A Platform for Assessing Physical Education Activity Engagement

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Abstract. Physical activity is an important part of the healthy development of children, improving physical, social and emotional health. One of the main challenges faced by physical educators is the assembling of a physical education program that is compelling to all individuals in a diverse group. Recent advances in Human Activity Recognition (HAR) methods and wearable technologies allow for accurate monitoring of activity levels and engagement in physical activities. In this work, we present a platform for assessing the engagement of participants in physical education activities, based on a wearable IoT device, a machine learning HAR classifier and a comprehensive experiment involving 14 diverse volunteers that resulted in about 1 million data samples. Targeting at a replicable research, we provide full hardware information and system source code.

Keywords: Physical education · Human Activity Recognition
Wearable computing and wearable sensing · Healthcare systems

1 Introduction

Physical education and school sport (PESS) aims at (i) developing children's cognitive capacity and motor skills, (ii) teaching about health and the benefits of physical activity and (iii) fostering emotional intelligence [1]. Recent research on successful PESS programs shows a strong correlation between physical activity and learning performance, school attendance and academic success of children and young people [2]. Bevans [3] discusses that an adequate exposure to PESS during school day increases children energy expenditure and allow for the maintenance of a healthy weight, and [4] suggests that physically active children have reduced chances of experiencing chronic disease factors and becoming obese throughout adolescence. However, while studies such as [5] consider that an adequate exposure to PESS for school-age children is at least 60 min per day, other studies such as [6] and [7] point out that the average physical activity level of children worldwide is low and decreasing, and there is a correlated increase in childhood obesity.

This work addresses one of the main challenges of PESS, which is the engagement of school-age children in the physical activities. By proposing a foot-based wearable IoT device and a Human Activity Recognition (HAR) classifier that can assess the

activity level of an individual during a planned physical activity, we aim at offering an alternative for PESS teachers to appraise their programs and tailor them to meet the needs of each class. The main contributions of this work are an experiment with 14 diverse individuals that resulted in about 1 million data samples for analysis and, above all, a wearable IoT device and a HAR classifier that can assess the activity level of an individual during a planned physical activity. The prototyping of the wearable IoT device, sensors deployment and replication information are shown on section Building the HAR Classifier, along with the details of the experiment conducted to develop the activity model, collect ADL data and build the HAR classifier. Section Assessing Activity Level shows the assessment of the activity level and discusses the results, and Section Conclusion presents the findings and future work.

2   Literature Review

This section presents a literature review of HAR research based on feet movement and posture information focused on health and sports activities.

2.1   Recognition of Common Movement Activities

Common movement activities recognition is the most common type of research found in this literature review. Many works, such as [8], [9] and [10] rely on plantar FSR pressure sensors to classify user activity according to a previously elaborated activity model. Other works, such as [11] and [9], rely on inertial motion units (IMUs) located on user's feet for that purpose. Sensor fusion - FSRs and IMUs - is employed by works such as [12], [13] and [14] achieving good overall results. Only a few of the surveyed works used sensors other than ground contact force (GCF) sensors and IMUs, such as infrared sensors [15] or capacitive sensing technology [16] and [17]. Some positioned extra sensors in other places beyond the user's feet, such as [18]. They all use very similar activity models comprising sitting, standing, running, walking and slope-walking activities, with the main difference being the machine learning algorithms applied and the context of the experiments.

2.2   Recognition of Specific Activities

Many of the surveyed studies were conducted in the recognition of activities related to healthcare well-being, such as (i) the research presented in [19], that aims at recognizing caregiver's patient handling activities (PHA) and movement activities to help prevent overexertion injuries, (ii) the work presented in [20], that measures activity in people with stroke, (iii) the work presented in [21], that recognizes activities and postures to provide behavioral feedback to patients recovering from a stroke, and (iv) the research proposed by [22], in which researchers present a pair of shoes that offer low-cost balance monitoring outside of laboratory environments and uses features identified by geriatric motion study experts. The lightweight smart shoes are based on the MicroLEAP wireless sensor platform [23], that uses an IMU and FSR pressure sensors embedded inside each insole for data acquisition.

Some other shoe-based wireless sensor platforms, such as the SmartStep [24], were used by many different healthcare related works. In [25], the former platform was used to develop an Android application to capture data from the wearable device and provide real time recognition of a small set of activities. In [26] and [27], the SmartShoe platform is used for energy expenditure estimation after the classification of the activities performed by the user, and in [28] it is further used to predict body weight. The same platform is then used by [29] and [30] to identify activity levels and steps in people with stroke.

2.3 Literature Review Discussion

The measuring of GCFs is the most prevalent approach used by the surveyed works for the task of recognizing user activity, followed using IMUs and sensor fusion. No work thoroughly addresses the challenge of adequately positioning the GCF sensors, although studies such as [14] and [19] recognize that this is a very important factor for HAR. Considering the wearable devices presented in the literature, two characteristics impair their reproducibility: (i) the lack of information about sensor positioning and orientation and the (ii) absence of sensor model information or specification. Most of the works analyzed provided detailed information regarding the activity model of its HAR classifiers, but few studies detailed the validation techniques used for building the activity classifiers. The success rate of activities classification, with one notable exception, fell into the 80%–100% range. It was also observed that although most works informed the number of participants, only a few informed the dataset size. Detailed knowledge of datasets is especially important to assess (i) works that use similar activity models and sensor placement and (ii) machine learning classifiers results. As discussed in [18], dataset disclosure is crucial for benchmarking purposes, given that classification algorithms rely heavily on datasets.

The prevailing suggestions for future works and contribution found in the literature follows the conclusion of the review presented in [31]: (i) increase the data set through longer data collection intervals and the diversification of participant's profiles, (ii) improve the classifier algorithms and (iii) adapt the activity model to a specific challenge, such as helping patients to avoid falls.

3 Building the HAR Classifier

On this Section, we describe the stages followed to develop the HAR classifier – prototyping the wearable device, conducting the experiment and building and validating the model.

The wearable device comprises two components: an insole that houses the plantar pressure sensors and an external protective case that houses the microcontroller and the other sensors. The insole employs four GCF sensors for monitoring plantar pressure distribution, following the recommendations found in works such as [14], in addition to the lessons learned from the prototype presented in [31]. The main component of the external protective case is a WIFI enabled microcontroller that collects and transmits sensor data to the database. The ABS 3D printed external protective case also holds the

accelerometer, gyroscope, magnetometer, barometer and range finder sensors. The prototype is powered by a 2,200 mAh lithium ion battery pack.

The first experiment, aimed at building the HAR classifier, was conducted with twelve volunteers carefully selected for their diverse characteristics. We collected 12 h of activity data - 1 h of feet posture and movement data from each volunteer. The activity model we developed for the experiment comprises 10 activities: walking straight (2 km/h), walking slope up (2 km/h), walking slope down (2 km/h), slow jogging (6 km/h), slow jogging slope up (6 km/h), slow jogging slope down (6 km/h), hopping, ascending stairs, descending stairs and sitting. The experiment was conducted in 4 distinct sessions, where participants performed a subset of the planned activities. During the data acquisition stage, a stream of raw, unprocessed signals of the combined sensors was stored in the microcontroller in JSON format and periodically sent to the application server. The same data acquisition, data processing, feature extraction and feature selection pipeline proposed in [31] was employed. Different strategies were then experimented to build the classifier, and the Random Forest Algorithm with Leave-one-out Cross Validation was selected for classification achieving an average accuracy of 91.26%.

In the second experiment, our goal was to use the prototyped wearable IoT device and the HAR classifier to assess activity level of different individuals during a planned physical activity - as a proof of concept that both could be used for investigating engagement in PESS programs. Considering the most commonly practiced PESS activities of country in which the study was conducted - soccer, basketball and volleyball -, basketball was chosen to avoid exposing the foot-based device to direct physical contact in the case of football or falls to ground in the case of volleyball. Two volunteers were selected for this experiment, both without professional experience in basketball. All sessions were performed on a basketball inside a private condominium. The experiment was conducted in one session that lasted for 10 min, and data collecting followed the first experiment model. The two participants were asked to play against each other in a friendly game, without any reward for the winner.

This activity level of both participants were successfully assessed, even when we account for the error of the classifier. This result indicates that both the wearable IoT device and the HAR classifier can be used to measure activity levels of individuals and groups of individuals during physical activities. Those activity levels can be used by a qualified PESS teacher to (i) understand how an individual responds to an activity or PESS program when compared to other individuals or to his own past records, (ii) assess how a group of individuals - i.e. a class - responds to a particular activity or PESS program when compared to other groups, thus allowing for continuous improved based on this real time feedback and (iii) experiment on different PESS programs with the support of quantitative data.

4   Conclusion

In this work, we conducted two experiments: (i) the first with 12 volunteers, to evaluate the recognition of 10 different activity classes through a machine learning HAR classifier based on feet movement and posture information and (ii) the second with 2

volunteers, as a proof of concept of an alternative to investigate the engagement of individuals in PESS and validate the feasibility of our model. We were also able to expand the activity model by more than 65% - when comparing to the 6-activity classes model presented in [31] - with a drop of only 2.12% in the overall accuracy. This result suggests that the proposed wearable IoT prototype can be used for further investigation of HAR-related challenges and employed by other researchers in PESS studies.

Currently, we are employing the proposed wearable IoT device prototype in a study that aims to assess group and individual engagement in basketball PESS activities at a technical high school. We are now performing tests and reworking the protective case to allow for the experiment to commence, since the original case was not resilient enough to be used in prolonged games.

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