoccia:
Monitoring elderly while playing Boccia gameplay

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Abstract: The size of the aging population has been increasing over the last years, leading to a search for solutions that can increase the quality of life of the elderlies. One of the main means of action is focused on their physical activity. A non-sedentary life can help in disease prevention and disability reduction, leading to an independent living with quality. Moreover, the practice of physical exercise can decrease fall risks and its consequences. Furthermore, it is desirable that the solutions can be accessed by anyone, with a low inherent cost. The Boccia game is a good way to promote physical activity to the elderly, due to its simplicity and easy adaptability to the physical limitations of the elderly. Following this trend, this paper presents iBoccia, a novel framework to monitor elderly while playing Boccia game, through wearable sensors, Mio Fuse band and pandlet (inertial sensor), and a non-wearable device, Kinect camera. Several performance metrics are expected to be measured during the gameplay. Using the pandlet we calculate wrist rotation angles and force applied during ball throw, using the Kinect we recognize facial expressions and from the Mio Fuse band we retrieve heart rate.

1 INTRODUCTION

Physical inactivity is one of the main causes of several health diseases, as heart diseases, beyond being correlated to overweight and obesity (Lee et al., 2012; Blair et al., 1999; Warburton et al., 2006). (Lee et al., 2012) estimated that physical inactivity is the cause of 6% of the burden of disease from coronary heart disease, 7% of type 2 diabetes, 10% of breast cancer and 10% of colon cancer. Moreover, it is the cause of 9% of premature deaths, causing the death of more than 5.3 million of the 57 million deaths occurred in 2008 worldwide (Lee et al., 2012). The practice of physical exercises may increase cardiorespiratory and muscular fitness, functional health, improve bones and joint health, and cognitive functions (Warburton et al., 2006; Lee et al., 2012).

The physical inactivity tends to become more pronounced while aging, making the elderly the most sedentary age group. Therefore, it is important to find solutions that may solve this problem, encouraging physical activity practice. For this, it is essential to give the elderly the necessary motivation, with pleasant, social and fun solutions, achieved through games in order to promote social activity and interaction, and improve self-confidence and quality of life. Boccia is a simple game that can be adapted to the age and limitations, and beyond the practice of physical activity, it promotes the contact with others. Therefore, this paper discusses the possibility of monitoring a group of elderly people playing the boccia game. The objective is to collect performance and affective information as well as movements data.

For the elderly it can be seen as a way to monitor the game through the suggestion of performance improvement of some of the movements.

For formal caregivers besides the playful aspect, it may be interesting for them to realize what kind of moves were made during the game, access the affective state of the patient and to detect physical or cognitive declines by analyzing the data collected.

For the system development it will be important to collect acceleration data of the player's arm as well as through the Kinect to extract facial cues, determine the angles, and to analyze movements during the game. In a first phase the game results of each player will be manually inserted into the system and it may help in suggesting improvements in the movement of the ball. Subsequently, the system can be improved by incorporating an analysis of the play and rating through processing and analysis the position of the ball in the game.

This article is organized as follows: in section 2 the Boccia game scenario is explained. Section 3 presents the state of the art solutions for monitor physical activity. The system architecture is presented in section 4. The article finishes with section 5 concerning the conclusions and future work.

2 BOCCIA GAME

Boccia is an indoor precision game played with six blue and six red leather balls and one white. The objective is to score by throwing the colored balls as close as possible to the white one. It is allowed to throw the balls with hands, kicked with feet or, in a case of a severe disability, launched with aid instruments. This modality can be played individually, by pairs or by teams (Fong et al., 2012; BISFed, 2016).

Originally designed for individuals with cerebral palsy, Boccia has become a Paralympic Game in 1984, being played by athletes with different physical and functional abilities (Fong et al., 2012; BISFed, 2016). Apart from its competitive side, Boccia game can also be used as an alternative to rehabilitation exercises, as well as be adapted to be played by elderly, encouraging the physical activity practice, assisting in balance and coordination and increasing strength and flexibility. Moreover, it can help in self-confidence and appreciation, as well as self-esteem improvement. In addition helps the player to develop character and to understand social norms, by playing as a team.

3 STATE OF THE ART

With a large application areas, as health, fitness and safety, the demand for physical activity monitoring has been increasing, following the technological advances (Choudhury et al., 2008; Figueira et al., 2015). Herewith, several solutions have been commercialized, with increasingly features and functionalities. These solutions are mostly based on wearable or smartphone built-in sensors, and are focused on fitness, calculating the number of calories lost, steps given and distance traveled, on safety, with emergency buttons to call for help, or on physiological field, monitoring the heart rate and body temperature, for example (Guo et al., 2013; Mukhopadhyay, 2015).

Regarding targeted systems for seniors, several systems have been developed in order to measure their movements and discriminate between everyday movements and emergencies, like being laying down or falling. These systems are suitable for elderly monitoring living at home or institutions (Charlon et al., 2013; Van Kasteren et al., 2010; Ohta et al., 2002). Gociety has two physical activity and fall monitoring solutions, targeted primarily for the elderly: the GoLivePhone and the GoLiveWear. GoLivePhone is an Android application that detects falls and evaluates its associated risks. When a fall is detected an emergency message is sent to the caregiver. It also has an emergency button, where one touch is enough to alert professionals and caregivers. It also notifies about taking medication and collects physical activity data (number of steps taken, calories lost and time spent in different activities such as walking or standing). In addition, caregivers can also receive notifications when the user is inactive for a certain period of time. GoLiveWear is a waterproof clip-on device with a built-in emergency button that, connected to the GoLivePhone application, can access to all of its features without the need of having the smartphone always around (Gociety, 2016). Among other features, the AT&T's EverThere Emergency Response System has also a call button that notifies caregivers if the senior experiences a fall or other emergency (EverThere, 2017) and the Flowie solution is a persuasive tool which aims to encourage the elderly to walk more (Albaina et al., 2009).

Despite all the existing solutions, there is none adapted to a gaming environment, monitoring the elderly while playing, for example, a Boccia gameplay.

4 SYSTEM ARCHITECTURE

The architecture was designed envisioning the integration of different sensors to monitor the game movements and user's face expressions in order to suggest improvements of the game movements to the players. The system will also provide and log this sensor data and provide it to caregivers to assist them in the detection of physical or cognitive decline. In Figure 1 the system architecture is presented. The user's movements and acceleration are collected using a sensor in the wrist called pandlet. Additionally, a kinect is used to collect the user's gestures, body position, posture and face expressions. On the wrist another

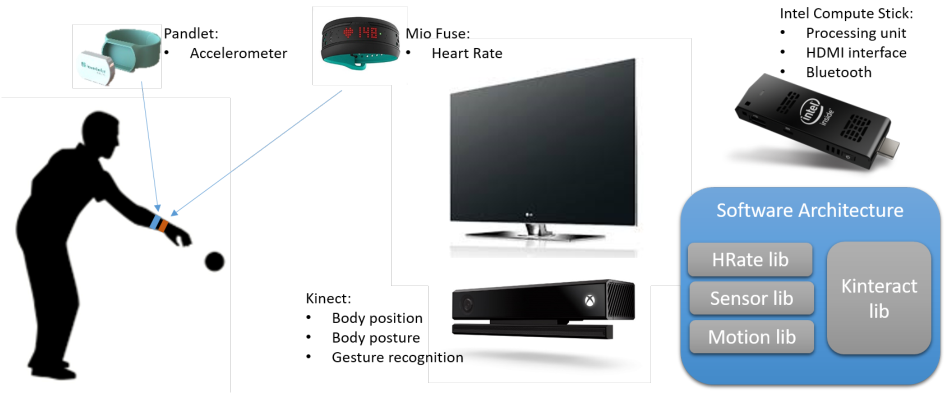

Figure 1: iBoccia architecture.

sensor, Mio Fuse, collects the user's heart rate. The pandlet and Mio Fuse communicates by employing the Bluethooth 4.0 low energy (BLE) protocol, which is an industry-standard and allows devices to run for long periods. The kinect is connected through an USB cable to the Intel Compute Stick which is used to retrieve the data from the different sensors and display in the LCD this information to the user. The software architecture is based on a three-tier framework that organizes modules (games) into dynamic categories, acting as a launcher and providing them a set of APIs for common functionalities such as sensor communication (HRate lib, Sensor lib, motion lib) user profile and game session management. The proposed system architecture allows the modules to be agnostic on which sensors are currently supported and being used, as well as which backend server may be used to manage user profiles and store game session data. The API (Matos et al., 2014) for sensor communication provided by the framework is implemented as shared library/DLL in pure native code (C++) and supports most of the existing platforms: Windows, Linux and Android. The library is responsible for all communication details with any sensor. The received data from sensors is processed and merged into a single protocol and send to any client (game) that asked for it and provided a callback. The protocol considers data from inertial sensors, gestures, body tracking, hand tracking, face's expressions, and heart rate. The processing algorithms use this that to for gesture recognition and facial expression recognition. The gestures recognition algorithm is used to evaluate the performance of the player movement and suggest improvements based on the game classification. The facial expression recognition algorithm is used to detect emotions, opinions, and clues regarding player's cognitive states. The next sections include further detail about the sensors that are used and also the algorithms adopted to achieved the proposed goals.

4.1 Sensors

The main purpose of this project is to be used in community or nursing home unsupervised contexts, employing standard and relatively inexpensive equipment to monitor elderly players during a Boccia game scenario. Thus, currently there is support for a small set of available sensor devices, such as the Kinect sensor, a Mio Fuse, and pandlet (Figure 1). To study the behavior of each player during the game, all the sensory information is going to be combined, allowing to actively track the player movements and his/her emotional state.

4.1.1 Kinect

There is a connection between affective states and exercise in real life (Schöndube et al., 2016). Understanding this association may be important for creating successful exercise promotion programs. Moreover, the strongest factor that contributes to the maintenance of the exercise behavior can be the positive affective valence (Schöndube et al., 2016). The user affective state might affect exercise in daily life.

The Microsoft Kinect V2 is a depth sensor that employs the time of light technique for tracking the user's body movements, extract facial features, and recognizing gestures. It has a built-in a 1080p color camera, a 3D depth sensor, and a microphone array. A Software Development Kit (SDK) was released by Microsoft, giving access to the raw sensor data streams as well as skeletal tracking. In order to accomplish the goals of this work the Kinect V2 is going to be used along with its SDK and the Kinteract (Matos et al., 2014) library to extract facial features, track the player, and recognizing gestures, allowing to monitor the user activity during a Boccia game scenario. The APIs for the Kinect allow to retrieve the position (in high detail) of up to 36 facial landmarks and it gives access to a skeleton model composed of 25 joints that can be used to track each joint position (Microsoft, 2017). Additionally, the Kinteract library can compute the angles enabling, together with the Kinect SDK, the employment of gesture recognition.

4.1.2 Inertial Sensors

The Pandlet (Letting Everything Sense) is a bracelet with a novel architecture of embedded electronics for wireless devices that can be used to develop Wearable and IoT solutions. It includes an accelerometer, magnetometer, and gyroscope that can be used to track the user movements during the game, with a 100 Hz frequency. Moreover, the Pandlet is composed by an ARM M0+, running at 16 MHz and an environmental measurement unit. It is also charged wirelessly (QI compliant) and Bluetooth Smart (fully compliant with Bluetooth Core Specification v4.0). The radio range is 40 meters in line of sight, and in a high 2.4 GHz polluted environment. Although the kinect can detect the player movements the force applied when launching the ball is hard to assess. Using the pandlet and by knowing the ball mass we can easily estimate the force applied to the ball and estimate the landing point. The pandlet's acceleration fused with the kinect's tracking of player's movements will provide the required data to the gesture recognition algorithm to access the player performance in the game.

4.1.3 Heart Rate Monitor

Physical exercise has proven its benefits in the health of a patient. Thus, the risk of heart diseases is reduced. However, there are limits to the exercise which considers the maximum heart rate (HR_{max}), calculated as $220-$ age in years (Atwal et al., 2002). Surpassing this limit may lead to severe problems due to excessive heart stress. The heart rate is retrieved by the Mio Fuse, which is placed on the patient's wrist. Through this device the caregiver may control the user heart health and, if necessary, stop the game in an earlier stage.

4.2 Processing Algorithms

4.2.1 Gestures Recognition Algorithms

Gestures recognition can be considered as a supervised classification problem, if annotated gestures sequential data is given to a classifier as a time series. Some of the common used approaches rely on: Support Vector Machines, K-Nearest Neighbors or Naïve Bayes. These algorithms use labeled data (in this case, the gestures) to train the classifier, which becomes able to map new inputs (Wilde, 2010). On the other hand, for supervised learning and for an in-depth study of gestures recognition, it has been also considered the Hidden Markov Models (HMM), which aims to present results from the present outcomes through probabilities. HMM can model conditions of the occasions that may happen repeatedly over time or predictable events that take place over time (Fosler-Lussier, 1998). Dynamic Time Warping (DTW) (Muhammad and Devi, 2016) is another algorithm commonly used for time series similarity evaluation, which aligns each sequence prior to establishing the distance measurement. Moreover, Recurrent Neural Networks have also been used to gesture recognition (Eleni, 2015; Murakami and Taguchi, 1991).

The authors have been working in gesture recognition. With this, several projects and master thesis have concerned the classification of gestures using HMM, DTW or other classification algorithms. Some examples are the (da Silva, 2013), where hand gestures where recognized with a smartphone, (da Costa et al., 2015) classified activities of daily-living in post-stroke patients and (Freixo, 2015) combined electromyography and inertial sensor for gesture detection and control.

The proposed system will rely on supervised algorithms, that will be trained with annotated data from the Boccia game movements. Boccia is characterized as a throwing sport, so the movements to recognize will focus on ball throw. Since the objective is to get close to the "jack" ball, force is not always necessary to reach the better position. So, precision is occasionally worth than long throws. With practice, players develop their own strategies to win the game, as the way they throw the ball or roll depends on players' body movements. The goal of this system, is to provide user movements' feedback during the game, as for example, when a user is given with specific information of ball throw and given the ball position on the court, users can understand witch movements result better and try to improve their performance. As the physics mechanisms applied to the ball on the court could not be inferred by the system, due to uncontrolled parameters (opponent's balls positions, jack position, rolling on the floor, etc.), we can not relate movements performance with game scoring. However, the player is able to infer such relation and relate higher scores with different body movements. Focusing on game related movements, the system could be able to recognize and characterize ball throws into their main movements: wrist movements for ball preparation, body position adjustment during court observation, wrist rotation angle and force applied during ball throw. For the caregiver point of view, these movements' characterization could be useful to evaluate players' arm movements, that are important for upper body rehabilitation.

4.2.2 Facial Expression Recognition Algorithms

Facial expressions are innate in any communication and interaction between humans. They can transmit emotions, opinions, and clues regarding cognitive states. Several psychological studies have been conducted in order to decode the information contained in a facial expression. For example, the system developed by Ekman and Friesen (Ekman and Friesen, 1978), the Facial Action Codding System (FACS), allowed researches to analyze and classify facial expressions in a standardized framework. This system associates the action of the muscles to the changes in facial appearance. The measurements of the FACS are called Action Units (AUs) which are actions performed by a muscle or a group of muscles. There are two main approaches regarding facial expression recognition, the feature-based ones, which uses textural or geometrical information, and the template based ones that uses 2D or 3D head and face models (Kotsia and Pitas, 2007). Usually, these systems try to classify the six basic emotions, also considered the six universal emotions – happiness, sadness, anger, surprise, fear, and disgust. Some researchers are using machine learning techniques to detect such patterns.

(Silva et al., 2014) proposed an automatic human facial expression recognition frame-based system that classifies six basic facial expressions plus the neutral state. The proposed framework compared the performance of three different classifiers (Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA) and k-Nearest Neighbor (k-NN)). Other authors, (Silva et al., 2016; Youssef et al., 2013), used Support Vector Machines (SVM) in order to classify the user's emotional state.

5 FINAL REMARKS

The present paper concerns the development of physical and cognitive monitoring technologies to support and promote exercise programs, focusing more in elderly people. Nowadays, physical inactivity can be one of the main causes of several illness. Physical inactivity tends to be more present in the elderly. Following this trend, the main purpose of the present work is to develop a system for collecting performance and affective information as well as movements data. As stated before, affective states should be considered in creating effective interventions to foster exercise behavior and enhance maintenance. The system is composed of a Kinect sensor, a Mio Fuse band, the pandlet, and an Intel compute stick.

The developed system is going to be evaluated in different scenarios in order to assess its performance. This evaluation will be based on several metrics, taking into account the wrist rotation angles and force applied during the ball throw calculated by the Pandlet. Through the Kinect, facial expressions recognition will also be performed and with the Mio Fuse band the heart rate will be retrieve, too. First, the system is going to be tested in a laboratorial environment with a set of 12 participants, simulating a Boccia game. This first evaluation step is going to be conducted with the purpose of detecting the system constraints and to tune the conditions of the experimental scheme. Several Boccia movements should be defined and validated by the proposed system. Also, emotional states should be simulated by the test group and correctly detected and correlated by the system. After this first validation in a controlled environment, a second test should be developed in a real-world context. So, an evaluation will be performed with a set of 12 elderly participants in a nursing room. In this evaluation, the participants are going to be monitored on site by professionals, and the research team is going to oversee the progress of the game, and monitor the system. The detection of the movements and the degree of engagement in the game should be correctly monitored. iBoccia will then be subjected to extensive tests in order to validate it as an adequate tool to promote physical activity in the elderly.

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