Physical Activity Intensity Monitoring of Hospital Workers using a Wearable Sensor

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ABSTRACT

Monitoring physical activity can be important to maintain a healthy lifestyle. This is the case with shift workers, who, due to their unorthodox sleep schedules, can develop health issues. This paper presents a model for classifying physical activity intensity into four levels: sedentary, light, moderate, and vigorous. The model uses data from a wearable accelerometer and is independent of the wearable location. A classifier was trained with 20 participants, obtaining an average accuracy of 83%.

CCS CONCEPTS

• **Applied computing → Health informatics**;

KEYWORDS

Activity Monitoring, Physical Activity Intensity, Wearable Sensors, Healthcare Workers, Shift Work

Figure 1: Smart Badge – a wearable sensor used to monitor physical activity intensity.

1 INTRODUCTION

Recent advances in wearable sensor technology provided the opportunity to measure physical activity. Physical activity has a direct impact in human physical and mental health and adequate levels of physical activity has been shown to correlate with the prevention of several conditions [10]. This means that self-monitoring physical activity can increase self-awareness which fosters behavior change and avoids health problems [6, 7].

Hospital workers could directly benefit from monitoring their physical activity since they experience several disturbances associated with shift work [3]. For example, shift work can disrupt human circadian rhythms, leading to physiological and psychologically effects, such as cardiovascular problems, diabetes and metabolic disturbances, and stress, fatigue and depression, respectively [2, 3, 5]. This way, physical activity self-monitor through wearable sensors can help hospital workers perceive and self-reflect about their physical effort while working, reducing the risk of health problems.

This study documents the development of an algorithm for monitoring intensity of physical activity of hospital workers using a wearable sensor in different positions. Since hospitals enforce strict antiseptic practices, a Smart Badge (Figure 1) equipped with an accelerometer was used. Signal processing techniques were implemented to extract features from accelerometer signal that were then fed to a classifier. The Smart Badge achieved an accuracy of 83% in the classification of four activity intensity levels: sedentary, light, moderate, and vigorous.

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2 BACKGROUND

The benefits of physical activity are documented in the literature, but keeping track of physical activity is complex. Physical activity includes a broad range of bodily movements performed in various contexts, therefore, it is difficult for most people to keep track of their physical activity and reach desired levels. To overcome tracking difficulties, commercially available solutions included wearable sensors mainly in the form of wrist bracelets or chest straps [4], and developed algorithms to count steps, classify activities, estimate distance, and infer caloric expenditures.

Furthermore, several studies analyzed wearable sensor data to classify qualitatively periods of physical activity intensity. Generally, accelerometer data was converted to activity-counts, and cut-point thresholds were defined to assess activity level [9]. However, these studies were developed in specific populations. Due to this limitation, researchers have used machine learning models to improve accuracy of classification of physical activity intensity. This approach was explored in research studies which used accelerometer data from sensors placed in different parts of the body, such as the waist [11], the hip [8], and the thigh [12].

3 MATERIALS AND METHODS

A machine learning algorithm was trained for classifying physical activity intensity into four different levels: sedentary, light, moderate, and vigorous. These levels were selected according to the Compendium of Physical Activities [1] which classifies physical activity based on activity intensity. The classifier was trained using data from multiple positions due to interviews held with hospital workers.

Since hospital workers need to engage in antiseptic practices, a Smart Badge was used as a wearable sensor. The Smart Badge used in this study contains a PCB which includes a microcontroller, a bluetooth low-energy driver, and an Inertial Measurement Unit.

Data Collection

The data collection protocol was defined considering activities workers reported to do at the hospital. For real scenario conditions, data collection protocol should be performed at the hospital. However, ethical concerns of disturbing patients or professionals during their work led to performing the collection in a laboratory.

The data collection protocol consisted of 14 activities that simulated tasks of hospital workers (Table 1). Each activity was performed for 2-6 minutes in order to acquire a total of 10 minutes in each activity intensity level. A total of 20 participants were included in this study. From this set, 14 were males and 6 females. The average age was 27 ± 3 years old, average height of 172 ± 40 centimeters, and average weight of 65 ± 15 kilograms. All participants provided informed consent before starting data collection.

Table 1: Activities and physical activity level.

Activity	Activity Level
Laying on bed	Sedentary
Sitting (not moving)	Sedentary
Standing (not moving)	Sedentary
Organizing material on shelves	Light
Cleaning table	Light
Cleaning small object (smartphone)	Light
Typing on a computer	Light
Walking (free) on different directions	Moderate
Pushing person on wheelchair	Moderate
Walking on treadmill (4.5 km/h)	Moderate
Descending stairs	Moderate
Mopping floor	Moderate
Running on treadmill (6.5-8 km/h)	Vigorous
Climbing stairs (fast pace)	Vigorous

The 14 activities were described to each participant prior to the start of data collection. Each participant wore 4 Smart Badges in 4 different body locations which were selected based on interviews: on the neck (loosen), clipped to the uniform on the chest, inside the trousers pocket, and clipped to the trousers pocket. To account for all possible orientations, the orientation of the Smart Badge was changed and used inside different pockets (right and left) between participants.

For collecting data to train and test the classifier, data was sent to a smartphone via Bluetooth Low Energy. Data was annotated in the smartphone using an application especially developed for that purpose. A sampling frequency of 100Hz was used.

Machine Learning Pipeline

We employed *scikit-learn* v0.19.1, a Python Machine Learning library, on Python 2.7.13. The library was used to extract meaning from the collected data in pre-processing, feature extraction, feature selection, and classification. The computational cost of each operation was considered to minimize power consumption and enable the implementation in an embedded device.

Signal pre-processing. The Smart Badge accelerometer measures acceleration caused by gravity or tilting action on the three physical axes (x, y and z). However, due to its degrees of freedom and the requirement of being used in different positions and orientations, only the magnitude of the acceleration was computed, since it is independent of the accelerometer orientation. To study different frequency rates, data was collected at 100Hz and then was down-sampled to lower rates, namely, 10, 20, 30, and 50Hz. An example of the

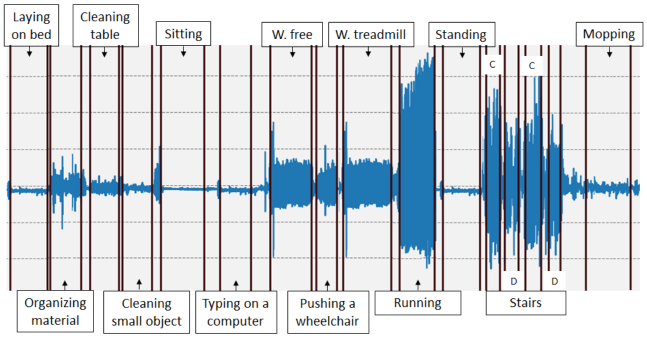

Figure 2: Magnitude of acceleration for 14 activities. The activities presented are listed on Table 1 (stair climbing and descending are represented by letters C and D, respectively).

magnitude signal of the Smart Badge clipped to the uniform for all activities performed is depicted in Figure 2.

Feature Extraction and Selection. For feature extraction, magnitude signals of each Smart Badge's accelerometer were segmented into fixed length windows without overlapping. Different window lengths were tested, namely, 1, 5, and 10 seconds. Fixed windows were chosen to reduce power consumption and memory. For each time-window, only time-domain features were extracted since they have lower computation cost. Features such as mean, median, maximum, minimum, autocorrelation, difference between maximum and minimum, median absolute deviation, standard deviation and percentiles (10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th}) were extracted (using Python *numpy* v1.11.3). A total of 13 features were computed. After feature extraction, it was possible to see that many of the features were correlated and could be removed without loosing information, therefore, Forward Feature Selection was applied.

Classification. The overall dataset was divided into train and test sets. The train set was composed by 15 participants ant the test set by 5 participants. The test set was never used for training the classifier. A classification model based on decision trees was selected beacause it is computationally fast and does not include complex mathematical operations. To train an independent position classifier, samples of the four Smart Badge's placements were fed to the classifier and labeled as sedentary, light, moderate or vigorous. During the training phase, for validation purposes and selection of parameters such as resampling frequency and window size, leave-one-user-out cross-validation was employed.

Performance. For performance evaluation, the trained decision tree was used to classify activity intensity levels of the test set. Confusion matrix and accuracy were computed to assess misclassification, and sensitivity and specificity were computed for each activity level class.

Table 2: Total duration (minutes) and sample size (number of 10 seconds windows) for the 4 activity intensity levels.

Activity Level	Train Total time	Train Windows	Test Total time	Test Windows
Sedentary	551	3308	175	1047
Light	562	3368	161	965
Moderate	485	2909	166	993
Vigorous	312	1871	92	556

4 RESULTS

Overall, more than 41 hours of data were recorded for 14 activities divided into 4 activity intensity levels. The dataset was divided into train and test sets and details regarding the content of the dataset are provided in Table 2.

As mentioned in the methods, some parameters regarding signal pre-processing and feature extraction were tested to achieve better differentiation between classes and reduce computational cost. From the range of resampling frequencies tested, reducing sampling frequency to 30Hz resulted in acceptable accuracies and fixed time windows of 10 seconds achieved better results. Forward Feature Selection was performed to select the most discriminant features. Computing just 2 features reached an accuracy that did not significantly improved by adding more features. Features selected were median absolute deviation, which is an indicator of signal variance, and signal mean which relates to signal intensity.

Table 3 shows the results of activity level classification, which reached 83,21% as an overall averaged accuracy across all activity levels. As it can be seen, major confusions were obtained between light and sedentary levels and some between light and moderate, which led to 69 (6,5%) instances of sedentary misclassified as light, 346 (35,8%) instances of light misclassified as sedentary, and 159 (16%) instance of moderate misclassified as light.

Light intensity predictions had lower sensitivity since a considerable number of positives for light intensity were misclassified as sedentary. This led to the lower specificity of the sedentary predictions, since a considerable number of non-sedentary predictions were classified as so. This result was due to the fact that light intensity activities such as a cleaning a table, cleaning small object, and typing on a computer did not produce leg movement which was probably perceived as sedentary behavior for the two Smart Badges positioned in the trousers pocket. This confusion between light and sedentary intensity levels was expected since activity level labeling must consider the activity which is being executed despite some of the Smart Badge positions not being the most adequate to perceive the movement of that specific activity.

Table 3: Confusion matrix, sensitivity and specificity for prediction of sedentary, light, moderate and vigorous. Overall accuracy of 83,21%. Rows represent true labels and columns list predicted labels.

	Sedentary	Light	Moderate	Vigorous	Sensibility (%)
Sedentary	978	69	0	0	93,41
Light	346	602	17	0	62,38
Moderate	0	159	831	3	83,69
Vigorous	0	0	4	552	99,28
Specificity (%)	86,24	91,22	99,18	99,90	

5 DISCUSSION

The trained classifier achieved an accuracy of 83%, which is appropriate, considering users should only need a baseline of their activity for self-reflecting about their physical effort and potentially avoid health complications.

The obtained results cannot easily be compared with previous work, because studies have employed different protocols for data collection and different types of classifiers. For example, Staudenmayer et al. [11] used Artificial Neural Networks (ANN) to distinguish activity levels securing sensors solely on the waist and achieved and accuracy of 88% in classifying activity type into low-level, household, locomotion and vigorous. Zhang et al. [13] compared different machine learning models applied to a wrist-worn sensor, reporting accuracies of 92% in classifying four types of daily activities including sedentary, household, walking and running activities. Trost et al. [12] also applied ANN to accelerometer data from the thigh, obtaining a 80% accuracy in classifying 5 distinct physical activity types: sedentary, walking, running, light intensity household activities or games, and moderate-to-vigorous games and sports. Montoye et al. [8] compared body positions and used ANN to classify physical activity into sedentary, light and moderate-to-vigorous intensity, achieving accuracies of 91%, 99% and 90% for hip, thigh and wrist positions, respectively.

The accuracy of our classifier compares with the outlined approaches, even achieving a high accuracy, considering our classifier was trained to recognise accelerometer data from multiple body positions.

6 CONCLUDING REMARKS

The aim of this study was to monitor physical activity intensity of hospital workers using a wearable sensor, enabling them to identify intensity of work, and thus monitor the amount of effort they invested during each shift. This paper presented a first approach for classifying physical activity intensity of hospital workers with a Smart Badge. Since the previous data collections were focused on simulated activities, future work will focus on validating the model in a real scenario by collecting activities of workers at the hospital.

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