Activity Recognition in Outdoor Sports Environments: Smart Data for End-Users Involving Mobile Pervasive Augmented Reality Systems

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ABSTRACT

Activity recognition is an increasingly relevant topic in the context of the most varied end-user services. In outdoor environments, activity recognition based on close-to-real-time information is key in providing awareness to the user about their surroundings in a timely and user-friendly manner, thus allowing to the user to improve its overall use (Quality of Experience). In this context, it is relevant to understand how data extracted from multiple sensors can be fused, interpreted and classified, to best provide feedback to the user. Having as target case Mobile Augmented Reality Systems for outdoor environments, this paper presents a first analysis on how smart data captured via multiple sensors can assist activity recognition and adequate feedback to the user. The paper also debates the existent restrictions imposed by applications' usage in these environments, describing possible use scenarios and presenting results of an experiment for discriminating activities when using common sensors, such as the accelerometer.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

UbiComp/ISWC '19 Adjunct, September 9–13, 2019, London, United Kingdom

ACM ISBN 978-1-4503-6869-8/19/09…$15.00
https://doi.org/10.1145/3341162.3349299

KEYWORDS

Activity Recognition; Outdoor Sports Environments; Auto-Adjustment System; Smart Data; Meaningful Feedback.

ACM Reference Format:

Rui Miguel Pascoal, Ana de Almeida, and Rute C. Sofia. 2019. Activity Recognition in Outdoor Sports Environments: Smart Data for End-Users Involving Mobile Pervasive Augmented Reality Systems. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2019 International Symposium on Wearable Computers (UbiComp/ISWC '19 Adjunct), September 9–13, 2019, London, United Kingdom.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3341162.3349299

1 INTRODUCTION

Pervasive Augmented Reality systems *(PARS)* are today integrated into different aspects of social living and activities. Up until recently, PARS for outdoor activities were based on dedicated hardware, as is the case of *smart glasses.* However, the integration of multiple sensors into the most varied sets of mobile personal devices, such as smartphones and smartwatches, brings in the possibility to consider classifying tracked data (e.g., movement, temperature) in a way that can improve *Augmented Reality (AR)* feedback to users. This aspect is particularly relevant in heterogeneous environments such as outdoor sports as these embody high topological variability, intermittent connectivity, constrained devices, and a need for constant middleware readjustment, based on the user's sensed indicators (*smart data*). Smart data here stands for captured surrounding context; individual device usage indicators. Smart data therefore relates with small, individual data sets. Thus, it is necessary to re-think PARS to devise more flexible systems that can support mobility, i.e., systems that can be easily adjusted to mobile personal devices and that can easily adapt to the interpreted smart data - *Mobile PARS (MPARS).*

There are several aspects that need to be considered to truly take advantage of the sensing power available today in personal devices [16]. Personal sensing applications are designed for a single individual and are often focused on data collection and analysis. Typical scenarios include tracking the user's exercise routines or automating diary collection [10]. Regarding data capture, there is the need to clearly identify which sensors best assist the tracking and recognition of specific activities. In what concerns data classification, there is the need to support data fusion on-the-go and to push both data fusion and classification as close as possible to the end-user.

One aspect that is, in our opinion, one of the most relevant ones to tackle is the issue of customizing feedback to the end-user in close-to-real-time. The adjustment of MPARS needs to go beyond location aspects [10], which is commonly and usually opportunistically done, and to consider other types of context: whether or not this environment is usual to this specific individual, the level of acquired fitness, goals of the individual, temperature, humidity, etc. To be able to provide *meaningful feedback* in close-to-real-time, a MPARS solution must engage in several processes, often in parallel: i) data capture (*sensing*), ii) learning (*interpretation*), iii) classification (*processing*), iv), adaptation (*adjustment*).

Data capture is made possible by sensors of smart mobile systems, such as smartphones, with a growing set of cheap powerful embedded sensors [10]. Data capture is often performed passively via *opportunistic* sensing [15] and with the aid of multiple sensors [7] that today abide in mobile personal gadgets (e.g., accelerometer, gyroscope, compass, microphone, GPS, Wi-Fi, Bluetooth, etc). Data capture is also performed actively, i.e., with the direct participation of the user (*participatory* sensing) via biometric sensors, such as heart rate, and galvanic skin response. Data (raw or classified individually) is then sent to the cloud to be further verified and treated. In outdoor activities, where there is a need for *close-to-real-time feedback*, context recognition can assist in avoiding rejection of the technology due to information overload [13] derived from data obtained via multiple sensors. It assists also in improving the system performance, e.g., by preventing unnecessary energy consumption [17]. Therefore, being able to simplify learning and classification via a better definition of the surrounding context and a better placement of classification mechanisms is essential to provide close-to-real-time feedback in MPARS. These are nonetheless challenges in outdoor environments, as end-users are engaged in dynamic activities, where mobility is high, and where Internet access is often intermittent. A second aspect that is required to provide close-to-real-time feedback, is to re-think computation and to consider distribution of the aforementioned tasks. These need to be supported locally, so that cloud computation is only used if local computation cannot be achieved.

This paper contributes with a first analysis on a data capture and a data fusion model based only on on accelerometer and GPS sensors, which are today two of the most common sensing interfaces available in personal devices.

The rest of the paper is organized as follows. Section II summarizes related work and briefly discusses the need for an MPARS to receive just enough adequate smart data to recognize activity and adjust the feedback provided within outdoor sports contexts. Section III presents possible usage scenarios of MPARS while Section IV describes methodology for data acquisition and sensing data evaluation results in terms of activity similarity analysis. Section V shows the classification approach for the support of activity recognition in MPARS. Section VI presents the conclusions and future work.

2 RELATED WORK

Context awareness and in particular context recognition systems have been available for long in different fields of computer science. With the introduction of wearable devices and of smart applications, context recognition systems are now in under intensive research since wearables, as well as mobile personal devices with a large variety of sensors, are carried by users almost 24 hours per day. Several works have focused on the best way to adapt activity recognition systems in embedded devices. Choudhury et al. [4] is such an example.

In terms of sensor mapping to specific activities, several works have employed data available from the accelerometer. This line of work is focused in the accuracy of pervasive sensing systems. For instance, Casale et al. [3] developed a novel wearable comfortable system easy to use. They collect data only from the accelerometer sensor achieving good results for activity recognition, with low-power requirement, e.g., for longer battery life outdoors. Bayat et al. [1] also only use the accelerometer sensor from smartphones in their experiments to recognize certain types of human physical activities combine them into an optimal set of classiïňĄers, and develop a model that is capable of recognizing sets of daily activities under real-world conditions.

Roza and Postolache use an experiment to measure the heart rate, heart rate variability, and the galvanic skin response, to analyze the citizens' emotions [14]. Data acquisition from volunteers shows how they feel based on a concrete scale of emotional status (e.g., happy, sad, fear, surprise, disgust, neutral, anger, and boredom). Demonstrating the variety of feelings that citizens deal daily i.e., a variety of emotions due to a set of factors such as, violence, street illumination or car noises, trash and pollution, for instance. However, these sensors to read the emotions of users can easily cause noise in the data for accurate recognition of outdoor sports activity.

Other studies by Zhou *et al.* investigate some action fields of AR technology such as tracking and display, development tools, input and interaction, and social acceptance. For instance, mobile devices present new opportunities for hybrid tracking, as they include not only cameras but other relevant sensors for tracking such as accelerometer and gyroscope, GPS, as well as wireless interfaces, which can be combined to provide a highly accurate estimation of tracking, i.e., improve activity recognition. [2]. Related work has also been delving with pervasive sensing and classification models for multiple factors to assist in more complex activity recognition, e.g., social interaction [15] [14].

Another line which is closer to our work concerns is the definition of criteria to select the specific information that is provided to the user under specific conditions, with the aim to prevent information overload [13]. Preventing information overload is based on the equilibrium between the share and type of given information [12].

3 SENSORS FOR DATA ACQUISITION

There are several sensors which can be considered to support an adequate activity recognition in an outdoor environment and which are today present in almost all personal devices. The most common are: 1) accelerometer, 2) GPS, 3) biometric sensors (e.g., heart rate, and galvanic skin response) [8]. Ideally, and in an attempt to simplify activity tracking and to minimize the device's energy consumption, sensing should be reduced to one, maybe two sensors.

The *accelerometer* comprises measurements based on three axes providing three separated data time series for acceleration (g-force [16].) on each axis: A_x, A_y, A_z. This sensor has been used heavily in tests using smartphone sensors for non-intrusive activity recognition. Its popularity is due to the wide availability of both hardware and software libraries for movement detection. If a user changes from walking to race walking or running, it will reflect the change in the signal shape of the acceleration reading along the vertical axis A_y, with an abrupt change in the amplitude. Moreover, the acceleration data could indicate the motion pattern within a given time period, which is helpful for activity recognition. The accelerometer is often used to identify walking, running, race walking, biking, and others, as well as to identify the absence of movement.

GPS is a satellite-based positioning mechanism that provides position, working with the assumption that the receiver has total or partial line of sight of GPS satellites (three, at least). Obstacles such as mountains and buildings' walls block the GPS signals. This can be an excellent sensor for refining activity recognition, as speed can be derived from GPS data [5].

Biometric sensors, such as heart rate and galvanic skin response are influenced by internal factors (e.g., weight, height, age, physical condition, anxiety), and external factors (weather, relative humidity, etc). These sensors require adequate calibration and prior end-user configuration of wellness characteristics [11]. It also requires continuous adjustments (correlation) towards environmental aspects such as temperature, relative humidity, and altitude[9]. They are also intrusive, in the sense that the user needs to carry specific hardware or to carry personal devices close to the body.

Heart Rate is one of the most relevant biometric indicators of health in the human body. It measures the number of times per minute that the heart contracts or beats (Medical News Today[1]). External environments also influence the performance of heart rate [6]. The problem when considering heart rate alone is that several internal/external factors can influence heart rate of the end-users and it will not give accurate calculation for activity recognition. One must take into account human variables, such as: activity level, fitness level, body position (e.g., standing up or lying down), emotions, air temperature, age, height, weight, gender, etc.

Galvanic Skin Response (GSR), also known as *electrodermal response*, measures changes in electrical resistance across two regions of the skin. This electrical resistance of the skin, which is typically large and varies slowly over time, fluctuates quickly during mental, physical and emotional arousal. The change in conductivity can be used to infer differing arousal states in individuals. Unfortunately, several physical and operational factors can influence the readings and the GSR sensor does not automatically adjust to these changes and must be adjusted for each individual wearing the sensor in an intrusive manner and it is external to the smartphone.

Our work contributes beyond related work, by addressing the specific case of MPARS in heterogeneous environments, of which outdoor environments are one of the most relevant examples. To better explain this contribution, this work considers six examples of outdoor activities.

Figure 1 summarizes the sets of sensors used in the different activities which are also expected to be useful in other scenarios.

4 METHODOLOGY

Figure 2 illustrates the main steps for an MPARS solution to be able to provide close-to-real-time *meaningful feedback* to the user. Smart data processing needs to begin by capturing data through the needed sensors to enable learning. After a model has been learned, classification of new data allows the system adjustments for the recognized activity to provide adequate (contextual) and meaningful feedback to the user. The main goal is to avoid information overload and providing

[1]https://www.medicalnewstoday.com/articles/235710.php

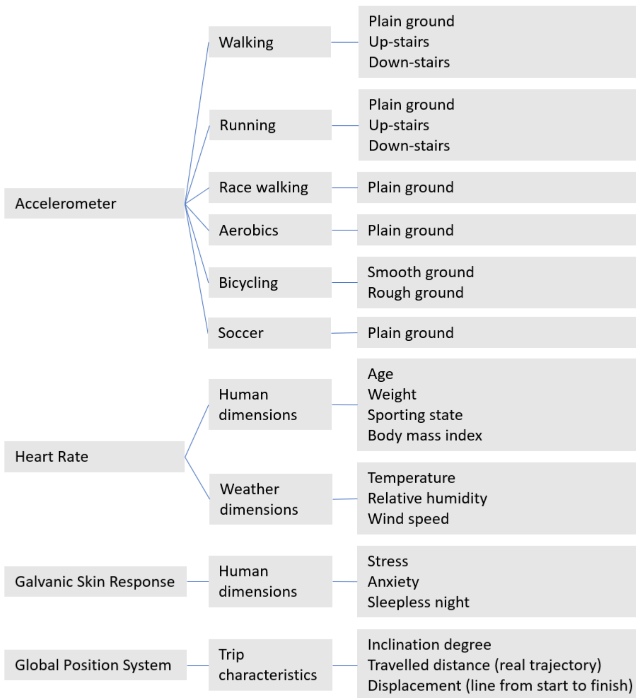

Figure 1: Sensors, activities, and features.

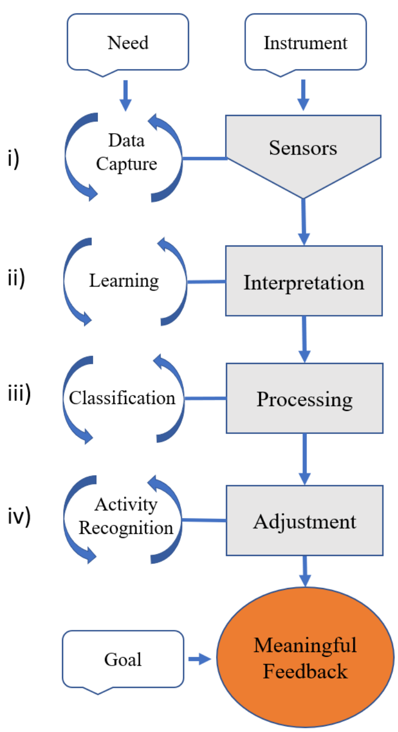

Figure 2: Smart Data Process - display required information by type of outdoor sport activity (meaningful feedback).

the user with the best *Quality of Experience (QoE)* when engaged in an outdoor sport.

As previously stated, sensing should occur opportunistically and with the minimum possible number of active sensors so to minimize energy expenditure but still enabling activity pattern recognition. As such, an experiment has been devised to understand the activity discriminating power when using only accelerometer or GPS sensing.

We have deployed an experimental environment involving ten volunteers, male and female, between 16 to 51 years of age (16, 21, 24, 27, 36, 37, 38, 43, 44, 51). The volunteers each carried a smartphone holding a Kirin 620 CPU and 2.0GB of RAM using an Android version 6.0, accelerometer sensor vendor $ROHM_KX023$, sensor Resolution of $0.009576807 m/sec^2$, Max Range: $39{,}02266 m/sec^2$, Min Delay: 10.000 *microseconds*.

The measurements have been performed during the period of November 30, 2018 until January 22, 2019. The volunteers performed all of the next described activities during 15 seconds each: walking and running (on plain-ground, upstairs or downstairs), race walking (plain-ground), aerobics, biking (smooth and rough grounds) and soccer. To assist in identifying activities, subjects were asked to stop and wait five seconds after each activity.

All of the different scenarios have then been repeated for GPS measurements, with the exception of aerobics (since this activity was performed in same place). GPS data has been collected with the Android application "GPS Speedometer" [2].

Accelerometer data collected between the start and stop times of an activity was labeled with the name of that activity. Each subject provided a total of 215 seconds activities and, from each activity, 150 logs were extracted (with 68 milliseconds between each log). The accelerometer data has been collected u sing the Google Android application "Accelerometer Analyzer" [3]. Sensor speed was adjusted to normal mode for better energy consumption (the high speed query mode of the accelerometer sensor consumes more energy [18]).

The logs were provided in text format (txt) from application, converted to comma separated values format (csv), and finally, saved in xlsx format. The data is publicly available at https://goo.gl/x212nx. In all the outdoor tests sampling relied on a rate of 15 frames per second (fps) and with gravity mode on. During data capture, the smartphones were carried by the users in the horizontal position.

Note that acceleration data varies widely for the same physical activity at different positions on a user's hands. In this study, we consider Equation 1, *Root Mean Square* (*RMS*), and Equation 2, *Acceleration Magnitude* (A_m) 2, as approaches for computing accelerometer data and understand, among

[2]https://play.google.com/store/apps/details?id=com.fragileheart.gpsspeedometer
[3]https://accelerometer-monitor.soft112.com/download.html

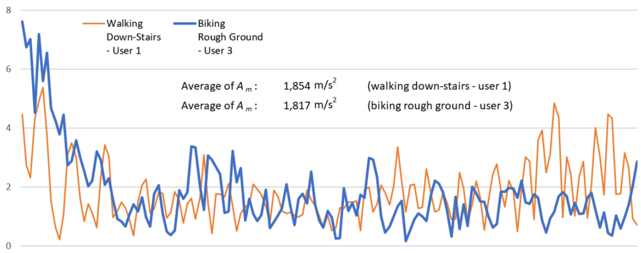

Figure 3: Walking and biking similarities.

other aspects, which best differentiates between activities.

$$RMS = \sqrt{\frac{A_x^2 + A_y^2 + A_z^2}{3}} \quad (1)$$

$$A_m = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (2)$$

5 RESULTS

Activity recognition using RMS and A_m. A first aspect analyzed concerns the suitability of 1 and 2, that is, which one presents a more differentiating value (a higher classification index). For this purpose, we analyzed a subset of logs and Table 1 shows examples of only two records for each of the activities of the accelerometer sensor.

Table 1: Classification index computed by Equations 1 vs. 2.

Activity	X	Y	Z	Equation 1 *RMS*	Equation 2 A_m
Walking	2.593	-1.243	2.556	2.221	3.847
	1.730	-0.868	1.869	1.553	2.690
Race Walking	1.851	0.785	2.196	1.718	2.977
	1.139	0.947	1.218	1.107	1.918
Running	5.794	0.594	2.610	3.685	6.383
	1.966	1.217	1.417	1.565	2.712
Aerobics	-4.187	8.999	1.326	2.536	4.392
	-3.58	-2.599	1.012	2.148	3.720
Biking	0.68	2.032	4.963	3.121	5.406
	0.336	1.812	4.604	2.863	4.959
Soccer	7.886	-2.068	4.706	5.434	9.413
	6.52	1.87	5.235	4.946	8.568

As it is possible to observe, Equation 2 always results in a higher classification index. Since this is a general finding throughout the several activities, the *Acceleration Magnitude* seems a better discriminant when compared to RMS.

Accelerometer Data Analysis. Table 2 provides the data from accelerometer and GPS sensors (walking, race walking, running, aerobics, biking, soccer), obtained from 10 subjects based upon 150 logs. The values of accelerometer on Table 2 show some activities are quite similar. For instance, walking and biking are quite similar (e.g., A_m =1,474m/s^2 and 1,012m/s^2, respectively). See it in Figure 3. Running, aerobics and soccer activities suffer from the same issue, see it in Appendix (Chars of accelerometer similarities.

Figure 4 provides the full set of results for all of the 10 users. It shows the collection of accelerometer data with the participation of all users developing all activities. The input data (ten samples) are shown, as well as the average and the variance, showing that accelerometer data is not always enough to clearly identify between all the diverse activities.

GPS Data Analysis. Evidently, (Figure 5) GPS data only does not in itself discriminative enough to completely recognize all the specific type of activity. However, data fusion may improve the discriminative quality of the data in order to enhance classification.

Accelerometer and GPS Data Fusion Analysis. We compiled all average results of ten users (Table of Data in the Appendix). A first aspect analyzed based on the fusion of the data concerns the similarity levels between the different activities. Since the accelerometer sensor values show that aerobics data is not so different from running up-stairs and the same happens for walking up-stairs and soccer activity, we propose a solution for this issue by using the GPS sensor, which can also add indicators such as speed. Thus, combining these two sources of data can help to better discriminate between activities, as shown in Figure 6.

Therefore, to increase the accuracy in the detection of activities for outdoor MPARS it is feasible to consider adding GPS data, given that this sensor is ubiquitously present in current smart systems and usually works well in outdoor environments. Furthermore, GPS data can provide other indicators like speed and help in improving activity recognition in a non-intrusive way. Note that, accelerometer variance is high when running down and upstairs, for aerobics and for biking in rough ground, but low for walking. The GPS variance is commonly low, but for biking it is high more details in the Appendix). Figure 7 shows average values from the data of the 10 users for the specified activities if using accelerometer data that is then fused with GPS data and shows that relative differences turn out to be much more discriminative.

The next step is to classify the different activities based on the fused data sources. Figure 8 helps to visualize both accelerometer and GPS velocity and how these variables help to differentiate between the labeled data. Each point in Figure 8 shows the relationship between the accelerometer and the velocity (extracted from GPS data).

A first analysis of some of the potential methods for data classification is presented. The selected classification methods are: Decision Tree; Bayesian Networks, K-Nearest Neighbors, and Artificial Neural Networks. We made a simple comparison of classification accuracy and precision with the Orange©data mining tool for the different classification methods.

Table 2: Data of Accelerometer and GPS.

Activity	Inputs	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10	Average	Variance
Walking	A_m.	1,474	1,206	1,237	1,348	1,470	1,399	1,613	1,652	1,610	2,026	1,504	0,057
(plain ground)	Km/h	3,2	3,1	2,7	4,2	3,8	3,7	4,1	4,0	3,9	3,4	3,6	0,2
Walking	A_m	2,690	2,130	2,807	2,568	2,981	2,960	1,857	1,649	1,748	2,028	2,342	0,266
(up-stairs)	Km/h	2,8	2,6	3,1	2,9	2,7	2,5	3,0	2,8	2,6	2,8	2,8	0,0
Walking	A_m	1,854	2,205	2,333	2,301	1,972	1,902	1,885	1,746	1,865	1,902	1,997	0,042
(down-stairs)	Km/h	2,9	3,1	2,8	3,2	3,0	3,3	3,1	3,0	3,2	2,9	3,1	0,0
Race Walking	A_m	1,760	1,794	3,150	2,389	2,569	2,720	2,391	2,391	1,842	2,042	2,305	0,202
(plain ground)	Km/h	5,6	5,2	5,1	5,4	5,0	4,9	5,8	5,6	5,7	5,9	5,4	0,1
Running	A_m	3,084	3,091	3,680	3,100	3,321	3,138	3,770	3,656	3,802	3,451	3,445	0,086
(plain ground)	Km/h	8,1	7,9	8,3	7,3	7,1	7,5	8,2	8,0	8,4	8,2	7,9	0,2
Running	A_m	3,322	5,002	3,911	3,658	3,375	3,127	3,044	2,168	2,315	2,275	3,220	0,749
(up-stairs)	Km/h	3,8	3,5	3,4	3,6	3,7	3,3	3,4	3,6	3,5	3,4	3,5	0,0
Running	A_m	2,360	2,655	2,787	3,749	3,091	4,776	4,741	3,612	3,357	3,710	3,484	0,666
(down-stairs)	Km/h	6,2	5,6	5,9	6,1	6,0	6,3	5,8	5,7	5,8	6,1	6,0	0,1
Aerobics	A_m	2,656	3,451	3,365	4,163	5,060	3,496	3,762	3,654	4,547	5,772	3,993	0,837
(same place)	Km/h	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
Biking	A_m	1,012	1,058	1,112	0,606	0,597	0,675	0,509	1,493	0,970	1,771	0,980	0,168
(smooth ground)	Km/h	10,2	11,1	15,8	14,2	14,7	15,2	16,1	14,9	13,9	15,1	14,1	3,8
Biking	A_m	2,328	2,796	1,817	1,401	1,660	2,059	2,059	2,513	2,909	3,572	2,311	0,427
(rough ground)	Km/h	14,4	15,6	12,7	11,9	11,6	13,2	12,3	9,1	10,0	10,4	12,1	4,0
Soccer	A_m	3,167	3,229	2,651	2,691	2,564	3,064	2,472	3,492	3,017	3,711	3,006	0,169
(plain ground)	Km/h	3,8	3,2	3,7	4,1	3,9	4,0	3,9	2,8	3,1	3,3	3,6	0,2

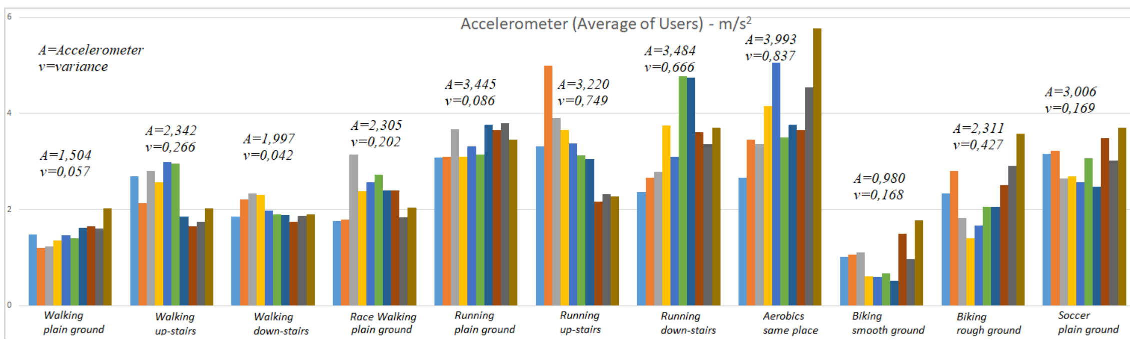

Figure 4: Accelerometer data of the ten subjects.

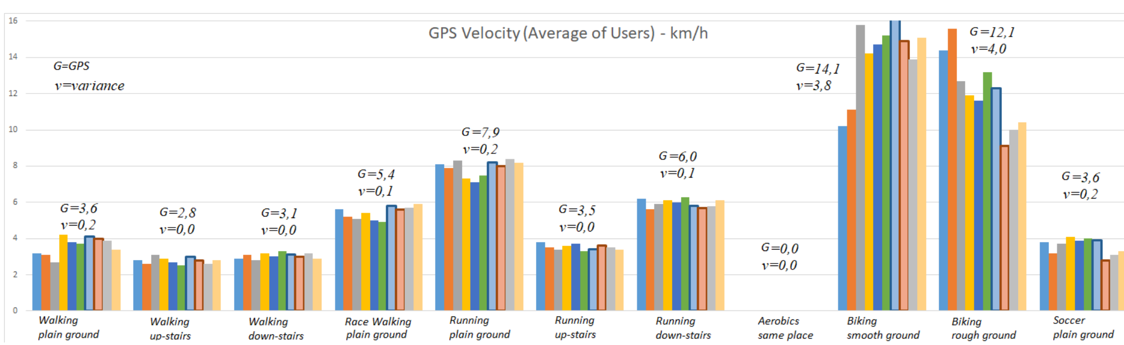

Figure 5: GPS data of ten subjects.

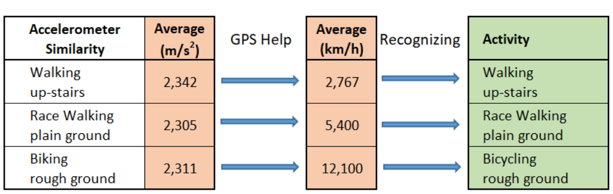

Figure 6: Accelerometer similarities and GPS help to tune.

In our simplified model, the input concerns the statistical average data for the different activities and different users with accelerometer & GPS, with a categorical target (activity). Bayesian Networks and ANN are the methods that provide better results.

6 CONCLUSIONS

This paper provides a simple yet meaningful study on sensing for activity recognition for context adjusted feedback in

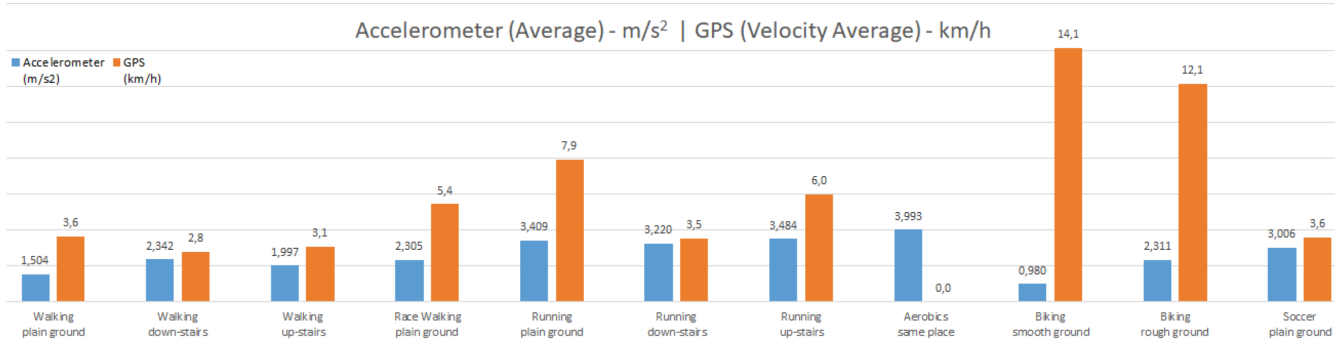

Figure 7: Accelerometer and GPS data (average) side by side.

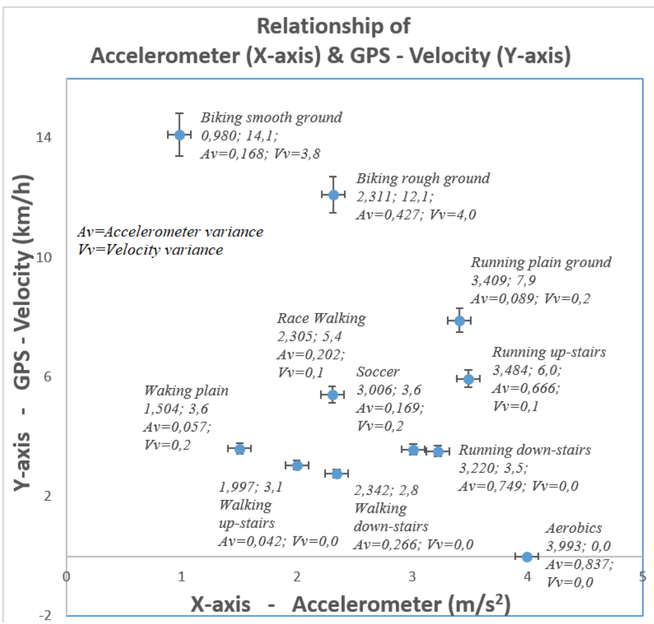

Figure 8: Activity Labeling by the relationship between accelerometer and GPS.

MPARS outdoor activity applications with the aim to raise awareness to the possibility to solely relying on a minimal set of non-intrusive sensors, such as accelerometer and GPS data. It is relevant to consider whether or not it is possible to detect, with a specific level of accuracy, differences between activities without necessarily recurring to other sensors as a trade-off for energy consumption.

Results obtained showed that Acceleration Magnitude values seem better discriminators for activities based on accelerometer data. Thus, to improve the discriminating power of the proposed sensing, speed values derived the GPS sensor data were proposed. A study on activity classification has then been provided, both with fused and individual data collected from the two sensors.

Future work involves a more extensive user data set and involving energy consumption values in outdoor environments contexts. This issue involves one of the MPARS requirements on the energy efficiency of autonomous mobile systems with the use of the automatic activity recognition tool. Raw data is constantly produced and delivered to the recognizer of the activity, causing the system to always consume energy. This necessary upgrade of the sorting process will also require computing resources.

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A ADDITIONAL DATA

Charts of accelerometer similarities

Following Charts show more similarities with accelerometer data in various activities, such as running and aerobics, and walking and soccer.

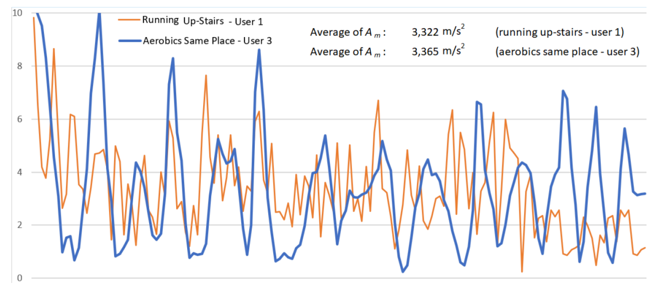

Figure 9: Running and aerobics similarities.

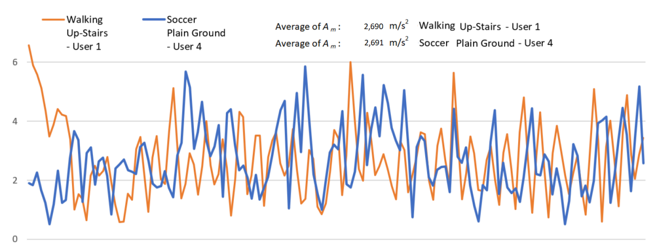

Figure 10: Walking and soccer similarities.