Investigating the Relevance of Sensor Selection: Recognition of ADLs Based on Feet Movement and Posture Information

Rafael de Pinho André, Pedro Henrique Diniz, Hugo Fuks
Department of Informatics
Pontifical Catholic University of Rio de Janeiro
Rio de Janeiro, RJ, Brazil +55 21 3527-1510
Email: randre,pfonseca,hugo@inf.puc-rio.br

***Abstract*—In this work, we present an analysis of the relevance of different sensor types for the recognition of activities of daily living based on foot movement and position. By conducting a comprehensive experiment with 12 diverse volunteers that resulted in about 1 million data samples, and employing a machine learning HAR (Human Activity Recognition) classifier developed for a 9-activity classes model, we were able to assess the impact of sensor selection on the activity recognition accuracy. Aiming at a replicable research, we provide full hardware information, system source code and a public domain dataset.**

***Keywords*–Clothes-based sensors; IoT (Internet of Things) devices; Mobile sensing applications.**

I. INTRODUCTION

Human Activity Recognition (HAR) is an active and fast-growing field of research that has seen an intense growth during the last five years, drawing attention of researchers from fields, such as mobile healthcare, sports performance and mass context inference. From the rehabilitation of stroke patients [1] to energy expenditure estimation of Activities of Daily Living (ADL) [2] [3], studies based on feet movement and posture show promising results and interesting applications. Current research works can be grouped into two main approaches for collecting user's feet movement and posture data: (i) image processing and (ii) clothes-based sensors. In this work, we address one of the current challenges of the clothes-based sensors approach: understanding which types of sensors are relevant for the recognition of ADLs. Since clothes-based sensors HAR is a comprehensive filed of research, we focus on feet movement and posture information.

Firstly, we performed a literature review on HAR using Internet of Things (IoT) devices and clothes-based sensors, discussed in Section II, which unfolded the intense growth on the number of publications related to the analysis of feet posture and movement in recent years. Throughout the review, we observed that (i) no previous work thoroughly addressed the relevance of the sensors employed for the assessed activity model, (ii) few works provided public datasets for benchmarking, (iii) there is no sufficient information on sensors deployment, (iv) few works addressed their sample rates and time window size choices and (vi) few works addressed the positioning of the plantar pressure sensors. The lack of published datasets, the insufficient information for the replication of these studies and the overall obliviousness of other work's results points to a lack of maturity of the area.

The main contributions of this work are (i) an analysis of the relevance of different types of sensors for the building of a HAR classifier based on feet movement and posture information, (ii) a comprehensive literature review focused on HAR research using clothes-based sensors for collecting feet movement and posture information and (iii) an IoT device blueprint for HAR research, an insole equipped with all the types of sensors used in the surveyed works along with novel sensors. In Section III, the design of the IoT device, sensors deployment and replication information are shown along with the details of the experiment conducted to collect ADL data. In Section IV, the development of the activity model, the classifier and the experimental results are presented and analyzed. In Section V, we conclude with an assessment of sensor relevance and additional findings.

II. LITERATURE REVIEW

This section presents a comprehensive literature review and meta-data analysis about HAR clothes-based sensors research projects using feet movement and posture information for ADL recognition. The literature review workflow was conducted in the following way: (i) definition of a research question, (ii) crafting of a search query string, (iii) definition of exclusion criteria and (iv) performing quantitative and qualitative data analysis. The research question posed in this review is: What are the clothes-based sensors HAR research projects conducted in recognition of ADL using feet movement and posture information?

This research question was further divided into sub-questions:

- What are the types, quantities and locations of the sensors used?
- How was the sensor mix chosen?
- What activities are present in the activity model?

Based on these questions, we formulated a search query string and refined it by the publication year range filter to exclude works not published during the last 10 years. With over three hundred search results combining the searched databases, we applied a very strict exclusion criteria and obtained 24 articles for analysis. Whenever available, from each article, we collected the (i) types and quantity of sensors used, (ii) activity model and machine learning technique, (iii) number of subjects and samples collected and (iv) test technique and results.

The metadata associated with the IoT devices and clothes-based sensor selection presented by these works is summarized in Table I, where the articles are grouped into three distinct research categories: (i) works using Ground Contact Force (GCF) sensors, (ii) works using Inertial Motion Units (IMUs)

 ISBN: 978-1-61208-660-6

sensors and (iii) works employing sensor fusion and other non-conventional sensors.

TABLE I. SUMMARY OF SENSOR SELECTION AND POSITIONING.

Name	*Sensor*	*Positioning*
Crea [4]	FSR	Insole
De Santis [5]	FSR	Insole
Drobny [6]	FSR	Insole
el Achkar [7]	FSR	Insole
Fukahori [8]	FSR	Sock
Holleczek [9]	FSR	Sock
Lin [10]	FSR	Insole
Zhu [11]	FSR	Shoe and Waist
Kong [12]	GCF	Insole
Ugulino [13]	Accelerometers	Waist, Thigh, Arm and Ankle
McCarthy [14]	Gyroscope	Shoe
Doppler [15]	IMU	Insole and Shoe
Ghobadi [16]	IMU	Shoe
Edgar [1]	FSR, IMU	Insole
Lin [17]	FSR, IMU	Insole and Shoe
Tang [18]	FSR, IMU	Insole
Zhang [19]	FSR, IMU	Insole and Shoe
Zhang [20]	FSR, IMU	Insole and External
Noshadi [21]	FSR, Gyroscope and Accelerometers	Insole, Shoe and External
Sazonov [2]	FSR, Accelerometers	Insole and Shoe
Sazonov [22]	FSR, Accelerometers	Insole and Shoe
Jiang [23]	IR	Shoe
Matthies [24]	Capacitive Sensing	Insole
Haescher [25]	Capacitive Sensing	Chest, Leg and Insole

A. Recognition of Common Movement Activities

The recognition of common movement activities, such as walking, standing, sitting, climbing stairs and running, is the most common type of research found in this literature review. Those works, such as [5] [7] [9] [15], rely mostly on plantar Force Sensitive Resistor (FSR) pressure sensors to classify user activity according to a previously elaborated activity model. Other works, such as [6] [14] [16], rely on IMUs located on the user's feet for that purpose. Sensor fusion of FSRs and IMUs is employed by works such as [2] [17] [18] [26], achieving good overall results. Only four of the surveyed works used sensors other than GCF sensors and IMUs: infrared sensors in [23], capacitive sensing technology in [24] [25] and air bladders in [12]. Some works positioned extra sensors in other places beyond the user's feet, such as [13], where extra sensors are positioned onto user's waist, thigh, arm and ankle and [25], where extra sensors are positioned onto user's chest and leg. They all use very similar activity models composed of sitting, standing, running, walking and slope-walking activities, the main differences being the machine learning algorithms used and the context of the experiments. Two of the activity models proposed by the works of this section are more comprehensive than the prevailing standing-walking-running activity models [17] [20]. Both relied on sensor fusion techniques to classify user's activities and obtained promising results.

Many of the surveyed studies were conducted in the recognition of activities related to healthcare and well-being, such as (i) the research presented in [10], that aims at recognizing caregiver's Patient Handling Activities (PHA) and movement activities to help prevent overexertion injuries, (ii) the works presented in [19] [27], that measure activity in people with stroke, (iii) the work presented in [1], that recognizes activities and postures to provide behavioral feedback to patients recovering from a stroke, and (iv) the research proposed by [21], in which researchers present a pair of shoes that offer low-cost balance monitoring outside of laboratory environments using features identified by geriatric motion study experts. The lightweight smart shoes are based on the MicroLEAP wireless sensor platform [28], which uses an IMU and FSR pressure sensors embedded inside each insole for data acquisition. Some other shoe-based wireless sensor platforms, such as the SmartStep [29], were used by many different healthcare-related researches. In [30], the platform was used for developing an Android application to capture data from the IoT device to recognize activities and real time feedback provision. Works, such as [3] [22], employ the SmartShoe platform for energy expenditure estimation after the classification of the activities performed by the user, and in [31] it is used to predict body weight and energy expenditure. The same platform is then used by [27] [32] to identify activity levels and steps in people with stroke. Although the majority of the works focused on healthcare and well-being, some, such as [8], investigated the use of foot-based gestures, known as Foot Plantar-Based (FPB) gestures, to control computing devices.

B. Literature Review Discussion

The measuring of GCFs is the most prevalent approach used by the surveyed works for the task of recognizing user activity, being present in 16 of the 24 studies, while the second most common approach, present in 12 of the 24 studies, is the use of IMUs. Although the challenge of adequately positioning the GCF sensors is recognized as a very important factor by studies, such as [33] [34], it is not thoroughly addressed by most of the surveyed works. Considering the IoT devices presented in the literature, two characteristics impair their reproducibility: (i) the lack of information about the IMUs orientation and the (ii) absence of sensor model information or specification. Most of the works analyzed, 22 out of 24, provided detailed information regarding the models of its activity classifiers, but only 12 studies detailed the test techniques used in the activity classifiers – 7 of which used k-fold cross validation and 5 used leave-one-out. Although most studies stated that tests were performed, they provided no detailed information about these tests. The success rate of ADL recognition of the surveyed works fell into the 80% - 100% range. No work addressed the sensor mix choice besides stating that its selection is commonly found throughout the literature.

It was also observed that 21 out of 24 works provided information on the number of participants, but only 6 of the 24 studies provided information on the dataset size. The main issue detected in the literature review is the absence of publicly available datasets, impairing that way the understanding of the results. Knowledge of datasets is especially important to assess works that use similar (i) sensor selection, (ii) sensor placement and (iii) activity models. As discussed in [11], dataset disclosure is crucial for benchmarking purposes, given that classification algorithms rely heavily on datasets. Beyond dataset size, sample rates and time window durations also affect the understanding of the results. Only 16 of the 24 surveyed works provided information on the sample rates, and 8 of those 16 also provided information on the time window size. The prevailing suggestions for future works and contribution found in the literature are to (i) increase the data set through longer data collection intervals and the diversification of participant's profiles and (ii) adapt the activity model to a specific challenge, such as helping patients to avoid falls. To make the literature review presented in this article replicable, all surveyed publications are available in RIS (Research Information Systems) format in [35].

III. Methods

A. IoT Device Prototyping

In this section, we present the IoT device prototyped to collect user data. Aiming at a highly replicable research, we provide detailed software and hardware information – types, quantities and models of every sensor, along with their exact positioning and orientation, and source code of the embedded software and the application server. Since battery lifetime is a major concern for studies outside of a laboratory environment and the participants came from diverse technological backgrounds, the key design goals were to develop a (i) low power consumption device capable of extended operation that (ii) was easy to use during the experiment. The IoT device comprises two components: an US men's size 8 insole that houses the plantar pressure sensors and an external protective case that houses the microcontroller and the other sensors. The insole component was developed with six GCF sensors, and their placement followed literature's recommendations found in [33] [36]. We used the FSR 402 by Interlink Electronics, a Polymer Thick Film (PTF) device that exhibits a decrease in resistance as the force applied to its active surface increases. Given that each sensor needs a static resistor to create a variable voltage for the microcontroller's Analog to Digital Converter (ADC) inputs, we placed six 10KΩ 1/4W resistors inside the insole next to them. We opted to use a single insole in the experiment to reduce prototyping costs, since the literature suggested that the loss of information when compared to experiments collecting data from both feet is minimal [23]. The external protective case is built around a Particle Electron, a 2G-enabled microcontroller from Particle.io that collects and transmits sensor data to the database. For the accelerometer, gyroscope and magnetometer sensors responsible for monitoring the feet posture, we used the LSM9DS1 by STMicroelectronics, a system-in-package component that is part of the Photon microcontroller board. The LSM9DS1 is a digital sensor, automatically calibrated by its firmware when the device is powered up [37]. The barometer selected for the experiment is the MPL3115A2, by Freescale Semiconductor, a low power, high-precision altitude, pressure and temperature sensor. The MPL3115A2 sensor is factory calibrated for sensitivity, offset for both temperature and pressure measurements, and has a built-in altimeter calculator. Under normal operation, there is no need for further calibration [38]. For the range-finder sensor, we used the VL6180 by STMicroelectronics. Although other sensors are capable of greater sampling rates, the selected range-finder sensor is one of the few distance sensors adequate for the 10 Hz sampling rate used in the experiment. The VL6180 sensor is calibrated using the Very High Voltage (VHV) calibration approach described in [39], and the method for free-calibration usage described by the manufacturer in [40] is also employed. The Electron microcontroller and its board, along with the MPL3115A2 and VL6180 sensors mentioned above, were positioned in the ABS 3D printed external protective case. The prototype is powered by a 2,200 mAh lithium ion battery pack by Sparkfun Electronics, allowing for an easier, faster replacement and improved usability. Its 7-segment LED (Light-Emitting Diode) charge level display helped us plan and execute the experiment session cycles. Since we needed a comprehensive sensor selection to investigate the relevance of sensor types for the recognition of ADLs based on feet movement and posture information, we decided to use all sensor types employed by the surveyed works and a novel sensor, the barometer.

The software model used in this work comprises two components: (i) the embedded software running on the microcontroller, responsible for acquiring, structuring and transmitting raw sensor data over a 2G connection to an iMac application server, and (ii) the application server itself, responsible for processing and logging the streamed data to a NOSQL (Non SQL) cloud database – tasks not suitable for the embedded microcontroller due to its hardware limitations. The authors made available the complete and commented source code of the embedded software and the application server in [35].

B. Procedure

Twelve volunteers carefully selected for their diverse characteristics participated in the experiment. One prevailing limitation of the surveyed works was the employment of young adults only as participants in their experiments. This study tries to circumvent this problem with the participation of people with disabilities, two Class II obesity individuals, two overweight individuals, two knee-injured patients and one ankle-injured patient, a balanced mix of male and female participants and one third of senior adult volunteers. Since the insole and shoes are US men's size 8, we selected participants in the 7.5 to 8.5 shoe size range. We collected 24 hours of activity data, which is 2 hours of feet posture and movement data from each volunteer. Compared to the other studies, the number of subjects in our study is not that different from the others, considering the average of 7 in the surveyed works. However, the number of samples in our study – around 950,000 – is significantly higher than the average number of samples – around 50,000 – found in the surveyed works. We developed a comprehensive activity model for the experiment, since we were aiming at assessing the relevance of different sensor types for the recognition of ADLs based on feet movement and posture information. It comprises 9 activities: walking straight (2km/h), walking slope up (2km/h), walking slope down (2km/h), slow jogging (6km/h), slow jogging slope up (6km/h), slow jogging slope down (6km/h), ascending stairs, descending stairs and sitting. The experiment was conducted in four distinct sessions, where participants performed a subset of the planned activities. Due to their availability, some participants performed more than one session per day. All sessions were performed on a garden area inside the university campus. The first session lasted for 50 minutes, and each participant performed 5 cycles of 10 minutes (8 minutes walking followed by 2 minutes resting). The second session also lasted for 50 minutes and consisted of 5 cycles of 10 minutes (4 minutes slope walking up, 4 minutes slope walking down and 2 minutes resting). In the third session, each participant performed 5 cycles of stair climbing interleaved with sitting for a total of 20 minutes (1 minute ascending stairs, 1 minute resting, 1 minute descending stairs, 1 minute resting). Finally, in the last session, participants performed 3 cycles of slow jogging and sitting – this section was performed two months after the initial experiment, when we added 3 more activities to our activity model, namely: (i) slow jogging (6km/h), (ii) slow jogging slope up (6km/h) and (iii) slow jogging slope down

(6km/h). Subjects were free to perform the activities – the IoT device did not restrict in any way their movement and the instructions provided did not specify how the activities were to be performed. This way we were able circumvent a common limitation of most HAR works in which activities are performed in a non-natural way. It is important to note that we had removed running (8km/h) from the original model, because that would be a deterrent to some of the participants. For the sake of adding the last three activities to the activity model, we had to remove one elder volunteer from the experiment, but kept the injured participants after consulting with a certified health professional. We accompanied all participants during the sessions to log any unusual occurrence.

IV. Data Analysis

In this section, we describe the stages followed to develop the HAR classifier, data acquisition, data processing, feature extraction, feature selection, classification and validation, and our findings regarding sensor relevance. The full dataset is available in [35].

A. Data Acquisition

During the data acquisition stage, a stream of raw, unprocessed signals was acquired from the insole's sensors and stored in the microcontroller in JSON format. This raw data combined the accelerometer, gyroscope, magnetometer, six FSR sensors, altitude, temperature and range-finder sensor signals, resulting in 17-feature set entries to the dataset. We used the 10 Hz sampling rate recommended by [41]. As discussed in [42], we understand that this sample rate may not be adequate for recognizing similar activities or subtle variations within the same activities. However, these concerns were not relevant to our research. To reduce energy consumption and allow for an extended operating time, the JSON formatted data was periodically sent to the application server in small packages of 100KB.

B. Data Processing and Feature Extraction

The data processing stage occurs in three steps. First, data unrelated to the specific planned activities for the experiment is discarded, given that the prototype starts collecting feet movement and posture information immediately after it is powered. Then, the dataset is labelled for supervised learning, and activity class information is appended to each entry according to the activity performed in the experiment. Finally, all sensor data is normalized to make their scales equivalent, partly address sensor drift and reduce the possibility of model overfitting.

In the feature extraction stage, we used descriptive statistics, standard deviation, variance, minimum, maximum and average values, to generate derived features from each of the 17 original features:

- Six FSR sensor readings;
- Three gyroscope axis data;
- Three magnetometer axis data;
- Three accelerometer axis data;
- Altimeter reading; and
- Range-finder sensor reading.

Moreover, (i) the cumulative difference between samples for each feature and (ii) the Euler angles of pitch, roll and yaw were also used to generate additional derived features, for a total of over 100 features for selection.

C. Classification and Validation of the Baseline Model

To build and validate our baseline model, a model that makes use of all sensor raw and derived features, we used the Leave-one-out Cross Validation method, in an attempt to decrease the chances of overfitting. Although there is no evidence to support this assumption, this method at least guarantees that both training and test splits do not share any example data. Different strategies were then experimented to build the classifier for our 9-activities activity model, and the Random Forest Algorithm was selected for classification, given that its average performance of 91.26% was superior to the other ones. The individual validation results for each of the 12 examples were: 89.17%, 90.86%, 92.42%, 94.82%, 97.41%, 90.18%, 79.78%, 94.14%, 95.01%, 88.31%, 91.98% and 91.01%. In total, 12 features were utilized to build the classifier: 2 axis of the gyroscope, 2 axis of the magnetometer, 1 axis of the accelerometer, 4 FSRs, 2 Euler angles and the cumulative difference between samples of the barometer. The features selected for the baseline classifier provided valuable insights for the next step, the analysis of sensor type relevance.

As discussed in [43], after experimenting several time window sizes during the classifier construction, we decided to use a 0.3s one based on our model validation results, registering an accuracy improvement of about 19% when contrasting the selected window (0.3s) and the largest time window experimented (2.0s).

D. Analysis of Sensor Type Relevance

After building the baseline model, we were able to investigate the relevance, correlation of a feature with the average classifier accuracy, of each sensor type for the achieved results. We used Hall's algorithm [44] based on correlation with its default "Best Fit" configuration, a backtracking greedy strategy. This method was selected based on its superior performance when compared to the other feature selection methods found in the surveyed works. Ugulino et al. [13] also use this same method to reduce feature redundancy and still achieve better-than-average results. Based on the results commonly found in the literature, we already expected to see gyroscope, accelerometer and FSR features showing high correlation and being used in the building of the classifier. However, the results achieved by Hall's algorithm suggested which features were relevant and to what extent. Considering the baseline model, the distance sensor showed a very low correlation and was not used in the building of the classifier. Although distance sensors were successfully employed by works such as [23], when presented with a broader sensor selection the classifier did not make use of it. FSRs 5 and 6 showed a medium to low correlation and were not employed, while the remaining FSRs showed a high correlation. Considering that some of the surveyed works also used between three to four FSRs with similar positioning, further investigation could lead to evidence as to where to position the sensors for better recognition accuracy of the selected activities. Euler angles showed a high correlation and were utilized by some of the surveyed works, making a strong case that they should be evaluated during the

 ISBN: 978-1-61208-660-6

feature engineering phase for similar activity models. Finally, the barometer provided the feature with the second highest correlation score, suggesting that this type of sensor should also be evaluated for similar activity models. The topic of feature engineering and its methods are beyond the scope of this work, so we used the features employed by the surveyed works in our analysis.

After that initial assessment, we evaluated each sensor, raw and derived features, separately, employing the same methods used to build the baseline classifier: (i) Leave-one-out Cross Validation and (ii) Random Forest Algorithm. The average accuracy results are shown in Table II, where all values are rounded to the nearest whole number and ordered by average accuracy.

TABLE II. SINGLE SENSOR CLASSIFIER ACCURACY.

Sensor	*Model Accuracy*
IMU	66%
FSRs	60%
Barometer	29%
Distance	17%

Following that analysis, we combined the two most successful sensor types, FSRs and IMUs, with all available sensor types. We built and validated a classifier for each combination, and the average accuracy results for the better performing combinations are shown in Table III, where all values are rounded to the nearest whole number and ordered by average accuracy.

TABLE III. SENSOR MIX CLASSIFIER ACCURACY.

Sensor	*Model Accuracy*
IMU (9-axis) and FSRs	81%
FSRs and Barometer	71%
IMU (9-axis) and Barometer	70%
FSRs and Gyroscope	65%
FSRs and Accelerometer	60%
FSRs and Magnetometer	59%
IMU (9-axis) and Distance	57%
FSRs and Distance	55%
Distance	17%

Although the results shown in Table III take into account the combined FSRs, FSR1 to FSR4, we also evaluated FSR5 and FSR6 for the same combinations, achieving less than 1% increase in average accuracy. The experimental results show that (i) 9-Axis IMUs, (ii) 4-FSR arrays and (iii) barometers were the most relevant sensor types for the recognition of ADLs based on feet movement and posture information, when considering a typical activity model with the stand, walk, run and climb stairs activities. Above that, we learned that accuracy can be greatly improved (15%) by the IMU and FSR sensor fusion, so that approach should be considered in future research if it is needed to (i) differentiate between similar activities or (ii) identify subtle variations of the same activity. Lastly, the barometer sensor allowed for an increase of the average accuracy by more than 10%, making a strong case for its adoption whenever possible.

V. CONCLUSION AND FUTURE WORK

In this work, we expanded the research conducted in [42] by (i) enhancing the IoT device's sensor array, (ii) improving the machine learning HAR classifier, (iii) increasing the number of participants and activity classes in the experiment and, above all, (iv) focusing on assessing the relevance of different sensor types for the task of recognizing ADL using foot movement and posture information. The main contributions of this work are:

- An analysis of the relevance of different types of sensors in the building of a HAR classifier based on foot movement and posture information, discussed in Section IV;
- A public domain dataset with about 1 million samples and 9 activity classes, available in [35];
- A comprehensive literature review about clothes-based sensor HAR researches, presented in Section II; and,
- A clothes-based sensor IoT device, presented in Section III, for the data collection of feet movement and posture information.

Despite not taking any measures to address FSRs' drift over time, the overall classifier accuracy was satisfactory - achieving top quartile performance when compared to the surveyed works. After the experiment, we developed a new version of the IoT device with the purpose of helping reduce injury risk during functional exercise sessions. Our goal is to employ sensor fusion and machine learning techniques to provide users with real time feedback of the exercises, helping them to improve and avoid injuries. Currently, we are conducting an outdoor experiment with 18 volunteers - including two sight impaired participants - to investigate the extent to which we can detect correct execution of the exercise routines. We were able to use the lessons learned from the experiment presented in this work to improve the new version of the IoT device developed for the new research, making changes, such as: (i) removing the range-finder sensors, and reducing the number of FSRs to 4, based on our findings, (ii) using sewable connectors for the FSR sensors to withstand the impact of jogging activities – all commercially available connectors disconnected the sensors at some point during the jogging sessions, forcing the session to pause to repair the prototype – and (iii) using Sparkfun Electronics' battery pack to turn the IoT device into a convenient and easy-to-use device that can be deployed outdoors without difficulty.

REFERENCES

[1] S. R. Edgar, T. Swyka, G. Fulk, and E. S. Sazonov, "Wearable shoe-based device for rehabilitation of stroke patients," in Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. IEEE, 2010, pp. 3772–3775.

[2] E. S. Sazonov, G. Fulk, J. Hill, Y. Schutz, and R. Browning, "Monitoring of posture allocations and activities by a shoe-based wearable sensor," IEEE Transactions on Biomedical Engineering, vol. 58, no. 4, 2011, pp. 983–990.

[3] N. Sazonova, R. C. Browning, and E. Sazonov, "Accurate prediction of energy expenditure using a shoe-based activity monitor," Med Sci Sports Exerc, vol. 43, no. 7, 2011, pp. 1312–21.

[4] S. Crea, S. De Rossi, M. Donati, P. Reberšek, D. Novak, N. Vitiello, T. Lenzi, J. Podobnik, M. Munih, and M. Carrozza, "Development of gait segmentation methods for wearable foot pressure sensors," in Engineering in Medicine and Biology Society (EMBC). IEEE, 2012, pp. 5018–5021.

[5] A. De Santis, E. Gambi, L. Montanini, L. Raffaeli, S. Spinsante, and G. Rascioni, "A simple object for elderly vitality monitoring: The smart insole," in Mechatronic and Embedded Systems and Applications (MESA), ASME. IEEE, 2014, pp. 1–6.

[6] D. Drobny, M. Weiss, and J. Borchers, "Saltate!: a sensor-based system to support dance beginners," in CHI'09 Extended Abstracts on Human Factors in Computing Systems. ACM, 2009, pp. 3943–3948.

[7] C. M. El Achkar, F. Massé, A. Arami, and K. Aminian, "Physical activity recognition via minimal in-shoes force sensor configuration," in Pervasive Computing Technologies for Healthcare. ICST, 2013, pp. 256–259.

[8] K. Fukahori, D. Sakamoto, and T. Igarashi, "Exploring subtle foot plantar-based gestures with sock-placed pressure sensors," in Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. ACM, 2015, pp. 3019–3028.

[9] T. Holleczek, A. Ruegg, H. Harms, and G. Troster, "Textile pressure sensors for sports applications 9th ieee sensors conf," Kona, HI, 2010.

[10] F. Lin, C. Song, X. Xu, L. Cavuoto, and W. Xu, "Sensing from the bottom: Smart insole enabled patient handling activity recognition through manifold learning," in Connected Health: Applications, Systems and Engineering Technologies (CHASE). IEEE, 2016, pp. 254–263.

[11] C. Zhu and W. Sheng, "Multi-sensor fusion for human daily activity recognition in robot-assisted living," in International conference on Human robot interaction. ACM, 2009, pp. 303–304.

[12] K. Kong and M. Tomizuka, "A gait monitoring system based on air pressure sensors embedded in a shoe," IEEE/ASME Transactions on mechatronics, vol. 14, no. 3, 2009, pp. 358–370.

[13] W. Ugulino, D. Cardador, K. Vega, E. Velloso, R. Milidiú, and H. Fuks, "Wearable computing: Accelerometers' data classification of body postures and movements," in Advances in Artificial Intelligence, SBIA. Springer, 2012, pp. 52–61.

[14] M. McCarthy, D. James, J. Lee, and D. Rowlands, "Decision-tree-based human activity classification algorithm using single-channel foot-mounted gyroscope," Electronics Letters, vol. 51, no. 9, 2015, pp. 675–676.

[15] J. Doppler, G. Holl, A. Ferscha, M. Franz, C. Klein, M. dos Santos Rocha, and A. Zeidler, "Variability in foot-worn sensor placement for activity recognition," in Wearable Computers, 2009. ISWC'09. International Symposium on. IEEE, 2009, pp. 143–144.

[16] M. Ghobadi and E. T. Esfahani, "Foot-mounted inertial measurement unit for activity classification," in Engineering in Medicine and Biology Society, EMBC. IEEE, 2014, pp. 6294–6297.

[17] F. Lin, A. Wang, Y. Zhuang, M. R. Tomita, and W. Xu, "Smart insole: A wearable sensor device for unobtrusive gait monitoring in daily life," IEEE Transactions on Industrial Informatics, vol. 12, no. 6, 2016, pp. 2281–2291.

[18] W. Tang and E. S. Sazonov, "Highly accurate recognition of human postures and activities through classification with rejection," IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 1, 2014, pp. 309–315.

[19] T. Zhang, G. D. Fulk, W. Tang, and E. S. Sazonov, "Using decision trees to measure activities in people with stroke," in Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE. IEEE, 2013, pp. 6337–6340.

[20] Z. Zhang and S. Poslad, "Improved use of foot force sensors and mobile phone gps for mobility activity recognition," IEEE Sensors Journal, vol. 14, no. 12, 2014, pp. 4340–4347.

[21] H. Noshadi, F. Dabiri, S. Ahmadian, N. Amini, and M. Sarrafzadeh, "Hermes: mobile system for instability analysis and balance assessment," ACM Transactions on Embedded Computing Systems (TECS), vol. 12, no. 1s, 2013, p. 57.

[22] E. Sazonov, N. Hegde, R. C. Browning, E. L. Melanson, and N. A. Sazonova, "Posture and activity recognition and energy expenditure estimation in a wearable platform," IEEE journal of biomedical and health informatics, vol. 19, no. 4, 2015, pp. 1339–1346.

[23] X. Jiang, Y. Chen, J. Liu, G. R. Hayes, L. Hu, and J. Shen, "Air: recognizing activity through ir-based distance sensing on feet," in International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct. ACM, 2016, pp. 97–100.

[24] D. J. C. Matthies, T. Roumen, A. Kuijper, and B. Urban, "Capsoles: Who is walking on what kind of floor?" in Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services, ser. MobileHCI '17. New York, NY, USA: ACM, 2017, pp. 9:1–9:14. [Online]. Available: http://doi.acm.org/10.1145/3098279.3098545

[25] M. Haescher, D. J. C. Matthies, G. Bieber, and B. Urban, "Capwalk: A capacitive recognition of walking-based activities as a wearable assistive technology," in Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments, ser. PETRA '15. New York, NY, USA: ACM, 2015, pp. 35:1–35:8. [Online]. Available: http://doi.acm.org/10.1145/2769493.2769500

[26] N. Hegde, M. Bries, T. Swibas, E. Melanson, and E. Sazonov, "Automatic recognition of activities of daily living utilizing insole based and wrist worn wearable sensors," IEEE journal of biomedical and health informatics, 2017.

[27] G. D. Fulk and E. Sazonov, "Using sensors to measure activity in people with stroke," Topics in stroke rehabilitation, vol. 18, no. 6, 2011, pp. 746–757.

[28] L. K. Au, W. H. Wu, M. A. Batalin, D. H. McIntire, and W. J. Kaiser, "Microleap: Energy-aware wireless sensor platform for biomedical sensing applications," in Biomedical Circuits and Systems Conference. BIOCAS. IEEE, 2007, pp. 158–162.

[29] N. Hegde and E. Sazonov, "Smartstep: A fully integrated, low-power insole monitor," Electronics, vol. 3, no. 2, 2014, pp. 381–397.

[30] N. Hegde, E. Melanson, and E. Sazonov, "Development of a real time activity monitoring android application utilizing smartstep," in Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the. IEEE, 2016, pp. 1886–1889.

[31] N. A. Sazonova, R. Browning, and E. S. Sazonov, "Prediction of bodyweight and energy expenditure using point pressure and foot acceleration measurements," The open biomedical engineering journal, vol. 5, 2011, p. 110.

[32] G. D. Fulk, S. R. Edgar, R. Bierwirth, P. Hart, P. Lopez-Meyer, and E. Sazonov, "Identifying activity levels and steps in people with stroke using a novel shoe-based sensor," Journal of Neurologic Physical Therapy, vol. 36, no. 2, 2012, p. 100.

[33] L. Shu, T. Hua, Y. Wang, Q. Li, D. D. Feng, and X. Tao, "In-shoe plantar pressure measurement and analysis system based on fabric pressure sensing array," IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 3, 2010, pp. 767–775.

[34] U. Manupibul, W. Charoensuk, and P. Kaimuk, "Design and development of smart insole system for plantar pressure measurement in imbalance human body and heavy activities," in Biomedical Engineering International Conference (BMEiCON), 2014 7th. IEEE, 2014, pp. 1–5.

[35] R. De Pinho André, P. H. F. S. Diniz, and H. Fuks, "Iwoar smart insole," https://goo.gl/6ozm26, 2017.

[36] J. Perry and J. M. Burnfield, "Gait analysis: normal and pathological function," Developmental Medicine and Child Neurology, vol. 35, 1993, pp. 1122–1122.

[37] ST, "Lsm9ds1 datasheet," https://www.st.com/resource/en/datasheet/lsm9ds1.pdf, 2018 (retrieved: june, 2018).

[38] NXP, "Mpl3115a2 datasheet," https://www.nxp.com/docs/en/data-sheet/MPL3115A2.pdf, 2018 (retrieved: june, 2018).

[39] ST, "Vl6180x datasheet," https://cdn-learn.adafruit.com/assets/assets/000/037/608/original/VL6180X_datasheet.pdf, 2017 (retrieved: june, 2018).

[40] STMicroelectronics, "Vl6180x product site," https://www.st.com/en/imaging-and-photonics-solutions/vl6180x.html, 2017 (retrieved: june, 2018).

[41] A. Harasimowicz, T. Dziubich, and A. Brzeski, "Accelerometer-based human activity recognition and the impact of the sample size," Advances in Neural Networks, Fuzzy Systems and Artificial Intelligence, 2014, pp. 130–135.

[42] R. De Pinho André, P. H. F. S. Diniz, and H. Fuks, "Bottom-up investigation: Human activity recognition based on feet movement and posture information," in Proceedings of the 4th International Workshop on Sensor-based Activity Recognition and Interaction, ser. iWOAR '17. New York, NY, USA: ACM, 2017, pp. 10:1–10:6. [Online]. Available: http://doi.acm.org/10.1145/3134230.3134240

[43] O. Banos, J.-M. Galvez, M. Damas, H. Pomares, and I. Rojas, "Window size impact in human activity recognition," Sensors, vol. 14, no. 4, 2014, pp. 6474–6499.

[44] M. Hall, "Correlation-based feature subset selection for machine learning," Thesis submitted in partial fulfillment of the requirements of the degree of Doctor of Philosophy at the University of Waikato, 1998.

 ISBN: 978-1-61208-660-6