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A mobile system for sedentary behaviors classification based on accelerometer and location data

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ABSTRACT

Background: Sedentary behaviors are 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 enough contextual information in order to recognize the specific sedentary behavior performed, e.g., sitting or lying watching TV, using the PC, sitting at work, driving, etc.
Objective: Propose and evaluate the precision of a mobile system for objectively measuring six sedentary behaviors using accelerometer and location data.
Results: The system is implemented as an Android Mobile App, which identifies individual's sedentary behaviors based on accelerometer data taken from the smartphone or a smartwatch, and symbolic location data obtained from Bluetooth Low Energy (BLE) beacons. The system infers sedentary behaviors by means of a supervised Machine Learning Classifier. The precision of the classification of five of the six studied sedentary behaviors exceeded 95% using accelerometer data from a smartwatch attached to the wrist and 98% using accelerometer data from a smartphone put into the pocket. Statistically significant improvement in the average precision of the classification due to the use of BLE beacons was found by comparing the precision of the classification using accelerometer data only, and BLE beacons localization technology.
Conclusions: The proposed system provides contextual information of specific sedentary behaviors by inferring with very high precision the physical location where the sedentary event occurs. Moreover, it was found that, when accelerometers are put in the user's pocket, instead of the wrist and, when symbolic location is inferred using BLE beacons; the precision in the classification is improved. In practice, the proposed system has the potential to contribute to the understanding of the context and determinants of sedentary behaviors, necessary for the implementation and monitoring of personalized noncommunicable diseases prevention programs, for instance, sending sedentary behavior alerts, or providing personalized recommendations on physical activity. The system could be used at work to promote active breaks and healthy habits.

1. Introduction

Sedentary behavior is frequently defined as any waking activity characterized by low levels of energy expenditure ($\leq$1.5 METs) while sitting or reclining [1]. Epidemiological evidence shows that sedentary behavior is associated to the development of non-communicable diseases (NCD) such as cardiovascular diseases (CVD), type 2 diabetes, and cancer [2]. Furthermore, some studies have demonstrated that high levels of sedentary time and low levels of moderate or vigorous physical activity are strong and independent predictors of early death from any cause [3].

A major future research topic identified in the literature is the improvement of the technology currently used for the objective measurement and characterization of sedentary behavior [3–6]. Methods for assessing sedentary behavior are typically classified as subjective and objective ones: subjective methods include self-report questionnaires, interviews and diaries; while objective measures include the use of devices such as accelerometers, inclinometers, heart rate (HR) monitors, etc. [4]. Subjective methods, especially self-report questionnaires, are widely used,

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feasible, cost-effective, and could obtain information about the context in which sedentary behaviors occur. However, reliability and validity limitations have been reported in the literature, caused among others, by the difficulty for a person to recall and recognize sedentary behaviors because they are sporadic, incidental and may occur in different locations [4,7]. As an example, the International Physical Activity Questionnaire (IPAQ), which is one of the more accepted instruments for measuring physical activity and sitting behavior has shown moderate reliability but moderate to poor validity compared to accelerometers [7].

Accelerometers and inclinometers are, typically, electronic devices used to estimate sedentary time based on the identification of low movement counts (the frequency and amplitude of acceleration of the body) at specified cut points [3]. These devices overcome some of the limitations of subjective methods, providing a more accurate and objective estimation of sedentary time [3,7]. However, as identified by a recent systematic review [7] and a Meta-Analysis [6], the main limitation of inclinometers and accelerometers for measuring sedentary behaviors is that these do not provide contextual information to recognize specific sedentary behaviors e.g., using computers, tablets, cellphones, TV viewing, sitting at work, driving, transportation, relaxing, etc. Geolocalization (e.g, using Global Positioning Systems – GPS) combined with accelerometry has been recognized as an alternative method to improve the accuracy of information about the context of sedentariness [3]. In this direction, 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 technology, its precision and availability in indoor locations (where most of sedentary behaviors occur) is not enough to provide an accurate measure of sedentary behavior location [8]. Radio-frequency identification (RFID) and Bluetooth Low Energy (BLE) beacons (iBeacons), as emerging technologies for "tagging" objects in the context of Internet of things (IoT), are mentioned in the review as technologies with the potential to be used for indoor location (here referred as symbolic location).

The objective of this paper is to propose and evaluate the precision of a mobile system for objectively measuring sedentary behaviors using accelerometer and location data collected from nearby BLE beacons. Two experiments were performed separately: one using accelerometer data from a smartwatch attached to the wrist and location data from BLE beacons, and another using accelerometer data from a smartphone put into the pocket and location data from BLE beacons. Finally, the precision of the classification is compared in two scenarios: one using accelerometer data only, and the other adding location data collected from the BLE beacons.

1.1. Related work

There is a large number of studies using accelerometers and other motion sensors for activity classification, fall detection, gait analysis, rehabilitation, balance training and identification of psychological states [9]. Some of them include the classification of sedentary behaviors as a type of low intensity physical activity, but the task of classifying specific sedentary behaviors such as watching TV, using PC, sitting at work, driving, etc.; has been little studied. In order to identify relevant studies providing the classification of specific sedentary behaviors, we performed a literature search on Pubmed, IEEE Xplore and Science direct databases. Our inclusion criteria were: 1) Papers published in English or Spanish languages. 2) Papers describing a system based on a physical activity monitor or other devices used to classify at least one sedentary behavior including its posture. The search query used was the following:

(*sedentary lifestyle OR sedentary activity OR sedentary behavior*) *AND* (*classification OR tracking OR monitoring OR recognition*) *AND* (*physical activity monitor OR wearable OR wearable monitor OR activity monitor OR system OR technology OR RTLS OR camera OR accelerometer OR indoor positioning system OR RFID OR RTLS OR PALMS OR BLE OR Bluetooth OR NFC OR location measurement system OR indoor tracking system*)

The search resulted in 91 papers. After applying the inclusion criteria, only 5 papers met the requirements. The selected papers are summarized in Table 1.

Most of the papers analyzed were based on traditional physical activity devices such as Actigraph, ActivPal, GENEActive, Actical, Actiheart, and Stepwatch, commonly used to recognize one or more typical postures such as lying, sitting or standing. However, only the study performed by Spinney et al. [14] included one of the emerging location technologies described above. The authors implemented a system composed by two modules: an ActivPal sensor for classifying walking, standing and sitting postures; and the OpenBeaconSystem, an RFID-based location system used to register where these postures occurred. The baseline precision level of that system was 86.1%, which is the precision related to the recognition of the place in which the person is located within the indoor environment. In [10], a precision of 100% was reached when classifying three body postures: sitting, standing and lying, but reached using simultaneously an inclinometer and an accelerometer on the hip and thigh, respectively. In [11], GENEActiv and ActivPAL devices worn in the wrist and thigh were used, in order to identify sitting and standing postures. A better precision was obtained when wearing the ActivPAL on the thigh to classify between sitting and standing. The IDEEA project [12] used a combination of 6 accelerometers which were located in different parts of the body. This study, unlike [10], recognized low-level postures such as lying on the side or face up, and tried to recognize when the person was reclining, but not obtaining good results. The study described in [13] did not report the precision of the classification of postures; instead, the data was used to infer the time the person was sitting.

2. Material and methods

The main component of the proposed system is a Classifier system, which automatically recognizes six sedentary behaviors: sitting watching TV, reclining watching TV, having breakfast/lunch/dinner, using a computer, driving a car, and being transported by car. These sedentary behaviors were selected based on the taxonomy of sedentary behaviors proposed by Chastin et. al [15]. A data mining process was carry out using supervised machine learning algorithms. To this end, labeled data from 15 people, 8 men and 7 women, performing sedentary behaviors were collected. Participants did not have physical limitations to carry out the requested tasks. The volunteers' average age was 44 years, ranging from 25 to 87 years.

Another important component of the system is the technology used for collecting user's location data. Based on the review presented in the introduction, RFID and BLE were considered. The two factors taken into account when choosing the type of indoor location technology were its required accuracy and its total cost of implementation. In our scenario, a very accurate indoor location system is not necessary, because obtaining the user's symbolic location is enough in order to identify his/her activities based on nearby objects (TV, Couch, desk, etc.).Regarding costs of the implementation infrastructure, the implementation of an RFID-based indoor localization system involved the use of several components (active tags, readers and their antennas, controller and its software) making it more complex and costly compared to a system based in BLE. In a BLE beacons system, the smartphone

Table 1
Overview of studies on sedentary behavior recognition.

Reference	Devices	Worn in	Classification result	Postures recognized	Reported Precision
[10]	CXTA02 inclinometer And CXL02LF3-R accelerometer	Hip and thigh	Body posture	Sitting, standing, lying	100%
[11]	GENEActiv, ActivPAL.	Wrist, thigh	Body posture	Sitting, standing	85% wrist 96% thigh
[12]	IDEEA	Chest, hip both thighs, both ankles	Body posture	Lying, reclining, sitting, standing	91%
[13]	ActivPAL, Actigraph.	Thigh	Body posture and Physical activity intensity	Sitting	n.a.
[14]	ActivPAL, OpenBeaconSystem	Thigh	Body posture + where activity occurs	Sitting, standing	86.1%

functions as reader and controller, and the beacons as active tags making it simpler and less expensive. In consequence, BLE beacons was the preferred technology used to obtain the symbolic location in our experiments, using low-cost BLE tags set in advertisement mode, so they can be detected by smartphones.

2.1. Data collection and transformation

Data was collected using three devices: a pebble classic smartwatch (Pebble, Redwood City, CA) a LG G3 smartphone (LG Electronics, Seoul, Korea), and four Estimote BLE beacons (Estimote Inc, New York, NY). The Pebble was chosen because it is one of the few smartwatches that provides access to raw accelerometer data through its Software Development Kit (SDK). The choice of Estimote beacons was due to their widely commercial use and availability of a SDK to develop Android mobile Apps. A “watchapp” was developed and installed in the smartwatch, which allows sending accelerometer data via Bluetooth to the smartphone. A mobile Android App was also developed and installed in the smartphone, which allows entering the ID of the person and the description of the sedentary behavior to be performed.

The data collection and annotation processes were performed using the implemented Android mobile App, which collects the acceleration data from the smartwatch and from its own accelerometer, and location data from the two closest beacons. The App creates a text file with the data received, and annotates it with the user’s entered labels for each sedentary behavior. The accelerometer data was collected every 40 ms, which is equivalent to 25 samples per second. The advertising interval value used by the beacons was 1000 ms; that is, each beacon sends the signal every second. Because standard classification algorithms cannot directly handle time series data [16], a feature extraction process was implemented. The feature extraction was performed using a desktop application adapted from the one used in [17]. For doing that, raw data from the text file generated by the mobile application was divided into segments of 5 s (called example duration), which is equivalent to taking 125 samples of raw data and transforming them into a single record (each segment is called an example). This record contained 22 features in total, 10- per used device (smartwatch or smartphone) and two based on the Beacons’ ID. The features calculated per each device included acceleration data in X, Y and Z axis: average acceleration, standard deviation and mean absolute difference for each axis, plus the average acceleration (10 features in total). The remaining two features were based on the proximity to the nearest beacons: average identifier of the closest beacon and average identifier of the nearest second beacon. Additional experiments were performed by extending the example duration (ED) to 10 s, as it is suggested in [17], in order to find a more accurate ED.

2.2. Experiment execution

A research assistant asked each participant to locate the beacons at home as follows: one in the place where he/she would normally eat his/her food (dining room), the second close to his/her TV, the third one close to his/her computer, and the last one was put inside a car. Participants were requested to wear the smartwatch in the non-dominant hand and the smartphone in the pocket on the same side of the smartwatch. Every sedentary behavior was recorded during five minutes, but for feature extraction only the 3 central minutes were taken into account as a strategy to transform data fully corresponding to the sedentary behavior performed. Consequently, using an ED of 5 s, the data set of each participant consisted of 180 examples, 36 for each activity. Four participants had 36 additional samples, corresponding to driving a car.

2.3. Selection of the classification model and algorithms

Once the dataset was collected and the feature extraction process was performed, the classification models were induced. Extended from physical activity recognition research field, there are three types of classification models that can be used for sedentary behaviors recognition [17]:

- Personal model: it is a classification model generated to be used by a single person; therefore, it is trained and evaluated with data from only the user for whom the model is built. This requires the collection of labeled data for each activity to be classified.
- Impersonal/universal model: It’s a classification model in which the training and test datasets have no common users, i.e., the evaluation set contains data from a person different from the panel of people who trained it. Unlike personal and hybrid models, this model does not need to collect labeled data from a new user to perform the classification task, but it may require many people to train it with the aim of obtaining a good level of accuracy in the classification. This is the preferred training model of the different physical activity monitoring devices and Apps.
- Hybrid model: this model is a combination of the previous model types. The training set has data from a panel of people, including data from the subject for whom the model is intended, for that reason, similar to the personal model, this model also requires training data and model generation for each new user. This could potentially outperform the personal model because it utilizes additional training data from other users.

The classification model selected in this experiment was the personal model because it provides a better precision, compared with the precision of impersonal or hybrid models [17], especially when a small data set is used. Moreover, only two examples (with an Example Duration of 10 s) are necessary to surpass the accuracy of impersonal models. It is important to mention that none of the relate works described mentioned the type of model used.

Finally, different classification algorithms included in the WEKA data mining suit [18] were evaluated in the experiments, including the default options and using 10-fold cross: neural networks (Multilayer perceptron), instance-based (NN), rule induction (J-Rip), naive Bayes (NB), logistic regression (RBF), support vector machines (SMO, LibSVM) and decision trees (J48, RF). 10-fold cross validation was preferred because, as described above for personal models, training and evaluation data comes from the same person.

Table 2
Confusion matrix for RF.

Analysis	(a) 15 participants – 5 activities					(b) 4 participants – 6 activities					
	a	b	c	d	E	a	b	c	d	e	f
A	498	14	9	**19**	0	131	6	3	2	1	1
B	15	516	3	4	2	10	130	2	2	0	0
C	8	4	519	8	1	4	2	128	10	0	0
D	**22**	5	12	501	0	4	0	11	129	0	0
E	1	0	3	0	536	0	0	0	0	139	**5**
F	–	–	–	–	–	0	0	0	0	**1**	143

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

3. Results

With the objective of comparing the precision of two different types of devices used (smartwatch or smartphone) and in consequence the place where accelerometer data would be acquired (wrist or thigh); two experiments were performed separately. In the first experiment, the 10 accelerometer based features were calculated from accelerometer data extracted from a smartwatch attached to the wrist, and 2 more features calculated from nearby BLE beacons. In the second experiment, the 10 accelerometer based features were calculated from accelerometer data obtained from a smartphone in the user's pocket and 2 more features extracted from nearby BLE beacons. To obtain class balance (equal number of examples per sedentary behavior), the two analysis were performed separately in each experiment. The first analysis comprised the classification of five of the six activities performed by all 15 participants: a) sitting watching TV, b) reclining watching TV, c) having breakfast/lunch/dinner, d) using a computer and e) being transported by car. The sedentary behavior "driving a car" was excluded because not all participants were able to drive a car. The second analysis included the classification of all the six activities performed by the four participants, therefore including the sedentary behavior "driving a car". This analysis was restricted to only 4 participants that were able to perform the driving a car task.

3.1. Experiment 1

Table 1 shows the average precision of the three classification algorithms offering better precision: RF, NN and J48. All three classification algorithms were tested employing an ED of 5 and 10 s. As shown in Table 1, higher average precision in the recognition of all sedentary behavior was obtained using an ED of 5 s.

Table 1 also shows that the percentages of precision in the classification of all the six studied sedentary behaviors exceeded 90%, being the RF algorithm the most precise one, with an average precision of 95,06% and 92,55% excluding and including the sedentary behavior "driving a car", respectively.

Table 2, analysis (a), shows that the easiest sedentary behaviors to learn were driving and being transported by car; and the most difficult sedentary behaviors to classify were "sitting watching TV" and "using a computer", due to the fact that most common misclassification occurred in the activity "using a computer", which was classified as "sitting watching TV" and vice versa, with 22 and 19 errors, respectively. It is important to note from Table 2, analysis (b), that only 5 errors occurred in the classification of the activity "being transported by car", which was classified as "driving a car", and only one error was presented in the opposite direction.

3.2. Experiment 2

The second experiment was configured likewise experiment one, but the acceleration data was taken from a smartphone placed in the pocket. Table 3 shows that, for analysis (a) considering only the first five activities performed for all 15 participants, the better precision was obtained with the RF algorithm, followed by the NN and J48 algorithms. In contrast, for analysis (b) with only four participants but six activities; the better result was obtained with the J48 algorithm, followed by the RF and NN algorithms respectively. The three classification algorithms were also tested employing an ED of 5 and 10 s, obtaining a higher average percentage precision using an ED of 5 s.

In analysis (a), the average percentage precision exceeded 95% for the three classification algorithms, being the highest percentage given by the RF algorithm with 98.28%. This result is similar to the one obtained in [17], where the most precise algorithm was Nearest Neighbor (NN), followed by Random Forest (RF). It is worth to mention that this previous study was focused on the classification of physical activity and also using a smartphone placed in the pocket.

It is important to note from Table 3, analysis (b), that the J48 algorithm best classifies the activities "being transported by car" and "driving car", for that reason it overcome the average precision of the RF algorithm. However, the total average percentage precision is quite low (84.9%) because, as shown in Table 4 – analysis (b), there were 39 misclassifications when classifying between "Being transported by car" and "driving car".

3.3. Precision of the system including and excluding symbolic location data

In order to explore the impact in the precision of the system when including or excluding the symbolic location data given by the beacons, the three aforementioned algorithms were trained including or excluding the two features based on the proximity to the nearest beacons (average identifier of the closest beacon and average identifier of the nearest second beacon). Table 5 shows the average precision of the system including or excluding the two features based on the proximity to the nearest beacons. The analysis included a verification of the statistical significance of the increased precision in the classification, applying a T- student significant test with a confidence interval of 0.5.

4. Discussion

The classification of physical activities has been widely studied; however the objective classification of sedentary behaviors using movement sensors and wearable devices constitutes a new research field. This type of behavior commonly happens in two body postures: sitting or reclining. Although there are devices able

Table 3
Average precision of the classification of sedentary behaviors using smartphone.

Analysis	(a) 15 participants – 5 activities						(b) 4 participants – 6 activities					
Algorithm	NN		J48		RF		NN		J48		RF	
ED	5s	10s	5s	10s	5s	10s	5s	10s	5s	10s	5s	10s
A	95.67	92.46	95.32	92.39	97.09	96.32	92.65	88.32	90.45	88.85	94.72	92.27
B	98.88	98.9	98.17	98.88	99.28	99.27	99.3	98.67	99.32	98.67	100	100
C	98.91	97.52	98.9	97.86	98.94	99.64	99.32	98.6	100	100	100	100
D	96.08	93.7	94.46	93.66	96.81	95.5	92.9	88.35	86.8	85.27	92.97	88.87
E	99.64	98.58	99.45	99.29	99.33	99.82	39.55	36.07	72.45	62.77	46.77	37.37
F	–	–	–	–	–	–	46.57	40.57	60.32	63.17	49.05	36.81
Overall	97.84	96.25	97.26	96.42	**98.28**	98.12	78.37	75.07	**84.9**	83.15	80.8	76.27

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

to classify these postures, the task of classifying specific sedentary behaviors or activities that a person is performing in those positions at specific moments requires contextual information. This paper demonstrates that the use of BLE beacons in conjunction with a smartwatch or smartphone can be used to precisely perform the classification of specific sedentary behaviors, supported by a supervised machine learning algorithm.

A first analysis of the precision of the system in the classification process was reported, considering the data obtained from 15 participants in the experiments, but restricted to five sedentary behaviors: sitting watching TV, reclining watching TV, having breakfast/lunch/dinner, using a computer and, being transported by car (analysis (a) in experiments 1 and 2). In this scenario, when acquiring the acceleration data from the smartwatch, the RF algorithm was the most precise one with an average percentage precision in the classification of 95.06%. When acquiring the acceleration data from the smartphone put into the pocket, a better precision was obtained (98.28%). This precision was obtained also with the RF algorithm. The improvement in the precision of the classification is assumed not due to the type of sensor used (smartwatch of smartphone) because the technology used is similar, but because of the position of the sensor in the body. As it has been reported in previous studies dealing with physical activity recognition, a better precision is obtained when accelerometers are put in the thigh, instead of the wrist [11,19].

A second analysis of the precision of the system included the classification of all the six activities performed by the four participants, therefore including the sedentary behavior "driving a car" (analysis (b) in experiments 1 and 2). Due to the fact that all participants were not able to drive a car, this analysis was restricted to only 4 of the 15 participants. In the case of the experiment using accelerometer data acquired with a smartwatch, the RF algorithm was the most precise one with an average percentage precision in the classification of 92.55%. When acquiring the acceleration data from the smartphone put into the pocket, the highest average precision obtained was lower than in the case of the smartwatch (84.9%), and it was obtained using the J48 algorithm.

Table 4
Confusion matrix for RF (analysis a) and J48 (analysis b).

Analysis	(a) 15 participants – 5 activities					(b) 4 participants – 6 activities					
	a	b	c	d	e	a	b	c	d	e	F
A	526	2	2	**10**	0	134	2	0	8	0	0
B	4	536	0	0	0	3	141	0	0	0	0
C	0	0	537	3	0	0	0	139	5	0	0
D	**10**	1	2	527	0	5	0	0	139	0	0
E	0	0	0	0	540	0	0	0	1	122	**21**
F	–	–	–	–	–	0	0	0	0	**18**	126

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

Using acceleration data from the smartphone inside the pocket provides in general a better precision than when using the smartwatch for most of the activities. However, it was very difficult to classify between "driving a car" and "being transported by car" using only the acceleration data taken by the smartphone placed in the pocket. It can be confirmed by comparing the confusion matrixes in analysis (b), Tables 2 and 4, where more misclassifications errors were found in the scenario using the smartphone. These results might mean that the acceleration data taken from the hand on which the smartwatch is wear while a person drives a car, is very relevant to differentiate between these two sedentary behaviors. It might be explained because of the movement of the hand when performing distinct sedentary behaviors is different, for example when driving a car or being transported by car, or when eating or using a computer, etc. In consequence, more research is necessary in order to determine the most appropriate place of the sensor in the body to acquire the acceleration data, for example from the wrist, hip or thigh. In order to do that, a new data set must be obtained which shall include more sedentary behaviors performed at the same place, for example writing, using a pc or a cellphone or doing nothing, at the desk. The taxonomy of Chastin et. al [15] describe those new sedentary behaviors.

A third analysis of the precision of the system was performed with the objective to assess the contribution of the BLE beacons data in the overall precision of the classifier system, as summarized in Table 5. The results demonstrate that the use of BLE beacons increased the average precision of the classifier in both experimental scenarios (using accelerometer data from a smartwatch or a smartphone) and for all three classification algorithms. Particularly, the precision in the classification using accelerometer data from the smartwatch was increased by 6.44% for the RF algorithm, 5.13% for the NN algorithm and 8.11% for the J48 algorithm when adding the BLE beacons data. In the scenario colleting accelerometer data from the smartphone, the precision in the classification due to the BLE beacons data was increased by 1.62%, 0.62% and 3.6% for the RF, NN and J48 algorithms, respectively. Moreover, in the experiment using the Smartwatch, the increased precision was statistically significant ($p < 0.05$) using the RF, NN and J48 algorithms, while for the experiment with the smartphone, only the average precision in the classification obtained with the J48 algorithm and using the BLE beacons was significant higher that the precision obtained without the BLE beacons. This could confirm on the one hand, that the better precision using the smartphone scenario was mainly influenced by the position of the accelerometer sensor in the pocket although, as described in the previous paragraph, it is necessary to collect more data in order to confirm this finding. On the other hand, it demonstrates that the symbolic location features offered by the beacons are very relevant in systems where acceleration data has

Table 5
Average precision of the system including and excluding symbolic location data.

	Experiment 1 (Smartwatch)				Experiment 2 (Smartphone)			
	Neglecting beacons	Including beacons	Dif	p	Neglecting beacons	Including beacons	Dif	p
RF	88.62	95.06	6.44	0.014	96.66	98.28	1.62	0.466
NN	88.88	94.01	5.13	0.022	97.22	97.84	0.62	0.252
J48	85.51	93.62	8.11	0.011	93.66	97.26	3.6	0.026

to be taken from the wrist, like in most wearable physical activity monitors and smartwatches. Furthermore, beacons location data was found more relevant for classifiers based on J48 and NN algorithms. These algorithms might be preferred over RF in some cases, for example, when processing and memory capacity is a limitation, as is the case when the models have to be induced in the smartphone; because RF requires higher processing and memory capability. Moreover, some studies claim that in some cases the RF algorithm tends to overestimate the level of precision [20].

For each of the 15 people included in the data set, a personal model was obtained. The biggest limitation in the process of obtaining a personal model for the recognition of sedentary behavior (and recognition of physical activity in general) is the need to collect labeled examples to obtain the training data set. As reported in [17], the retribution to overcome this limitation is a major improvement in the level of precision of the system, compared with the precision of impersonal or hybrid models. It should also be taken into consideration that each personal model was obtained with only three minutes recorded for each sedentary behavior, thus verifying that this type of model needs very few examples (36 per sedentary behavior in this case) to achieve high levels of precision. Although only 12 features were used in each experiment for obtaining the models, the precision reached was quite high.

Devices like Actigraph, Actical, Actiheart, Stepwatch, GENEActiv and/or activPAL are commonly used to estimate the time in which a person performs sedentary behaviors based on their body posture and/or intensity of physical activity as it was summarized in Table 1. However, to the best of our knowledge, no single study has been conducted to classify sedentary behaviors using localization data as presented in this paper. The most similar work is the one proposed by [14], but using RFID as location technology. The baseline precision level of that study was 86.1% which is the precision associated to the recognition of the place in which the person is located within the indoor environment. Other related works have classified daily living activities, including some specific sedentary behaviors such as dining and working on the computer [21], obtaining a precision in the classification of 76.3%, and dining, working on the computer and driving a car [22] with a precision of 79.1%. Therefore, our results improve the precision of those related systems. Future studies should consider the development of new data sets including new data channels, more sedentary behaviors and locations, e.g., at the work place, and complete description of the training and evaluation process of the classification as well as the precision of the classification algorithms. It is presumed that including more features from smartwatch-smartphone and/or beacon's environmental data such as acceleration, temperature, luminosity and distance from beacons to smartphone-smartwatch, the precision of sedentary behaviors recognition could also be increased. We are currently working on obtaining a data set with these characteristics including 24 different sedentary behaviors and also adding environmental data. Our current work also considers the improvement of the performance of the classification using a layered algorithm, exploring and assigning weights to the symbolic location features in order to improve the precision of the system. Finally, comparing data using the same sensor devices (smartphone or smartwatch) is also necessary, in order to prevent classification errors due to the sensor's accuracy. Regarding the indoor location technology used, some studies have provided comparative analyzes between the different technologies e.g., RFID, Bluetooth, WIFI, among others [23,24]. They concluded in general that the accuracy of Bluetooth-based system is similar to RFID-based localization system. However, more research is needed, especially with regards to its performance in real environments, and also considering not only accuracy but also other factors such as energy consumption, total battery life of the nodes (for example for BLE beacons or RFID active tags), discovery time, hardware requirements for location data processing, scalability, complexity and cost-effectiveness.

5. Conclusions

This paper describes a mobile system for objectively measuring sedentary behaviors using accelerometer and location data. It was demonstrated how BLE beacons could be used in conjunction with devices such as smartwatches or smartphones to perform the recognition of sedentary behaviors. The most important conclusion of this article is that symbolic location inferred using beacons allowed the recognition of specific sedentary behaviors with very high precision (95,06% using the smartwatch and 98,28% using the smartphone in five of the six sedentary behaviors studied), therefore improving the results of previous related works. Moreover, it was possible to statistically demonstrate significant improvement in the average precision of the classification of five sedentary activities when adding the symbolic location data given by the BLE beacons. The classification of postures (sitting and reclining) inferred from sedentary behaviors' classification in the experience is also accurate, especially considering that the data was obtained with a smartwatch located on the wrist, or a smartphone located in the pocket (thigh). Another important conclusion is that, unlike the recognition of physical activities where longer data sampling time is necessary (typically 10 s) the ED necessary for sedentary behavior classification was only of 5 s.

The proposed system has the potential to support future epidemiological research on sedentary behavior, improving the understanding of the context and determinants of these behaviors, as proposed by [16]. In addition, many practical applications of a mobile system for automatic sedentary behaviors recognition are foreseen. Cardiovascular diseases or other NCD prevention programs can use information about a person's sedentary behaviors for sending remainders, or providing personalized recommendations on physical activity. The system could be used at work to promote active breaks and healthy habits such as posture correction.

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References

[1] R. Viir, A. Veraksitš, Discussion of Letter to the Editor: standardized use of the terms sedentary and sedentary behaviours š Sitting and reclining are different states, Appl. Physiol. Nutr. Metab. 37 (2012) 540–542, doi:http://dx.doi.org/10.1139/h2012-123.
[2] M. Mansoubi, N. Pearson, S. a Clemes, S.J. Biddle, D.H. Bodicoat, K. Tolfrey, C.L. Edwardson, T. Yates, Energy expenditure during common sitting and standing tasks: examining the 1.5 MET definition of sedentary behaviour, BMC Public Health 15 (2015) 516, doi:http://dx.doi.org/10.1186/s12889-015-1851-x.
[3] A.J. Atkin, T. Gorely, S.A. Clemes, T. Yates, C. Edwardson, S. Brage, J. Salmon, S.J. Marshall, S.J.H. Biddle, Methods of measurement in epidemiology: sedentary behaviour, Int. J. Epidemiol. 41 (2012) 1460–1471, doi:http://dx.doi.org/10.1093/ije/dys118.
[4] R.M. Pulsford, E. Stamatakis, A.R. Britton, E.J. Brunner, M. Hillsdon, Associations of sitting behaviours with all-cause mortality over a 16-year follow-up: the Whitehall II study, Int. J. Epidemiol. 44 (2015) 1909–1916, doi:http://dx.doi.org/10.1093/ije/dyv191.
[5] J. Van Cauwenberg, V. Van Holle, I. De Bourdeaudhuij, N. Owen, B. Deforche, Older adults' reporting of specific sedentary behaviors: validity and reliability, BMC Public Health 14 (2014) 734, doi:http://dx.doi.org/10.1186/1471-2458-14-734.
[6] S. Qiu, X. Cai, C. Ju, Z. Sun, H. Yin, M. Zügel, S. Otto, J.M. Steinacker, U. Schumann, Step counter use and sedentary time in adults: a meta-Analysis, Medicine (Baltimore) 94 (2015) e1412, doi:http://dx.doi.org/10.1097/MD.0000000000001412.
[7] S.F.M. Chastin, C. Buck, E. Freiberger, M. Murphy, J. Brug, G. Cardon, G. O'Donoghue, I. Pigeot, J.-M. Oppert, Systematic literature review of determinants of sedentary behaviour in older adults: a DEDIPAC study, Int. J. Behav. Nutr. Phys. Act. 12 (2015) 127, doi:http://dx.doi.org/10.1186/s12966-015-0292-3.
[8] A. Loveday, L.B. Sherar, J.P. Sanders, P.W. Sanderson, D.W. Esliger, Technologies that assess the location of physical activity and sedentary behavior: a systematic review, J. Med. Internet Res. 17 (2015), doi:http://dx.doi.org/10.2196/jmir.4761.
[9] J.J. Yang, J. Li, J. Mulder, Y. Wang, S. Chen, H. Wu, Q. Wang, H. Pan, Emerging information technologies for enhanced healthcare, Comput. Ind. 69 (2015) 3–11, doi:http://dx.doi.org/10.1016/j.compind.2015.01.012.
[10] L.M. Lanningham-Foster, T.B. Jensen, S.K. McCrady, L.J. Nysse, R.C. Foster, J.A. Levine, Laboratory measurement of posture allocation and physical activity in children, Med. Sci. Sports Exerc. 37 (2005) 1800–1805, doi:http://dx.doi.org/10.1249/01.mss.0000175050.03506.bf.
[11] A.V. Rowlands, T.S. Olds, M. Hillsdon, R. Pulsford, T.L. Hurst, R.G. Eston, S.R. Gomersall, K. Johnston, J. Langford, Assessing sedentary behavior with the geneactiv: introducing the sedentary sphere, Med. Sci. Sports Exerc. 46 (2014) 1235–1247, doi:http://dx.doi.org/10.1249/MSS.0000000000000224.
[12] Y. Jiang, J.L. Larson, IDEEA activity monitor: validity of activity recognition for lying, reclining, sitting and standing, Front. Med. China. 7 (2013) 126–131, doi:http://dx.doi.org/10.1007/s11684-012-0236-0.
[13] C. English, G.N. Healy, A. Coates, L.K. Lewis, T. Olds, J. Bernhardt, Sitting time and physical activity after stroke: physical ability is only part of the story, Top. Stroke Rehabil. (2015) 1–10, doi:http://dx.doi.org/10.1179/1945511915Y.0000000009.
[14] R. Spinney, L. Smith, M. Ucci, A. Fisher, M. Konstantatou, A. Sawyer, J. Wardle, A. Marmot, Indoor tracking to understand physical activity and sedentary behaviour: exploratory study in UK office buildings, PLoS One 10 (2015), doi:http://dx.doi.org/10.1371/journal.pone.0127688.
[15] S.F.M. Chastin, U. Schwarz, D.A. Skelton, Development of a consensus taxonomy of sedentary behaviors (SIT): Report of Delphi round 1, PLoS One 8 (2013), doi:http://dx.doi.org/10.1371/journal.pone.0082313.
[16] G.M. Weiss, H. Hirsh, Learning to predict rare events in event sequences, Proc. 4th Int. Conf. Knowl. Discov. Data Min. 30 (1998) 8264 (10.1.1.30.8264).
[17] J.W. Lockharty, G.M. Weiss, The benefits of personalized smartphone-Based activity recognition models, 2014 SIAM int, Conf. Data Min. 9 (2014), doi:http://dx.doi.org/10.1137/1.9781611973440.71.
[18] I.H. Witten, E. Frank, M. a Hall, Data Mining: Practical Machine Learning Tools and Techniques (Google eBook), (2011) (0120884070,9780120884070).
[19] A.H.K. Montoye, J.M. Pivarnik, L.M. Mudd, S. Biswas, K.A. Pfeiffer, Validation and comparison of accelerometers worn on the hip, thigh, and wrists for measuring physical activity and sedentary behavior, AIMS Public Health 3.2 (2016) 298–312.
[20] M.R. Segal, Machine learning benchmarks and random forest regression, Biostatistics (2004) 1–14.
[21] E. Garcia-Ceja, R.F. Brena, J.C. Carrasco-Jimenez, L. Garrido, Long-term activity recognition from wristwatch accelerometer data, Sensors (Basel) 14 (2014) 22500–22524, doi:http://dx.doi.org/10.3390/s141222500.
[22] U. Blanke, B. Schiele, T. Huynh, Scalable recognition of daily activities with wearable sensors, 3rd Int Symp. Locat. Context. (2007) 50–67, doi:http://dx.doi.org/10.1007/978-3-540-75160-1_4.
[23] P. Vorst, J., Sommer, C. Hoene, P., Schneider, C. Weiss, T., Schairer, W. Rosenstiel, A., Zell, G. Carle, Indoor Positioning via Three Different RF Technologies, RFID SysTech 2008 – 4th Eur. Work. RFID Syst. Technol. 2008 10.
[24] A. Khudhair, S.Q. Jabbar, M.Q. Sulttan, D. Wang, Wireless indoor localization systems and techniques: survey and comparative study, Indonesian J. Electr. Eng. Comput. Sci. 3 (2) (2016) 392–409.