Exploring Complexity in Health: An Interdisciplinary Systems Approach
A. Hoerbst et al. (Eds.)

doi:10.3233/978-1-61499-678-1-804

Towards a Personal Health Record System for the Assesment and Monitoring of Sedentary Behavior in Indoor Locations

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Abstract. Background: Sedentary behavior has been associated to the development of noncommunicable diseases (NCD) such as cardiovascular diseases (CVD), type 2 diabetes, and cancer. Accelerometers and inclinometers have been used to estimate sedentary behaviors, however a major limitation is that these devices do not provide contextual information such as the activity performed, e.g., TV viewing, sitting at work, driving, etc. Objective: The main objective of the thesis is to propose and evaluate a Personal Health Record System to support the assessment and monitoring of sedentary behaviors. Results: Until now, we have implemented a system, which identifies individual's sedentary behaviors and location based on accelerometer data obtained from a smartwatch, and symbolic location data obtained from Bluetooth beacons. The system infers sedentary behaviors by means of a supervised Machine Learning Classifier. The precision in the classification of the six studied sedentary behaviors exceeded 90%, being the Random Forest algorithm the most precise. Conclusion: The proposed system allows the recognition of specific sedentary behaviors and their location with very high precision.

Keywords. Sedentary Behavior Recognition, Data Mining, Sensor Mining, Accelerometer, BLE Beacons, PHR, PHR-S

1. Introduction

Sedentary behavior is frequently defined as any waking activity characterized by low levels energy expenditure (≤1.5 METs) while sitting or reclining. Epidemiological evidence shows that sedentary behavior is associated to the development of noncommunicable diseases (NCD) such as cardiovascular diseases (CVD), type 2 diabetes, and cancer [1]. Furthermore, some studies have demonstrated that high levels of sedentary time and low levels of moderate to vigorous physical activity are strong and independent predictors of early death from any cause [2]. Accelerometers and inclinometers has been used for measuring sedentary behavior, but their main limitation is that these do not provide contextual information such as the activity performed, e.g., using computers, tablets, cellphones, TV viewing, sitting at work, driving, transportation, relaxing, etc. [3][4]. Loveday et al. performed a systematic review of technologies for assessing location of physical activity and sedentary behavior, concluding that despite GPS was the most widely used location-monitoring

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technology, its precision and availability in indoor locations (where most of sedentary activities occur) is not enough to provide an accurate measure of sedentary behavior location [5]. Furthermore, in a process of health promotion and disease prevention, it is important that people actively involved, identify his/her risk factors and there is a continuous communication with health professionals. That's why a Personal Health Record System (PHR-S) would be the right tool for evaluation and monitoring of sedentary behavior. One of its features is that it enables the use of medical, mobile devices or sensors to obtain health information. Finally, the implementation of a PHR-S for the evaluation and monitoring of sedentary behavior would help to establish the dose-response relationship between sedentary behavior and health outcomes of a person.

Considering the problems described above, this proposal attempts to answer the following research question: How support the objective assessment and continuous monitoring of sedentary behaviors in indoor locations? In this context, the main objective of the thesis is to propose and evaluate a Personal Health Record System to support the assessment and monitoring of sedentary behaviors.

2. Specific Objectives – Contributions

1. To design and implement the architecture of a symbolic location system of sedentary individuals in indoor locations.
2. To propose a classifier algorithm to classify sedentary behavior based on accelerometer and symbolic location data.
3. To develop a PHR-S to support the assessment and monitoring of sedentary individuals that integrates the symbolic location system and the proposed classifier.
4. To evaluate the accuracy of the assessment and monitoring sedentary behavior provided by the proposed PHR-S.

3. Methods

Until now we have experimented with a system that integrates a symbolic location system which provides a symbolic location for instance: close to the TV or PC, in the bedroom or in the car, and a classifier algorithm which recognizes six sedentary activities (Table 1) selected based on the taxonomy of sedentary behaviors proposed by Chastin [6]. A data mining process was carry out. To this end, labeled data from 15 people, 8 men and 7 women, performing each sedentary activity for 5 minutes were collected. The volunteers' average age was 44 years, ranging from 25 to 87 years and they did not have physical limitations to carry out the requested tasks. We used three devices: a pebble classic smartwatch (Pebble, Redwood City, CA) a LG G3 smartphone (LG Electronics, Seoul, Korea), and three Estimote beacons (Estimote Inc, New York, NY). We developed an android app that stores 25 samples per second of pebble acceleration data, the numeric identifier of the two closest beacons placed at home, the volunteer ID and the sedentary activity performed. For the feature extraction process, we took 125 or 250 samples and transforming them into a single record (an example). The features extracted were 10 based on data from acceleration values in X, Y and Z axis: average, standard deviation and mean absolute difference for each axis, and the average acceleration; and two based on the beacons: averages of the identifiers of the two closest beacons. Finally, we induce a personal model for each volunteer in the Weka data mining tool [7] using 10-fold cross-validation. This type of model is characterized by being trained and evaluated by only the same person who will use it.

4. Preliminary Results

To obtain class balance (equal number of examples per activity), two analysis are performed separately: a) classification of all the activities performed by all 15 participants, but excluding the driving activity and b) classification of all the activities performed by the four participants who performed the driving activity. Table 1 presents the average precision of the three classification algorithms which showed better precision: RF, NN and J48. The three classification techniques were run employing an example duration (ED) of 5 and 10 seconds (125 and 150 samples respectively). As shown in Table 1, higher average percentage accuracy in the recognition of all sedentary behavior is obtained using an ED of 5 seconds. Table 1 also shows that the percentages of precision in the classification of all the studied sedentary behaviors exceeded 90%, being the RF algorithm the most precise one, with an average of 95,06% and 92,55% excluding and including the driving activity, respectively.

Table 1. Accuracy of the classification of sedentary behaviors**.**

	Analysis (a) 15 participants - 5 activities						**Analysis (b) 4 participants - 6 activities**					
	NN		**J48**		**RF**		**NN**		**J48**		**RF**	
	5s	**10s**	**5s**	**10s**	**5s**	**10s**	**5s**	**10s**	**5s**	**10s**	**5s**	**10s**
a	91,81	85,28	89,20	82,28	90,98	87,88	91,75	85,15	87,35	82,05	87,90	86,77
b	94,36	88,95	93,10	88,76	95,77	92,64	91,47	88,07	91,42	84,72	94,22	92,07
c	93,78	94,00	95,26	94,76	94,94	94,33	86,77	84,12	86,07	90,05	88,65	85,45
d	90,42	90,72	91,28	85,46	94,18	90,82	84,25	84,72	87,7	89,45	90,27	86,00
e	99,64	99,27	99,28	99,29	99,46	99,64	98,52	98,60	97,25	97,27	96,05	97,12
f	-	-	-	-	-	-	95,97	93,42	97,20	94,70	98,57	96,25
Overall	**94,01**	**91,64**	**93,62**	**90,11**	**95,06**	**93,05**	**91,45**	**89,02**	**91,15**	**89,70**	**92,55**	**90,62**

a: Sitting watching TV, **b:** Lying down watching TV, **c**: Having breakfast/lunch/dinner, **d** : Using a computer, **e**: Being transported by car , **f** : Driving a car

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