Combining Smartphone and Smartwatch Sensor Data in Activity Recognition Approaches: an Experimental Evaluation

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***Abstract*—Activity recognition has been widely studied in ubiquitous computing since it can be used in several application domains, such as fall detection and gesture recognition. Initially, works in this area were based on research-only devices (body-worn sensors). However, with advances in mobile computing, current research focuses on mobile devices, mainly, smartphones. These devices provide Internet access, processing, and various sensors, such as accelerometer and gyroscope, which are useful resources for activity recognition. Therefore, many studies use smartphones as data source. Additionally, some works have already considered the use of wristbands and specially-designed watches, but fewer investigate the latest marketable wearable devices, such as smartwatches, which are less intrusive and can provide new opportunities to complement smartphone data. Moreover, for the best of our knowledge, no previous work experimentally evaluates the impact caused by the combination of sensor data from smartwatches and smartphones on the accuracy of activity recognition approaches. Therefore, the main goal of this experimental evaluation is to compare the use of data from smartphones as well as the combination of data from smartphones and smartwatches for activity recognition. We evidenced that the use of smartphone and smartwatch data combined can increase the accuracy of activity recognition.**

Keywords—Activity Recognition; Smartwatch; Smartphone; Wearable Devices; Experimental Evaluation.

I. Introduction

Activity Recognition (AR) consists in the identification of human physical activities (e.g., walking, running, etc.) [10]. The study of this issue is quite relevant, since AR approaches can be applied to several application domains, for example for physical activities and health monitoring, detection of falls, home automation, advertisement delivery, and social networks based on daily activities [10]. Several types of sensors can be used in the recognition process, such as GPS, gyroscope, and mainly, accelerometer [8].

In the early stage, works in this area were based on devices specifically designed for this task [19], which are usually very intrusive, or even huge and heavy to be carried by users. Thus, despite their positive results in terms of accuracy, these studies present limitations to be applied in realist environments. In the last years, AR has became a topic of interest for mobile and ubiquitous computing researchers [10], [5], especially due to the significant growth in the number of mobile devices available to users, which incorporate several types of sensors, such as gyroscope and accelerometer [8]. Thus, the latest works in the AR field have been carried out based on these less intrusive devices (e.g., smartphones [8], [10], [17], [19]), which achieve good results as data collection tools for activity recognition.

Recently, other mobile devices - wearable devices - are attracting the attention of the area, since they have reduced size and reasonable computational power [16]. Among the marketable wearable devices that can be used as data collection tool, stand out the smartwatches, because they are cheap and nonintrusive devices [13], can be worn 24 hours a day and be water resistant [2], and generally their battery life is more durable than smartphone ones [3]. Thus, they allow a less intrusive way to monitor physical activities and, consequently, the development of innovative applications [11], such as unsafe driving detection [9], the monitoring of user daily activities [16], and the assistance to people with visual impairments [13].

As can be seen, many works testify the applicability of the latest mobile devices (mostly, smartphones) in activity recognition, for example in [8], [19], [17], [7], [15]. However, other studies have already considered the use of body-worn sensors (i.e., sensors attached to user bodies) to complement smartphone data [7], aiming to obtain better results. But these body-worn sensors generally reduce the applicability of studies, since they are intrusive to be used in standard environments.

But, despite their applicability, to the best of our knowledge, there is no previous work that experimentally evaluated the impact on the accuracy of activity recognition with data from smartwatches combined with smartphone data. Because each device collects information from a different perspective,

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the combination of their data can improve the accuracy on activity recognition. For instance, smartwatches are usually located at the wrist of users, and smartphones are typically located at their front pocket. For an activity recognition scenario such as driving, data from smartwatches seem to be more useful to recognize this activity. For example, by using only smartphone sensor data as input, a machine learning classifier could not distinguish if a user is the driver or the passenger.

Therefore, the main goal of our work is to perform an experimental evaluation to compare the use of data from smartphones as well as the combination of data from smartphones and smartwatches for activity recognition. We perform this experiment with thirteen participants, mainly undergraduate students, aging between 20 to 35 years old. To accomplish that, we simultaneously collect accelerometer data from a smartphone along with a smartwatch and carry out the activity recognition. Then, we statistically compare the recognition accuracy of four types of physical activities – walking, sitting, standing and driving – with two types of input – data from smartphones, and data from smartphones along with smartwatches. Besides that, we investigate the results of three known classifiers (Decision Tree, Naive Bayes and SVM) and three types of feature vectors as classifier input, based on mean, standard deviation and both combined. The experiment has shown there is significant evidence that the use of data from smartphones combined with smartwatches increases the accuracy in the recognition of the studied activities.

The remainder of this paper is organized as follows. In Section 2, we discuss related work in the area of activity recognition with mobile devices. In Section 3, we outline the experimental design, detailing the research goal, the data collection and preprocessing, the hypotheses, the execution, the results, and the statistical analysis. In Section 4, we present the threats to validity of our work. Finally, in Section 5, we show the conclusions and future work.

II. Related Work

Research in activity recognition can be grouped into distinct phases. In a first moment, authors based their studies only on research devices that collect data through intrusive ways. They use, for example, very heavy devices that could not be used in realistic environments [12], and the devices are designed for a predefined task. The advances in mobile computing emerged a second phase, with works based on mobile devices, such as smartphones [19], and most recently, wearable devices [3]. In this context, data collection is less intrusive and the research achievements seem to be closer to the real world, since proposed solutions can be applied in daily situations. Therefore, some works in the literature focus on mobile activity recognition due to its applicability in many domains [10], [8], [19], [2], [7], [13]. Many of these application domains of activity recognition were summarized by Lockhart et al. [10] that described and categorized a variety of applications based on mobile activity recognition, aiming to direct and encourage other works in the area.

Some works use smarthphones for data collection. Among these works, Kwapisz et al. [8] proposed an activity recognition approach based on information collected from smartphone accelerometers. The authors argue that the use of mobile devices presents a less intrusive way to collect data, different from previous studies that are based on information collected by devices designed only for research purposes. In order to increase the recognition accuracy provided by smartphone data, Kawsar et al. [7] developed a multimodal system that uses data from pressure sensors of shoes along with accelerometer and gyroscope information from smartphones. According to the authors, the solution ensures the data collection even when users are not carrying their mobile devices, and despite using extra information in addition to smartphone data, the solution is wireless, which makes it less intrusive than others previously proposed. Although presenting important results, these works use only smartphones to provide data.

Recently, beside the smartphones, the wearable devices are attracting the attention of the area. Among these devices, stand out the marketable smartwatches. Bieber et al. [2] reported on identified requirements of smartwatch sensors for activity detection (e.g., walking, running, etc.), as well as for inactivity states (e.g., sleeping). The authors introduced a gravity free parameter for the acceleration in the three dimensional space, called Activity Unit. Additionally, they presented an algorithm to distinguish if the user is wearing the device or not and to identify if the user is sleeping. The authors argue that unlike smartphones, the use of smartwatches allows the constant monitoring of physical activities because smartwatches can be used 24 hours a day and some devices are water resistant. Bieber et al. [3] presented challenges and opportunities of smartwatches, as well as their potential applications for assistance and monitoring environments. According to the authors, smartwatches are a good alternative for activity recognition since they are generally used for a longer period than smartphones, most of them are water resistant, additionally, they present good battery life and several sensors that allow non-intrusive monitoring of physical activities. Other smartwatch applications addressed in the paper are gesture recognition (e.g., permanent remote control), sensing (e.g., accelerometer, light, and pressure), and haptic and fast feedback. Although presenting important results, these works use only smartwatches to collect data.

Other works employ smartphones and smartwatches. Among these works, Porzi et al. [13] presented a first prototype of a low-cost system to help visually impaired people, based on the use of a smartphone and a smartwatch. The data from smartwatch sensors is used as input to a gesture recognition algorithm, which runs in the smartphone. The algorithm is based on the Global Alignment Kernel with an SVM classifier. According to the authors, one of the main advantages of the system is that smartwatches can be worn without any prejudice, as they look similar to normal watches. Although this work use both smarphones and smartwatches, each device is used for a different task: the smartwatch for data collection and the smartphone for processing.

As shown in previously mentioned works, the use of sensor data from smartphones in activity recognition is already a reality. However, other devices are emerging as good options for data collection in addition to smartphones, such as smartwatches. But despite its proven applicability presented in some works, they did not experimentally evaluate the impact on the accuracy of the use of these devices combined for activity recognition. Therefore, unlike these studies, we experimentally evaluate the recognition accuracy with distinct scenarios, in order to investigate whether the combination of data from different devices (i.e., marketable smartwatches and smartphones) can really bring benefits to the area. To accomplish that, we perform human activity identification with different types of feature vectors and different classification methods.

III. Experimental Design

In this section, we present the main results achieved and tasks performed during our work. We specify the research goal, the dataset collection, the instrumentation, as well as specifications about the experiment, and the statistical analysis. Our focus relies on the analysis of a major parameter: accuracy of activity recognition approaches. Our experimental evaluation follows the guidelines presented by Andreas et al. [6].

A. Research Goal

The main goal of this experimental evaluation is to analyze the use of *accelerometer data from smartwatches and smartphones* combined for the purpose of *activity recognition* with respect to its *accuracy* from the point of view of *four physical activities (walking, sitting, standing and driving)* in the context of *pervasive computing*. Therefore, we simultaneously collect accelerometer data from a smartphone along with a smartwatch and carry out the activity recognition using data only from the smartphone and using data from the smartphone and the smartwatch combined.

B. Data Collection Procedure

In order to perform the experimental evaluation, we simultaneously collect sensor data from smartphone and smartwatch accelerometers. To accomplish that, we conduct an experiment in which users performed an average of four activities – walking, sitting, standing and driving[1] – using both devices. To collect the data, we perform the following steps for each participant of the experiment:

1) Enter the participant identifier, i.e., first name;
2) Place the smartphone in his front right trousers pocket, and the smartwatch in his right wrist (Figure 1);
3) Inform which activity will be performed, i.e, walking, sitting, standing or driving;
4) Enable the start of the accelerometer data collection by the smartwatch;
5) Execute 1 minute of data collection;
6) Repeat the steps 3 to 5 for each activity performed.

The participants were mostly undergraduate students aged 20 to 35 years old. At the end of the process, we gather a dataset with the following aspects:

- 13 participants without any physical disability. 12 males and 1 female;
- Information of 4 physical activities.
- 52 log files, each file containing accelerometer data from an activity performed by a participant, and each log containing about 200 lines with:

1) Timestamp of the smartphone in milliseconds;
2) *X*-axis value from the smartphone accelerometer;
3) *Y*-axis value from the smartphone accelerometer;
4) *Z*-axis value from the smartphone accelerometer;
5) Performed activity;
6) Timestamp of the smartwatch in milliseconds;
7) *X*-axis value from the smartwatch accelerometer;
8) *Y*-axis from the smartwatch accelerometer;
9) *Z*-axis from the smartwatch accelerometer.

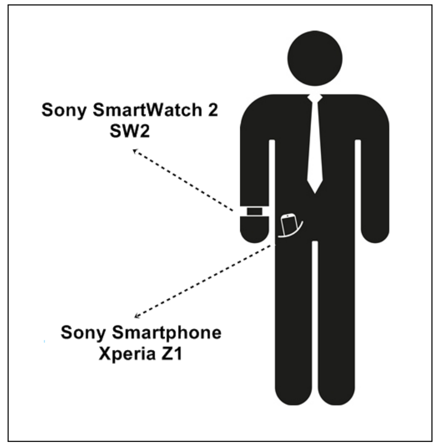

Fig. 1: Illustration of a user with the smartphone in his front right trousers pocket, and the smartwatch in his right wrist.

C. Instrumentation

Among the main tools we use during the experimental evaluation, stand out:

Sony SmartWatch 2 SW2. Android smartwatch that provides integrated accelerometer sensors. We use the SW2 during the data collection phase.

Sony Smartphone Xperia Z1. Android smartphone that provides integrated accelerometer sensors. We use the Z1 during the data collection phase.

Weka[2]. Data mining software in Java. Weka is a collection of machine learning algorithms for data mining tasks, which can either be applied directly to a dataset or called from your own Java code. We use Weka algorithms to classify the activities.

R[3]**.** Software environment for statistical computing and graphics. R provides a wide variety of statistics and graphical techniques, and is highly extensible. We use R in the statistical analysis.

D. Data Preprocessing

Before performing the activity classification, we preprocess the raw data collected from the 3-axis accelerometers. This step aims to improve the characterization of the activities and, consequently, to increase the recognition accuracy.

[1]We ask the participants to simulate the action of driving, it does not represent the real activity.

[2]http://www.cs.waikato.ac.nz/ml/weka/

[3]https://www.r-project.org/

TABLE I: Examples of feature vector generated from smartphone raw data.

AM X	AM Y	AM Z	STD X	STD Y	STD Z	Physical Activity
0.3052	-9.796	-0.287	1.072955	0.340536	0.479773	Walking
-3.219	-7.428	-6.486	0.021534	0.021778	0.017433	Sitting
1.636	3.624	-10.89	0.937653	0.510336	2.276427	Standing
2.888	-3.562	-9.418	0.246068	0.092064	0.148109	Driving
-0.2014	-9.486	-0.3109	0.675129	1.025669	1.922581	Walking
-3.224	-7.447	-6.47	0.024871	0.050183	0.036129	Sitting

We extract arithmetic mean and standard deviation from the raw data previously collected. To accomplish this task, we calculate both features for every 10 lines of log files. In Table I, it is possible to see some examples of feature vectors generated from the raw data collected from the smartphone, in which "AM X" and "STD X" represent, respectively, the arithmetic mean and the standard deviation based on 10 samples obtained from the x-axis accelerometer.

At the end of the process, we generate six *arff* files that represent the features vectors to be used as input data of classifiers[4].

E. Experiment Design

In our experiment, we have three independent variables as input source and one dependent variable as output information. The first independent variable is represented by the data source, with the following two levels:

1) **Smartphone data**: data collected from a smarphone accelerometer;
2) **Smartphone and smartwatch data**: data simultaneously collected from the smartphone and smartwatch accelerometers.

The second independent variable is represented by the classification method, with three levels as follows:

1) **Decision Tree**: *J48* classifier from the Weka software tool (default settings);
2) **Naive Bayes**: *NaiveBayes* classifier from the Weka software tool (default settings);
3) **SVM**: *LibSVM* classifier from the Weka software tool (default settings).

Finally, the third independent variable is represented by the feature vector, with three levels as follows:

1) **Arithmetic Mean (AM)**: feature vectors obtained by the arithmetic mean calculated from accelerometer raw data;
2) **Standard Deviation (STD)**: feature vectors obtained by the standard deviation calculated from accelerometer raw data;
3) **Standard Deviation and Arithmetic Mean (SA)**: feature vectors obtained by the combination of both features.

Our dependent variable is represented by the accuracy of the recognition achieved through a run based on a set of independent variables.

[4]Activity Recognition Repository: https://goo.gl/Y8NXP1

F. Hypotheses

The main research question we want to answer is the following:

P1. Does the use of accelerometer data from smartphones along with smartwatches improve the accuracy of the activity recognition compared to the use of only accelerometer data from smartphones?

To answer that, we formulate the following hypotheses:

H_0**:** there is no difference, in terms of accuracy, in the recognition of activities using accelerometer data collected simultaneously from smartphones along with smartwatches and compared to using data only from smartphones, for the classification method *i* and feature vectors based on *j*.

H_1**:** the use of accelerometer data from smartphones along with smartwatches achieves **greater** accuracy in activity recognition, for the classification method *i* and feature vectors based on *j*.

Where *i* is a classifier of type SVM, Naive Bayes or Decision Tree, and *j* is a feature vector based on AM, STD or SA. So that, we have 9 null hypotheses.

G. Execution

In order to evaluate the accuracy of classification approaches, in general, data is split into training and test sets, in which the training set comprises a larger portion of data, and it is used to train the approaches, i.e., to provide knowledge to the classification methods about the studied problem. On the other hand, the test set is used to evaluate the accuracy of the approaches [5]. These two datasets must be disjoint, i.e., they should not present elements in common to avoid bias on results.

In our work, we use the 10-fold cross-validation method, which randomly splits the dataset into 10 independent parts, and each part is used once as test set and the remaining as training set. Therefore, we separate the whole data into 90% for training and 10% for testing. Additionally, we repeat the execution three times for each classification method and each feature vector as input data. Thus, we have an amount of 30 result samples per round.

H. Results

In Table II, it is possible to see the average of the accuracies achieved using feature vectors based on standard deviation. For example, the accuracy achieved for J48 approach (i.e., decision trees) using as input source smartphones only is 66.72%. On the other hand, the same approach with input data from smartphones along with smartwatches obtained greater accuracy of 68.46%.

TABLE II: Average accuracy achieved by 30 runs, using feature vectors based on standard deviation as input data.

Classification methods	Smartphone	Smartphone and smartwatch
J48	66.72%	**68.46%**
NB	50.73%	**59.30%**
SVM	56.41%	**62.62%**

In Table III, it is possible to see the average of the accuracies achieved with feature vectors based on arithmetic mean for the classification methods J48, NB and SVM.

TABLE III: Average accuracy achieved by 30 runs, using feature vectors based on arithmetic mean as input data.

Classification methods	Smartphone	Smartphone and smartwatch
J48	**79.40%**	78.36%
NB	55.91%	**62.05%**
SVM	78.30%	**81.63%**

Finally, in Table IV, it is possible to see the results obtained with feature vectors based on the combination of both features, standard deviation and arithmetic mean.

TABLE IV: Average accuracy achieved by 30 runs, using feature vectors based on standard deviation and arithmetic mean as input data.

Classification methods	Smartphone	Smartphone and smartwatch
J48	**87.91%**	87.33%
NB	74.59%	**80.09%**
SVM	**89.63%**	88.47%

To identify which of the approaches obtained the best accuracy in fact, we perform a pairwise comparison (statistical analysis) for each treatment with one classification method and one feature vector as input data.

I. Statistical Analysis

In statistical analysis some tests are known for two by two comparisons (our case), for example, t-test (parametric) and Wilcoxon test (non-parametric) [4]. Before using t-test, some requirements must be met in both compared samples, data normality and homoscedasticity. Therefore, to choose the proper statistical test, firstly, we verify all the sample profiles, by performing Shapiro-Wilk test to evaluate data normality and Levene's test to evaluate data homoscedasticity. Afterwards, we use t-test in the cases these requirements were met, and Wilcoxon test, otherwise.

We compare the results achieved by three classification methods using data from smartphones only, and data from smartphones and smartwatches combined. Additionally, we investigate three types of feature vectors as input of the classifiers. Because of that, we analyze three hypotheses for each classification method. Besides the smartphone data, as a preliminary result, we also investigated the use of smartwatch data alone. However, it produced lower results, because of that we compare only the smartphone data as well as the combination of both devices.

In Table V, it is possible to see the results of the statistical tests performed during our study to evaluate the 9 proposed hypotheses (Subsection III-F), each test with 95% of confidence (i.e., α = 0.05). In order to identify which dataset obtained the greater accuracy, we consider two alternative hypotheses for each null one.

After performing the tests, we have the following results:

- **For J48 classifier:** we accept H_0 for feature vectors based on AM and SA. In the other hand, we reject H_0 and accept H_1 for feature vectors based on STD;
- **For NB classifier:** we reject H_0 and accept H_1 for all types of feature vectors;
- **For SVM classifier:** we accept H_0 for feature vectors based on SA. In the other hand, we reject H_0 and accept H_1 for feature vectors based on AM and STD.

Therefore, we can conclude with 95% of confidence that on 6 of the 9 cases the addition of smartwatch accelerometer data improved the accuracy of activity recognition. Additionally, we do not achieve greater results on any of the 3 remaining situations using only smartphone data as input source.

We still observe that the preprocessing phase used to create the feature vectors directly affects the results. For example, we obtain an accuracy of 56.4% with SVM classifier and feature vectors based on AM (data from smartphones only) and an accuracy of 89.6% with the same classifier, but taking feature vectors based on SA. These results represent a significant improvement in the accuracy of the recognition.

IV. Threats to Validity

A. Construct Validity

In this work, we just evaluate the accuracy of activity recognition. However, several evaluation metrics could be applied, for example, precision, recall, insertion, merge, overfill, and confusion matrix [14]. Thus, we suggest in future replications of this experiment to investigate these metrics too.

B. Conclusion Validity

Due to the low number of participants in the dataset collection phase, we have a threat to conclusion validity, since it is recommended to have a larger dataset, for matters of statistical power. Therefore, we intend to continue the dataset collection process with other participants, in order to replicate the experiments with a larger dataset, with different classifiers and different feature vectors.

V. Conclusion and Future Work

In this paper, we performed an experimental evaluation to investigate the impact, in terms of accuracy, of the activity recognition using accelerometer data from smartwatches along with smartphones as input source.

For the best of our knowledge, this is the first experimental evaluation to measure and statistically analyze the impact of accuracy in activity recognition, achieved by combining simultaneously collected data from marketable wearable devices sensors (i.e. smartwatch accelerometer) and from smartphones. Although some previous works present studies with

TABLE V: Statistical Analysis

Classification methods	Feature vectors	Normal data	Equal variance	*p-values*
J48	Mean	Yes	Yes	0.7974
	Std	Yes	Yes	**0.04658**
	Mean and Std	No	N/A	0.9073
NB	Mean	Yes	Yes	**7.878e-09**
	Std	Yes	Yes	**7.927e-12**
	Mean and Std	Yes	Yes	**0.0002158**
SVM	Mean	Yes	Yes	**0.009503**
	Std	Yes	Yes	**1.373e-07**
	Mean and Std	Yes	Yes	0.8867

these devices, they did not perform experiments evaluating the accuracy of the recognition with different input feature vectors and different classifiers, as we showed in our work. Furthermore, our work presents significant evidences that the use of marketable smartwatch sensor data in addition to smartphone data can increase the accuracy of activity recognition approaches. Therefore, our study can be used as baseline of future experimental works.

We found some works in literature that focus on features extraction approaches [18], [1]. Therefore, as future work, we will carry out a study about different ways to extract features from accelerometer raw data and replicate this experiment with different input vectors, in order to obtain more representative activity feature vectors, and hence, to get greater accuracy in the activity recognition. Another possible future work is to investigate a greater range of activities based on sensor data from smartwatches and smartphones combined, for example complex activities (e.g., cooking, watching TV, etc) [17]. Additionally, we could do a comprehensive discussion on the sensor data that may affect the physical activity recognition, since mobile devices are equipped with many sensors and provide many kinds of data from them. Then, we could propose new techniques or frameworks to accomplish the activity recognition with these collected data.

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REFERENCES

[1] A. Akl and S. Valaee. Accelerometer-based gesture recognition via dynamic-time warping, affinity propagation, and compressive sensing. In *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, pages 2270–2273, March 2010.

[2] G. Bieber, M. Haescher, and M. Vahl. Sensor requirements for activity recognition on smart watches. In *Proceedings of the 6th International Conference on PETRA*, PETRA '13, pages 67:1–67:6, New York, NY, USA, 2013. ACM.

[3] G. Bieber, T. Kirste, and B. Urban. Ambient interaction by smart watches. In *Proceedings of the 5th International Conference on PETRA*, PETRA '12, pages 39:1–39:6, New York, NY, USA, 2012. ACM.

[4] S. Boslaugh and P. A. Watters. Nonparametric statistics. In *Statistics in a Nutshell: A Desktop Quick Reference (In a Nutshell (O'Reilly))*, pages 207–223. O'Reilly Media, 2008.

[5] A. Bulling, U. Blanke, and B. Schiele. A tutorial on human activity recognition using body-worn inertial sensors. *ACM Comput. Surv.*, 46(3):33:1–33:33, Jan. 2014.

[6] A. Jedlitschka and D. Pfahl. Reporting guidelines for controlled experiments in software engineering. In *Empirical Software Engineering, 2005. 2005 International Symposium on*, pages 10 pp.–, Nov 2005.

[7] F. A. Kawsar, S. I. Ahamed, and R. Love. Smartphone based multimodal activity detection system using plantar pressure sensors. In *Proceedings of the 29th Annual ACM SAC*, SAC '14, pages 468–469, New York, NY, USA, 2014. ACM.

[8] J. R. Kwapisz, G. M. Weiss, and S. A. Moore. Activity recognition using cell phone accelerometers. *SIGKDD Explor. Newsl.*, 12(2):74–82, Mar. 2011.

[9] L. Liu, C. Karatas, H. Li, S. Tan, M. Gruteser, J. Yang, Y. Chen, and R. P. Martin. Toward detection of unsafe driving with wearables. In *Proceedings of the 2015 Workshop on WearSys*, WearSys '15, pages 27–32, New York, NY, USA, 2015. ACM.

[10] J. W. Lockhart, T. Pulickal, and G. M. Weiss. Applications of mobile activity recognition. In *Proceedings of the 2012 ACM Conference on UbiComp*, UbiComp '12, pages 1054–1058, New York, NY, USA, 2012. ACM.

[11] B. Milosevic and E. Farella. Wearable inertial sensor for jump performance analysis. In *Proceedings of the 2015 Workshop on WearSys*, WearSys '15, pages 15–20, New York, NY, USA, 2015. ACM.

[12] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen. Activity classification using realistic data from wearable sensors. *Information Technology in Biomedicine, IEEE Transactions on*, 10(1):119–128, Jan 2006.

[13] L. Porzi, S. Messelodi, C. M. Modena, and E. Ricci. A smart watch-based gesture recognition system for assisting people with visual impairments. In *Proceedings of the 3rd ACM International Workshop on IMMPD*, IMMPD '13, pages 19–24, New York, NY, USA, 2013. ACM.

[14] A. Reiss, D. Stricker, and G. Hendeby. Towards robust activity recognition for everyday life: Methods and evaluation. In *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2013 7th International Conference on*, pages 25–32, May 2013.

[15] S. Tragopoulou, I. Varlamis, and M. Eirinaki. Classification of movement data concerning user's activity recognition via mobile phones. In *Proceedings of the 4th International Conference on WIMS*, WIMS '14, pages 42:1–42:6, New York, NY, USA, 2014. ACM.

[16] M. Uddin, A. Salem, I. Nam, and T. Nadeem. Wearable sensing framework for human activity monitoring. In *Proceedings of the 2015 Workshop on WearSys*, WearSys '15, pages 21–26, New York, NY, USA, 2015. ACM.

[17] Z. Yan, D. Chakraborty, S. Mittal, A. Misra, and K. Aberer. An exploration with online complex activity recognition using cellphone accelerometer. In *Proceedings of the 2013 ACM Conference on UbiComp Adjunct*, UbiComp '13 Adjunct, pages 199–202, New York, NY, USA, 2013. ACM.

[18] Y. C. Z. F. Yu Liu, Le Wang and Y. Ou. The improvement of behavior recognition accuracy of micro inertial accelerometer by secondary recognition algorithm. *Sensors & Transducers*, 172(0):1 – 6, 2014.

[19] K. Zhao, J. Du, C. Li, C. Zhang, H. Liu, and C. Xu. Healthy: A diary system based on activity recognition using smartphone. In *MASS, 2013 IEEE 10th International Conference on*, pages 290–294, Oct 2013.