Human Activity Recognition using On-body Sensing

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Abstract. Human Activity Recognition (HAR) based on wearable sensors is gaining increasing attention by the pervasive computing research community, especially for development of context-aware systems. This paper presents our approach for HAR based on wearable accelerometers and supervised learning algorithms. We present the HARwear device, a wearable for HAR. Using HARwear we collected data and we developed a classifier for postures and movements. The classifier is able to identify 2 postures and 3 types of movements with an accuracy of 99.4%. Based on the lessons from experimental evaluation, we propose an improved version, the HARwear version 2, which is also presented on this paper.

1. Introduction

Human Activity Recognition – HAR – has emerged as a key research area in the last years. There are many potential applications like: elderly monitoring, life log systems for monitoring energy expenditure and for supporting weight-loss programs, and digital assistants for weight lifting exercises.

Early HAR approaches were mainly computational vision-based. Later on an increase of publications about HAR wearables is noticeable such as presented in the literature survey presented in [Ugulino *et al.*, 2012]. In on-body sensing approaches, the most effective technique for recognizing activities is supervised learning algorithms. These algorithms make inferences about the performed activity based on raw data captured from wearable sensors, like accelerometers and gyroscopes. This approach, however, requires a large amount of annotated data in order to provide accurate results [Riboni & Bettini, 2011]. One can use unsupervised learning algorithms as an alternative, but their accuracy has been lower than supervised ones, as shown in [Ugulino *et al.*, 2012]. Finally, semi-supervised approaches have been much less explored in literature, but most results also present lower accuracy rates when compared to the supervised ones.

In order to explore the on-body sensing approach for HAR, we built HARwear: a wearable device for Human Activity recognition. Later on we defined a classification task and designed the experimental part of this research. For solution of the classification task we investigated several supervised learning algorithms. We found higher accuracy with the combination of ten C4.5 decision trees trained with AdaBoost ensemble learning technique. The accuracy rate is of 99.4%, which is equivalent to top results found in the literature. From the lessons learned with the first wearable prototype and classifier, we designed a new version of the wearable.

This paper is organized as follows: Section 2 presents a literature review on HAR based on wearable accelerometers. Section 3 presents the first prototype of the HARwear device. We discuss the recognition task on Section 4. Section 4 also presents the experimental results we found. The new version of the HARwear prototype is presented on Section 5. Finally, conclusion and future works are presented on Section 6.

2. HAR based on wearable accelerometers' data

In order to provide a literature review, we searched for publications on HAR based on wearable accelerometers. The investigated topics were: classification accuracy and the test modes used by the authors, number of sensors used – regarding the list of tasks, and technique used for activity recognition. A qualitative assessment was made, especially considering necessary information for replicating the studies.

Regarding the test mode and evaluation, the most widely used test mode is the k-fold cross-validation; however, less-dependable tests and even non-standard tests were performed in some recent works. Another important data identified in the literature is that most works present a percentage starting at 90% of success rate in the activities' classification. However, only seven papers informed the dataset size.

Regarding the number of sensors, we observed the use of up to 4 accelerometers in the collection of data for the most of the works. We highlight the Atallah's research that specifically focuses on the development of classifiers adaptable to different amounts of accelerometers [Atallah *et al.*, 2011]. We also observed a discussion on the importance of the location of the accelerometers on the body. Waist, chest, forearm (around biceps), and thigh are the most common positions in which the sensors were mounted.

About the technique for recognizing activities, most of the works use machine learning, mainly supervised learning techniques. Threshold-based algorithms are usually tailored by the authors and also present good accuracy results, but the authors usually don't use standard tests for check accuracy rate. Finally, a small number of works have used other approaches, like fuzzy finite state machines, symbolic reasoning, etc. Despite the absence of a standard list of activities, we observed that most works include "walking", "sitting", and "standing".

We also observed that the subject independent analysis has been less explored: only 3 out of 69 articles presented a subject independent analysis. The primary alternatives presented by the authors in order to improve the prediction performance in subject independent tests are: (1) increase of dataset, performing the data collection from subjects of different profiles; (2) adapting learning to a subject from data collected from subjects with similar physical characteristics [Maekawa & Watanabe, 2011]; and (3) investigation of subject independent features and more informative of the classes [Xu *et al.*, 2011]..

There is a lack of information about the orientation of the sensors axis in most papers, although the location is usually well described. In some research it was not informed the model of sensor used. The absence of information about orientation and sensors model impairs the replication of the wearable devices. A list of metadata drawn from the most recent publications (2012 and 2011) is shown on Table 1.

Table 1. HAR based on accelerometers' data from 2012 and 2011 (IEEE database)

Research	# of sensors	Accelerometers' position	Solution	# of users	Learning mode	Test mode	Correct (%)
Liu *et al.,* 2012	1	hip, wrist (no info about orientation)	SVM	50	Super-vised	leave-one-out	88.1
Yuting *et al.,* 2011	3	chest and both thighs (no info about orientation)	Threshold-based	10	--	--	98.6
Sazonov *et al.,* 2011	1	Foot	SVM	9	Super-vised	4-fold cross validation	98.1
Reiss & Stricker, 2011	3	lower arm, chest and foot	Boosted Decision Tree	8	Super-vised	8-fold cross validation	90.7
Min *et al.,* (2011)	9	torso, arms and legs	Threshold-based	3	--	Comparison with k-means	96.6
Maekawa & Watanabe, 2011	4	wrists of both hands, waist, and right thigh	HMM	40	Unsupervised	leave-one-out	98.4
Martin *et al.,* 2011	2	hip, foot and chest	Threshold-based	5	--	--	89.4
Lei *et al.,* 2011	4	waist, chest, thigh, and side of the body	Naive Bayes	8	Supervised	Several, w/ no cross validation	97.7
Alvarez *et al.,* 2011	1	centered in the back of the person	Genetic fuzzy finite state machine	1	Supervised	leave-one-out	98.9
Jun-ki & Sung-Bae, 2011	5	forehead, both arms, and both wrists	Naive Bayes and SVM	3	Supervised	leave-one-out	**99.4**
Ioana-Iuliana & Rodica-Elena, 2011	2	right part of the hip, lower part of the right leg	Neural Net-works	4	Supervised	66% training vs. 33% test	**99.6**
Gjoreski *et al.,* 2011	4	chest, waist, ankle and thigh	Naïve Bayes, SVM, C4.5, Random Forest	11	Supervised	Leave-one-person-out	90
Feng, Meiling, and Nan ,2011	1	Waist	Threshold-based	20	--	--	94.1
Czabke, Marsch, and Lueth, 2011	1	Trousers' Pocket	Threshold-based	10	--	--	90
Chernbumroong, *et al.,* 2011	1	Non-dominant wrist (watch)	C4.5 and Neural Networks	7	Supervised	5-fold cross-validation	94.1
Bayati *et al.,* 2011	--	Simulations instead of real accelerometers	**E**xpectation **M**aximization	--	Unsupervised	Not men-tioned	86.9
Atallah *et al.,* 2011	7	ear, chest, arm, wrist, waist, knee, and ankle	Feature Selection algorithms*	11	Supervised	Not applied	--
Andreu *et al.,* 2011	1	Not mentioned	fuzzy rule-based	--	Online learn-ing	--	71.4

It was observed a very limited number of public datasets, which restrains the comparison of results between approaches. From all papers, we found only 3 research groups that made their datasets public. For the maturity of this research area, it is imperative to have public datasets in order to enable benchmark evaluations. The importance of disclosing datasets for benchmarking is also commented by Yang & Lianwen [2010] as it acknowledges that "*the recognition algorithms rely heavily on the dataset*". Yang & Lianwen [2010] and Reiss & Stricker [2012] have also verified the unavailability of datasets in the area and denounced the existence of unpublished proprietary datasets. As a form of contribution, they made available a dataset for benchmark in HAR, in addition to details on the location, orientation and model of sensors used. The dataset provided is an important step towards the maturity of this research area. Table 2 lists the public datasets found on this literature review.

Table 2. Public Datasets for HAR

Author	Sensor	Subjects	Classes	Samples
Reiss & Stricker (2012)	Colibri IMUs (±16g)	9 subjects	lying, sitting, standing, walking, running, cycling, Nordic walking, watching TV, computer work, car driving, ascending stairs, descending stairs, vacuum cleaning, ironing, folding laundry, house cleaning, playing soccer, rope jumping	3,850,505 annotated examples (with missing data)
Xue & Jin	ADXL330 (±3g)	44 subjects (34 males, 10 females)	Step walking, Jumping, Cycling, Walking, Walking backward, Walking quickly, Running, Relaxing, Downstairs, Upstairs	1278 annotated examples
Albinali *et al.*	Not informed	24 subjects (10 males, 14 females) (with detailed information)	Sitting (5 variations), Standing (3 variations), Lying down, Walking (3 variations), Washing windows, Cycle (4 variations), Vacuuming, Mopping, Air dyne 30 rpm, Stepping on platform, Jog 5 mph	48h of annotated data

As observed on Table 2, there is no standard list of classes, which makes impossible to compare these results. Although the absence of a standard list of classes, we observed in the 69 papers analyzed that "sitting" and "standing" are the most common postures listed as classes. The movement present in every publication is "walking". These findings helped the definition of the classification task for the experimental step of this research.

3. HARwear: a wearable prototype for Human Activity Recognition

Our wearable device comprises 4 tri-axial ADXL335 accelerometers connected to an ATmega328V microcontroller. All modules are of the Lilypad Arduino toolkit. The wearable device and the accelerometers' positioning and orientation diagram are illustrated in Figure 1.
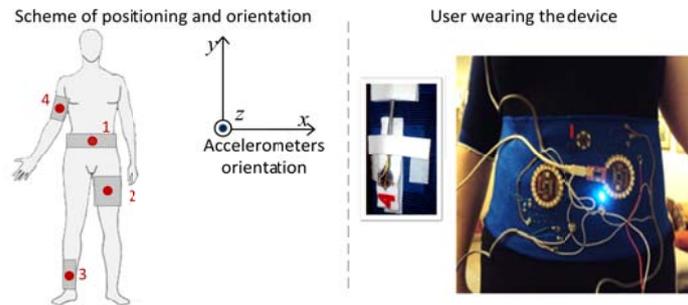

Figure 1. HARwear: a wearable for Human Activity Recognition

The accelerometers were respectively positioned in the waist (1), left thigh (2), right ankle (3), and right arm (4). These positions were decided after the literature review, as they were considered the most effective for similar set of activities (basic postures and movements). All accelerometers were calibrated in the construction step. The calibration consists of positioning the sensors and the performance of the reading of values to be considered as "zero". From the calibration, the read values of each axis during data collection are subtracted from the values obtained at the time of the calibration.

The calibration purpose was to attenuate the peculiar inaccuracy issues of this type of sensor. Because of this, the sensors were calibrated on top of a flat table in the same position. Another regular type of calibration is the calibration by subject [Lei *et al.*, 2011], in which the accelerometers are read and calibrated after positioned in the subjects' bodies. Calibration by subject may benefit the data collection if it enables the

obtainment of more homogeneous data. However, it makes more complex to use the wearable, because the user must follow certain procedure before using the device.

Even though the Lilypad Arduino platform was design to be used with conductive thread, we used wired cables in order to increase robustness, to enable on-the-fly changes in the circuit and to facilitate reprogramming the microcontroller. The assembly took into consideration the ease of move by the users. The source code (sketch in the *Arduino* Programming Language) is available at http://groupware.les.inf.puc-rio.br/har.

4. Posture and Movement Classifier

Based on the review presented on Section 2, we decide the postures and movements for the classification task: sitting, standing, walking, standing up (transient movement), and sitting down (transient movement). These are the most common and basic activities and their recognition have potential to be combined with contextual information to feed context-aware systems to support collaboration. From the raw data, we calculate derived features, according to the advices found on literature review and our own experimental results.

Task Definition

The goal is to classify subjects' posture or movement in "sitting", "sitting down", "standing", "standing up", or "walking" based on readings from 4 wearable accelerometers, mounted at waist (accelerometer #1), left thigh (accelerometer #2), right ankle (accelerometer #3) and right upper arm (around biceps – accelerometer #4). The orientation of the sensors must follow the schema presented in Figure 1.

Input data comprise the raw reading from accelerometers and some derived values automatically calculated by the Arduino microcontroller (source code available for download). The class is annotated during the data collection process.

```
@Accel1_readings: <x, y, z, m, r, p>

        x, y, z: raw acceleration data from accelerometers

        (m) Module of the acceleration vector

        (r) Rotation over the x axis

        (p) Rotation over the y axis

@class: nominal (sitting, standing, standing up, sitting down, walking)
```

Data Collection

We collected 8h of activities from 4 subjects, nearly 2 hours with each participant. The participants' profiles are illustrated in Table 3.

Table 3. List of participants and profiles

Participant	Sex	Age	Height	Weight	Instances
A	Female	46 y.o.	1.62m	67kg	51,577
B	Female	28 y.o.	1.58m	53kg	49,797
C	Male	31 y.o.	1.71m	83kg	51,098
D	Male	75 y.o.	1.67m	67kg	13,161

At total it was collected 165,633 samples for the study; the distribution of the samples between the classes is illustrated in Figure 2.
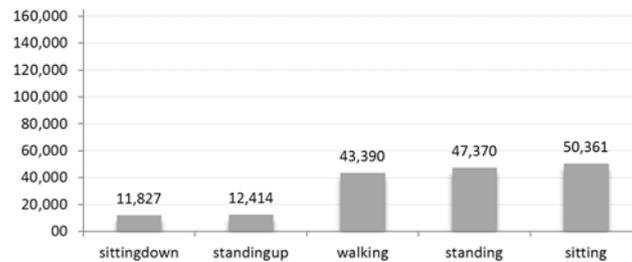

Figure 2. Frequency of classes between collected data

After the data collection, a pre-processing was made according instructions in [Jun-Ki & Sung-Bae, 2011]. We also normalized the data in order to test with SVM and neural networks.

Data Pre-processing

Pre-processing work comprised the generation of a time window of 1 second, with 150ms overlapping. Readings inside each window were statistically summarized according the instructions of Maziewski *et al.* [2009]. The reading frequency was set up to 10 Hz – due to hardware clock imprecision it is nearly 10 readings per second in fact. From the values inside the time window, we calculated the mean and variance of the acceleration vector module, roll, and pitch.

Feature Selection

We used Mark Hall [1999] algorithm to select most valuable features. The main goal is to decide the minimum amount of data necessary to make a good prediction. It is also useful to support decision making about discarding a sensor: if a sensor readings do not produce features providing information gain, then it is discarded. As a result, 10 features were selected from 4 sensors: (1) accelerometer on the waist: mean of acceleration module vector, variance of pitch and roll; (2) accelerometer on the right thigh: mean of acceleration module vector, acceleration vector module, and variance of pitch; (3) accelerometer on the right ankle: mean of acceleration module vector, and variance of pitch and roll; (4) accelerometer on right upper arm: acceleration module vector.

Experimental evaluation

The evaluation comprised 10-fold cross-validation tests. We tried Support Vector Machine (SVM), Voted Perceptron (one-against-all strategy), Multilayer Perceptron (Back Propagation) and C4.5 Decision Trees. The better result was with C4.5 with confidence factor of 0.15 (accuracy of 98.2%). Later on, we used the AdaBoost ensemble learning with 10 decision trees (C4.5). The AdaBoost method "*tends to generate distributions that concentrate on the harder examples, thus challenging the weak learning algorithm to perform well on these harder parts of the sample space*" [Freund & Schapire, 1996]. In a simplified manner, with the use of AdaBoost, the C4.5 algorithm was trained with a different distribution of samples for each iteration, thus favoring the "hardest" samples. The overall recognition performance was of 99.4% (weighted average) using a 10-fold cross validation testing mode. The confusion matrix is presented in Table 4.

Table 4. Confusion Matrix

Sitting	Sitting down	Standing	Standing Up	Walking		
50,601	9	0	20	1	Sitting	
10	11,484	29	297	7	Sitting down	**Actual class**
0	4	47,342	11	13	Standing	
14	351	24	11,940	85	Standing up	
0	8	27	60	43,295	Walking	

The accuracies per class follow: "sitting" 100%, "sitting down" 96.9%, "standing" 99.8%, "standing up" 96.9%, and "walking" 99.8%.

5. HARwear version 2

Some lessons were learned from the literature review and experimental evaluation. The HARwear version 2 is illustrated in Figure 3.

Figure 3. HARwear version 2

The most important modification is related to the orientation and position of sensors. From the literature, many publications do not specify sensors orientation, and some of them do not clearly specify the sensors position. During data collection we attempted to make sure that the users worn sensors in specified position and orientation. In order to enforce the guidelines we decided to put an orientation chart embroidered on the 2nd version of the wearable. Another important lesson is related to the sensing range value: some human movements are greater than ±3.6g, which is the sensing range of the ADXL335 sensor used. In order to avoid noise in readings that typically occurs when acceleration is over 3.6g, we tried a sensor with ±8g on the 2nd version. An experimental evaluation was planned to check if this is a good range. The problem in selecting a range over ±8g is that these sensors usually come with a resolution of 12bit, which means that configuring the sensor to its maximum sensing range impairs the quality of

the readings (as it has only 12bit resolution). The sensor on the upper arm was discarded as a result of the feature selection procedure.

6. Conclusion and Future Works

This paper presented an on-body approach for recognizing activities. A literature review was presented and its findings were useful for preparing the HARwear and the experimental part of the research. The overall performance of the classifier was of 99.4% correct, which is a good start for feeding real time systems with user specific data collection and training. From the lessons learned on the experimental evaluation, we built a new version of HARwear. Also from the literature review, we observed that recent publications are focusing on a combination of ambient and on-body sensing [Riboni & Bettini, 2011; Pfisterer et al., 2011]. Based on these findings, we plan to investigate some research opportunities in future works:

1. Hybrid approaches (combining ambient and on-body sensing);
2. Standardization of the activities list, by using ontologies or some hierarchical model;
3. Standardization of the sensors data: although there are many efforts in this direction, much of the research propose specific XML-schema, which impairs semantic interoperability.

Referências

Alvarez-Alvarez, A.; Trivino, G.; Cordon, O. Body posture recognition by means of a genetic fuzzy finite state machine. In IEEE 5th International Workshop on Genetic and Evolutionary Fuzzy Systems (GEFS). 2011.

Andreu, J.; Baruah, R.D.; Angelov, P. Real time recognition of human activities from wearable sensors by evolving classifiers. In IEEE International Conference on Fuzzy Systems (FUZZ). 2011.

Atallah, L.; et al. Sensor Positioning for Activity Recognition Using Wearable Accelerometers. Biomedical Circuits and Systems, IEEE Transactions on, 2011. 5(4): p. 320-329.

Bayati, H.; Millan, J. del R.; Chavarriaga, R. Unsupervised Adaptation to On-body Sensor Displacement in Acceleration-Based Activity Recognition. In 15th Annual International Symposium on Wearable Computers (ISWC). 2011.

Bettini, C.; Brdiczka, O.; Henricksen, K.; Indulska, J.; Nicklas, D.; Ranganathan, A.; Riboni, D. A survey of context modelling and reasoning techniques. In: Pervasive and Mobile Computing, Volume 6 (2), April 2010, pp. 161-180, ISSN 1574-1192, 10.1016/j.pmcj.2009.06.002.

Chernbumroong, S., Atkins, A.S. Hongnian, Y. Activity classification using a single wrist-worn accelerometer. In 5th International Conference on Software, Knowledge Information, Industrial Management and Applications (SKIMA). 2011.

Czabke, A.; Marsch, S.; Lueth, T.C. Accelerometer based real-time activity analysis on a microcontroller. In 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth). 2011.

Feng, W.; Meiling, W.; Nan, F. Research on Classification of Human Daily Activities Based on a Single Tri-Axial Accelerometer. In 1st International Workshop on Complexity and Data Mining (IWCDM). 2011.

Freund, Y.; Schapire, R. E. Experiments with a New Boosting Algorithm. In International Conference on Machine Learning, pages 148–156, 1996.

Gjoreski, H.; Lustrek, M. Gams, M. Accelerometer Placement for Posture Recognition and Fall Detection. In 7th International Conference on Intelligent Environments (IE). 2011.

Hall, M. A. Correlation-based Feature Subset Selection for Machine Learning. PhD thesis, Department of Computer Science, University of Waikato, Hamilton, New Zealand, Apr. 1999

Ioana-Iuliana, F.; Rodica-Elena, D. Detection of daily movements from data collected with two tri-axial accelerometers. In 34th International Conference on Telecommunications and Signal Processing (TSP). 2011.

Jun-Ki, M.; C. Sung-Bae. Activity recognition based on wearable sensors using selection/fusion hybrid ensemble. In IEEE International Conference on Systems, Man, and Cybernetics (SMC). 2011.

Lei, G.; Bourke, A.K.; Nelson, J. A system for activity recognition using multi-sensor fusion. In Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC. 2011.

Liu, S.; Gao, R.X.; John, D.; Staudenmayer, J.W.; Freedson, P.S. Multisensor Data Fusion for Physical Activity Assessment. IEEE Transactions on Biomedical Engineering, 2012. 59(3): p. 687-696. ISSN: 0018-9294.

Maekawa, T.; Watanabe, S. Unsupervised Activity Recognition with User's Physical Characteristics Data. In 15th Annual International Symposium on Wearable Computers (ISWC). 2011.

Martin, H.; Bernardos, A.M.; Tarrio, P.; Casar, J.R. Enhancing activity recognition by fusing inertial and biometric information. In Proceedings of the 14th International Conference on Information Fusion (FUSION), 2011.

Martinez, K.; Deroure, D.; Page, K.; Sadler, J.; Hutton, C.; Newman, R.; Roe, S. From sensors to semantic web: the SemsorGrid4env project. AGU Fall Meeting Abstracts, page C8, Dec. 2009.

Maziewski, P.; Kupryjanow, A.; Kaszuba, K.; Czyzewski, A. Accelerometer signal preprocessing influence on human activity recognition. In: Conference Proceedings of Signal Processing Algorithms, Architectures, Arrangements, and Applications (SPA), 2009. p. 95-99. ISSN: 978-83-62065-06-6.

Min, Xu; Goldfain, A.; Chowdhury, A.R.; DelloStritto, J. Towards accelerometry based static posture identification. In IEEE Consumer Communications and Networking Conference (CCNC). 2011.

Open Geospatial Consortium, "Sensor Web Enablement (SWE)," 2010.

Pfisterer, D.; Romer, K.; Bimschas, D.; Kleine, O.; Mietz, R.; Cuong Truong; Hasemann, H.; Kröller, A.; Pagel, M.; Hauswirth, M.; Karnstedt, M.; Leggieri, M.; Passant, A.; Richardson, R. *SPITFIRE: toward a semantic web of things*. In: IEEE Communications Magazine, vol.49, no.11, pp.40-48, November 2011. DOI: 10.1109/MCOM.2011.6069708

Reiss, A.; D. Stricker. Introducing a modular activity monitoring system. In Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC. 2011.

Reiss, A.; Stricker, D.; , "Introducing a New Benchmarked Dataset for Activity Monitoring," Wearable Computers (ISWC), 2012 16th International Symposium on , vol., no., pp.108-109, 18-22 June 2012. DOI: 10.1109/ISWC.2012.13

Riboni, D.; Bettini, C. COSAR: hybrid reasoning for context-aware activity recognition. In: Personal Ubiquitous Computing. Vol. 15(3). pp. 271-289. Springer-Verlag, March, 2011. DOI=10.1007/s00779-010-0331-7

Sazonov, E.S., et al. Monitoring of Posture Allocations and Activities by a Shoe-Based Wearable Sensor. Biomedical Engineering, IEEE Transactions on, 2011. 58(4): p. 983-990.

Ugulino, W.; Cardador, D.; Vega, K.; Velloso, E.; Milidiú, R.; Fuks, H. Wearable computing: Accelerometers data classification of body postures and movements. In: Advances in Artificial Intelligence - SBIA 2012. Barros, L.; Finger, M.; Pozo, A.; Gimennez-Lugo, G.; and Castilho, M. (editors). Lecture Notes in Computer Science, pp. 52–61. Springer Berlin / Heidelberg, 2012. DOI: 10.1007/978-3-642-34459-66.

Yang, X.; J. Lianwen. A naturalistic 3D acceleration-based activity dataset & benchmark evaluations. In: IEEE International Conference on Systems Man and Cybernetics (SMC), 2010. p. 4081-4085. ISSN: 1062-922X.

Yuting, Z.; Markovic, S.; Sapir, I.; Wagenaar, R.C.; Little, T.D.C.. Continuous functional activity monitoring based on wearable tri-axial accelerometer and gyroscope. In 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth). 2011.