Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 176 (2020) 2655–2664

Procedia Computer Science

www.elsevier.com/locate/procedia

24th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

Feature extraction and feature selection in smartphone-based activity recognition

Maryam Banitalebi Dehkordi[a,*], Abolfazl Zaraki[a], Rossitza Setchi[a]

[a]*Centre for Artificial Intelligence, Robotics and Human-Machine Systems (IROHMS), Cardiff University, Cardiff CF24 3AA, UK*

Abstract

Nowadays, smartphones are gradually being integrated in our daily lives, and they can be considered powerful tools for monitoring human activities. However, due to the limitations of processing capability and energy consumption of smartphones compared to standard machines, a trade-off between performance and computational complexity must be considered when developing smartphone-based systems. In this paper, we shed light on the importance of feature selection and its impact on simplifying the activity classification process which enhances the computational complexity of the system. Through an in-depth survey on the features that are widely used in state-of-the-art studies, we selected the most common features for sensor-based activity classification, namely *conventional features*. Then, in an experimental study with 10 participants and using 2 different smartphones, we investigated how to reduce system complexity while maintaining classification performance by replacing the conventional feature set with an optimal set. For this reason, in the considered scenario, the users were instructed to perform different static and dynamic activities, while freely holding a smartphone in their hands. In our comparison to the state-of-the-art approaches, we implemented and evaluated major classification algorithms, including the decision tree and Bayesian network. We demonstrated that replacing the conventional feature set with an optimal set can significantly reduce the complexity of the activity recognition system with only a negligible impact on the overall system performance.

Keywords: Activity recognition, feature extraction, feature selection, inertial sensor;

1. Introduction

Human Activity Recognition (AR) plays an important role in different applications such as smart home monitoring systems, assistive technologies and healthcare applications such as human activity monitoring for health assessment, rehabilitation, assistance for people with cognitive disorders, context-aware data acquisition for clinical purposes and child and elderly care [10, 38].

* Maryam Banitalebi Dehkordi. Tel.: +44-292-087-4278
E-mail address: banitalebidehkordim@cardiff.ac.uk

10.1016/j.procs.2020.09.301

AR is a system that receives as input the acquired sensory information associated with human body motion, manages and analyses the data flow, and returns the activity class as an output. Therefore, the common phases for AR are considered to be data acquisition, feature extraction and activity classification.

The data can be acquired using inertial sensors [17], wearable sensors [32, 39], vision-based motion capture sensors, etc. The acquired data is processed to extract low-level feature descriptors that fully represent the activities. To distinguish the human activities relevant to the acquired data, several classification methods have been developed: as decision trees, Support Vector Machine (SVM), k-nearest neighbours, naïve Bayes, neural network, Hidden Markov Model (HMM), Gaussian mixture models, etc [1, 12].

In developing an AR system, in addition to the type of the classifier, the efficiency of the AR system depends on the complexity of feature extraction process and the number of selected features. As reported in [42] increasing the number of features and including all features do not necessarily improve AR accuracy. Therefore, in this work we shed light on the importance of feature selection, in which by obtaining an optimal feature set (that can be employed instead of a group of features) the complexity of the AR system is reduced significantly. To investigate it, in our scenario we look for features, which are important cues for distinguishing different activities.

In this paper, we first presented an in-depth survey on the features that are widely used in sensor-based activity recognition systems, and then we selected the most common features which we called *conventional features*. Afterward, in an experimental study, we collected 100 minutes of labelled data of 10 participants and using 2 different smartphones, where users freely held a smartphone in their hands and were instructed to perform different static and dynamic activities. We then obtained an optimal feature set and by replacing the conventional feature set with an optimal set, we investigated the trade-off between AR complexity and overall performance. For this reason we implemented and evaluated different classification algorithms, including the Bayesian network and decision tree. Through an experimental evaluation we demonstrated that by replacing the conventional feature set with an optimal set the complexity of the AR system can be significantly reduced, with only a negligible impact on AR accuracy.

2. Related Works

Human activity recognition has received substantial interest recently, because of the various potential applications in different research fields, such as home automation [10, 15]. The literature review indicates that several AR systems have been proposed using inertial sensors.

Bulling et al. in [11] focused on AR using on-body inertial sensors, discussed the challenges and provided an overview of AR methods. They presented the AR chain as a general framework to design and evaluate AR systems. Following the described framework, they recognised different hand gestures using inertial sensors. Gupta and Dallas in [23] implemented an accurate AR system that recognised six daily living activities and transitional events using a single waist-mounted triaxial accelerometer. They performed feature selection algorithms to select the best features among a range of conventional features and the features they introduced. They carried out AR and compared the results using naïve Bayes and k-nearest neighbours algorithms. Capela et al. [12] used the embedded smartphone accelerometer and gyroscope sensors and collected the AR data of able-bodied, elderly and stroke patients. They calculated 76 features and selected the subsets of these features, which were then evaluated using naïve Bayes, support vector machine and J48 decision tree classifiers. They concluded that feature subsets resulted in better or similar accuracies compared to using the entire feature set. Bayat et al. [7] implemented an AR system to recognise various everyday activities using a single smartphone triaxial accelerometer. They have considered a new set of features and used different classifiers to evaluate recognition performance.

The remainder of this section presents an in-depth survey on the widely used features for AR in the state-of-the-art, as well as the classification methods.

2.1. State-of-the-art on Feature Extraction

Feature extraction plays an important role in an activity recognition system. The purpose of feature extraction is to obtain the common characteristics of the acquired signals associated to the same class of activities [4]. The term *feature* refers to data that is computed based on the sensor's raw signal using any desired method (e.g., mean value of

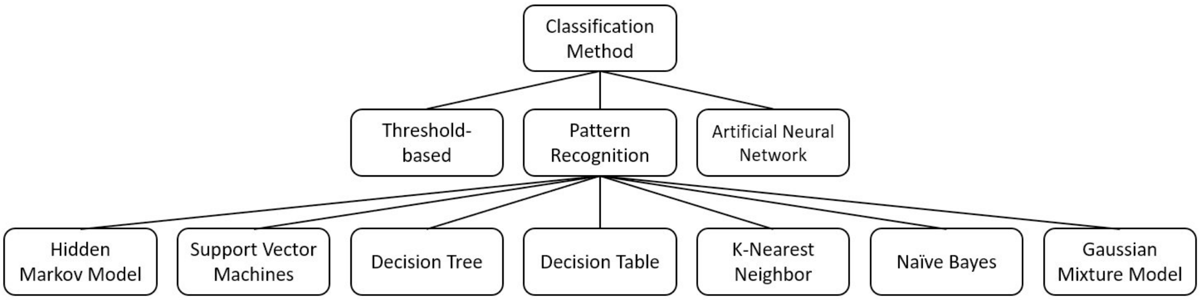

Fig. 1. Classification methods used for state recognition.

the acquired signal from the sensor). The complexity of obtaining the features and the number of features required for AR directly affect the system's performance, which is particularly crucial when using smartphones.

The literature review on the features used for AR shows that the commonly used features or conventional features can be categorised as frequency domain, time domain and time-frequency domain. Table 1 shows the widely used features in the state-of-the-art in all three categories. Each category is detailed as follows.

2.1.1. Frequency Domain

The features in the frequency domain provide information about the signal's periodicity, which can be used for recognition of activities that their relevant acquired signals have different periodic patterns. Converting a time series of acquired signals into frequency domain has an advantage of reducing the data dimension. Table 1 shows different widely used features in the frequency domain. Among them, the discrete Fourier transform (DFT) (e.g., in [42]) together with the enhanced fast Fourier transform (FFT) can be considered as the bases of frequency domain features. Other features such as single DFT coefficients, the 1^{st} and 2^{nd} dominant frequencies (e.g., in [46]) or spectral energy and entropy [51] that recognise the activities with the same level of energy are used in the state-of-the-art.

2.1.2. Time Domain

Time domain features provide signal statistics, and they are usually less computationally intensive [12]. The widely used features are mean, variance, energy and zero crossing rate. The time domain features can be obtained directly from the sensor's acquired signals applying different mathematical functions. More details on different time domain features in the state-of-the-art are reported in Table 1. Signal magnitude area (SMA) is another feature, which is used in several AR systems. Some works (e.g., [4]) categorised this feature as a heuristic feature; however, in this work we report it among time domain features.

2.1.3. Time-Frequency Domain

These features are useful for evaluating the characteristics of complex signals in both time and frequency domains [4]. The widely used features in the time-frequency domain are wavelet coefficients (e.g., [41]), signal-pair correlation (e.g., [51, 3]) and tilt features (e.g., [34]).

2.2. State-of-the-art on Classification Techniques

To distinguish the user's activity or state, the extracted features are being used as inputs of the classifiers. Avci et al. [4] considered the classification methods as three main categories: threshold-based, pattern recognition and artificial neural networks, which are illustrated in Figure 1.

Table 2 reports the comparison of different classification methods in the same framework. Table 3 summarises some of the IMU-based AR systems using different classification methods that reports in Figure 1.

Table 1. Conventional features used in activity recognition systems.

Features	References
Frequency Domain	
FFT and DFT coefficients	[31, 42, 11, 16]
1st and 2nd dominant frequencies of the acceleration	[46, 42, 45]
Amplitude of the 1st and 2nd dominant frequencies of the acceleration	[42, 45, 46]
Amplitude scale and difference of two dominant frequencies	[42]
Spectral entropy	[6, 51, 3, 27, 23, 20]
Power spectrum centroid	[51, 50]
Spectral energy	[52, 50, 23, 20]
Dominant frequency of gyroscope	[45, 46]
Time Domain	
Mean value of the acceleration along x-axis, y-axis, z-axis and norm of acceleration	[34, 44, 35, 42, 6, 51, 11, 13, 23, 12, 5, 7, 21, 14, 16, 20]
Mean and variance of sensory data	[43, 19, 29]
Mean value of the dynamic acceleration in the vertical and horizontal plane	[42, 23, 22, 7]
Mean value of the horizontal and vertical gravity free acceleration	[35, 42]
Variance of the acceleration along x-axis, y-axis, z-axis and norm of acceleration	[27, 46, 42, 11, 23, 21, 16, 20]
Variance of the dynamic acceleration in the vertical plane and horizontal plane	[42, 23]
Variance and mean value of the heading, and heading change	[42]
Zero crossing rate	[51, 11, 12, 5, 20]
Peak counting, amplitude, sum of the differences of peaks or time between peaks	[48, 13, 9, 14]
Time interval between peaks	[35]
Binned distribution and cumulative histogram	[35, 29, 14]
Accelerometer energy	[34, 6, 46, 27]
Gyroscope energy	[46, 45]
Percentile	[51, 44]
Interquartile range	[51, 12]
Signal Magnitude Area (SMA)	[52, 3, 24, 31, 20, 33]
Standard deviation	[35, 44, 24, 3, 51, 13, 5, 9, 7, 14, 16, 20]
Variance of gyroscopic signal	[45, 46]
Minimum and maximum of acceleration	[44, 7]
Root mean square (rms)	[13, 9, 7, 20]
Kurtosis and skewness, and kurtosis of gravity vector	[13, 12, 9]
Time-Frequency Domain	
Wavelet coefficients	[41, 13]
Signal-pair correlation	[6, 51, 3, 13, 12, 7, 21, 20]
Tilt angle features	[34, 20, 33]

Table 2. Comparison of classification methods (*a* > *b* means using classifier *a* resulted in the higher accuracy compared to classifier *b*).

Phone	Ref.	Method Comparison
No	[12]	Decision Tree > Naïve Bayes > SVM
Yes	[14]	Neural Networks > Decision Tree > Logic Regression
No	[11]	SVM > KNN > HMM > Naïve Bayes
No	[20]	Neural Networks > Decision Tree > KNN > SVM > Naïve Bayes
No	[19]	Neural Networks > Naïve Bayes > HMM
Yes	[7]	Neural Networks > SVM > Random Forest > LMT > Simple Logistic > Logit Boost
Yes	[41]	Naïve Bayes > Decision Tree > KNN > Neural Networks > SVM
Yes	[42]	LS-SVM > Decision Tree > Linear Discriminant Analysis > Quadratic Dis. Analysis > Bayesian Network-GMM
Yes	[44]	Quadratic Discriminant Analysis > KNN
Yes	[35]	Neural Networks > Decision Tree > Logistic Regression
Yes	[51]	Decision Tree > SVM > KNN > Naïve Bayes
No	[52]	Neural Networks > KNN
No	[6]	Decision Tree > KNN > Naïve Bayes > Decision Table

3. Experimental Evaluation and Feature Selection

In this work we consider commonly performed motions including pedestrians' static and dynamic activities, while having a smartphone freely in the hand. The dynamic activities refer to the activities where the user has significant displacement in the global coordinates, such as walking and going on the stairs. Static activities refer to the activities

Table 3. Categorization of related works on AR based on the classification methods.

Classifier	Ref.	Phone	Sensor	Accuracy(%)
Decision Tree	[12]	No	Accelerometer & Gyroscope	97.12
	[14]	Yes	Accelerometer	86.08(av.)
	[20]	No	Accelerometer	96.4
	[46]	No	Accelerometer & Gyroscope	97
	[51]	Yes	Accelerometer	90
	[6]	No	Accelerometer	84
Support Vector Machine	[12]	No	Accelerometer & Gyroscope	90.44
	[20]	No	Accelerometer	92.7
	[7]	Yes	Accelerometer	88.76
	[11]	No	Accelerometer & Gyroscope	96
	[42]	Yes	Accelerometer & Magnetometer	95.53
	[3]	Yes	Accelerometer & Gyroscope	89
	[34]	Yes	Accelerometer	90
K-Nearest Neighbour	[23]	No	Accelerometer	98.4
	[20]	No	Accelerometer	96.2
	[11]	No	Accelerometer & Gyroscope	94.1
	[30]	Yes	Accelerometer	NA
	[44]	Yes	Accelerometer	94.5
Naïve Bayes	[12]	No	Accelerometer & Gyroscope	97.43
	[20]	No	Accelerometer	89.5
	[23]	No	Accelerometer	97.8
	[11]	No	Accelerometer & Gyroscope	78.2
	[50]	No	Accelerometer, Gyroscope & knee angle sensors	NA
	[18]	No	NA	83.97
HMM	[11]	No	Accelerometer & Gyroscope	85.6
	[21]	No	Accelerometer	77
	[53]	No	Accelerometer	87.36
	[36]	No	Accelerometer, Microphone & Light sensor	90
	[49]	No	Accelerometer & Microphone	72.14
Gaussian Mixture Models	[28]	No	Accelerometer	88.76
	[2]	No	Accelerometer	76.6
Threshold-Based	[8]	No	Accelerometer	89.14
	[26]	No	Accelerometer & Gyroscope	NA
	[40]	No	Accelerometer	NA
Neural Networks	[14]	Yes	Accelerometer	88.76(av.)
	[20]	No	Accelerometer	96.8
	[47]	Yes	Accelerometer	NA
	[52]	No	Accelerometer	95

where the user has no displacement in the global coordinates, and includes standing, slight motions while standing, and can include a freely moving hand. Figure 2 shows a few sample activities considered in this work, which are described as follows:

In an experimental study, we instructed 10 users of both genders, different body constitution and age groups to hold a smartphone (either Samsung Galaxy or LG Nexus) in their left/right hands and performed different static and dynamic activities during a free walk inside and outside of multi-storey buildings at the Technical University of Munich, for 10 minutes each on average, in particular they performed all the dynamic (i.e., walking, and going on the stairs) and static (i.e., standing) activities, whilst they were able to choose unobtrusively the current activity using a graphical user interface of an app. We collected the labeled data measured by all of the smartphone built-in sensors with a sampling rate of 50 Hz, however since accelerometers are embedded in most of today's smart devices, in this work we focus on the features extracted from three-axial accelerometers. Figure 3 shows the sample data of accelerometer collected during static and dynamic activities. We windowed the acceleration signals over two-second intervals with 75% overlapping (to minimize the loss), which is sufficient for recognition of individual activities. The two-second intervals is chosen to support two periods of a periodic activity considering the fact that step periods typically lie below 1 second. We implemented signal processing and feature extraction, which resulted in extraction of above 600 features (refer to Table 1). We implemented different classification algorithms, including decision tree and

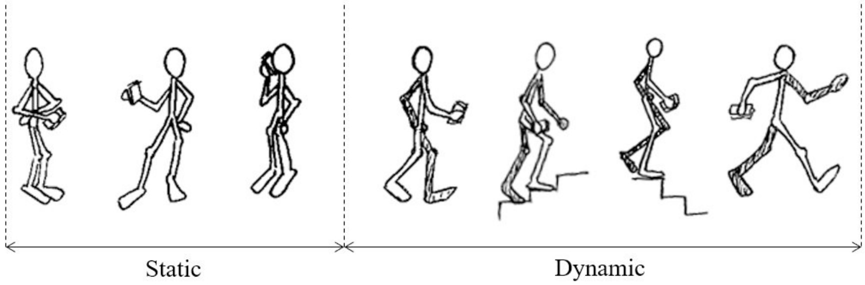

Fig. 2. The human static and dynamic activities.

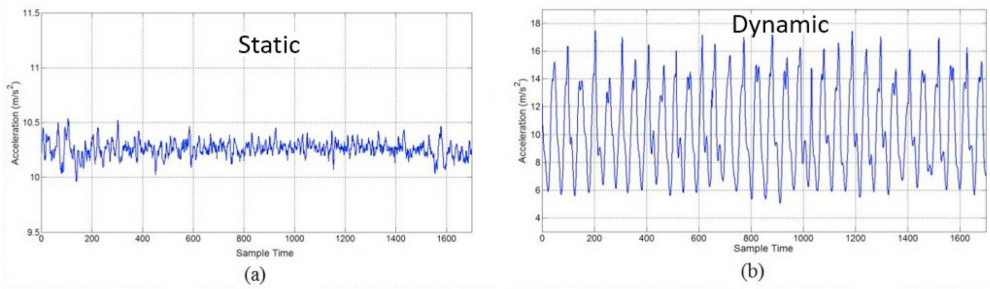

Fig. 3. Acceleration signals associated to different activities. (a) Static (b) Dynamic.

Bayesian network, and evaluated all of the extracted labelled features to identify the optimal set for AR. Classifiers were trained using the labelled data, while following [5] 10-fold cross-validation was performed.

We employed the supervised attribute filter [25] as a pre-processing method to perform feature selection for classifying activities. In order to apply feature selection techniques for identifying the most discriminative features, we applied a combined approach of forward/backward feature selection (which searches through the space of feature subsets) employing a hill-climbing algorithm [37], which has provided the best performance in this work and on our feature set. Afterward, in order to further investigate the resulting feature sets and select the optimal feature set, implementing a decision tree and naïve Bayes classifiers, we evaluated the performance of the AR system using each feature set. Amongst the classification algorithms we used decision tree and naïve Bayes following [41, 12] reported in Table 2. As a result of classification, the feature set that distinguished activities with the best performance was selected as an optimal feature set for recognition of static vs. dynamic activities.

4. Result and Discussion

As a result of experimental feature evaluation presented in section 3, we identified the features that resulted in the highest accuracy in recognition of static versus dynamic motions. Since using the other feature descriptors, presented in Table 1 resulted in the lower accuracy, we opted them out from the selected feature set. Table 4 reports the top three features together with the corresponding weighted accuracy using 10-fold cross validation, where using each of these features solely, the AR system can recognise the static motions versus dynamic motions with high accuracy. As shown, among these winner features, we selected the *range of acceleration along z axis*, which is obtained as the difference of the maximum and minimum values of the acceleration along the z axis over each segmentation. This feature is selected because it can be obtained with less computation compared to other ones, in addition to providing the best performance for the AR system.

In order to evaluate the importance of the obtained optimal feature, implementing a decision tree and naïve Bayes classifiers we compared the performance of the AR system using obtained optimal features and three different groups of features from the state-of-the-art. The first group includes the conventional features which are selected amongst the

Table 4. Selected features for distinguishing static and dynamic motions.

No.	Feature Name	Accuracy(%)
1	variance of horizontal acceleration	99.0
2	range of the maximum minus the minimum value of the acceleration in the vertical plane over the segmentation	98.9
3	range of the maximum minus the minimum value of the acceleration along z axis over the segmentation	**99.2**

most commonly used acceleration-based features as reported in Table 1. Furthermore, to provide practical evaluation and comparison, we employed two accelerometer-based groups of features presented in [46] and [42]. Table 5 presents the features of all three groups.

Table 5. Acceleration-based features taken from the state-of-the-art.

Name	Features
Group I [42]	1. Mean value of acceleration along x, y, z, and norm of acceleration 2. Variance of acceleration along x, y, z, and norm of acceleration 3. Mean value and variance of the horizontal acceleration and the vertical acceleration minus gravity acceleration 4. Variance and mean value of the dynamic accel. in the vertical and horizontal planes of the global coordinates 5. Amplitude of 1^{st} and 2^{nd} dominant frequencies of the acceleration 6. 1^{st} and 2^{nd} dominant frequencies of the acceleration 7. Amplitude scale and difference of two dominant frequencies
Group II [46]	1. Accelerometer energy 2. Variance of acceleration 3. Amplitude of 1^{st} and 2^{nd} dominant frequencies of the acceleration 4. Dominant frequencies of the acceleration
Conventional	1. DFT coefficients 2. Amplitude of 1^{st} and 2^{nd} dominant frequencies of the acceleration 3. 1^{st} and 2^{nd} dominant frequencies of the acceleration 4. Spectral entropy spectral energy 5. Variance of acceleration along x, y, z, and norm of acceleration 6. Mean value of the horizontal acceleration and the vertical linear acceleration 7. Mean value of acceleration along x, y, z, and norm of acceleration 8. Signal magnitude area 9. Percentile and interquartile range 10. Accelerometer energy 11. Binned distribution and cumulative histogram 12. Peak counting, amplitude and time interval between peaks 13. Zero crossing rate 14. Variance and mean value of the dynamic acceleration in the vertical and horizontal planes of global coordinates

Figure 4 illustrates the results of the AR performance evaluation and comparison for each feature set using a decision tree and naïve Bayes classifiers. As shown, there is no statistical significance among the groups and using the optimal feature has only a negligible impact on the overall system performance, while using the optimal feature solely instead of a group of features, significantly reduces the complexity of the activity recognition system. We used classifiers to distinguish between static versus dynamic motions and to support the recognition of wider range of activities such as walking versus going on the stairs in a single framework.

5. Conclusion

In this paper, we discussed the importance of feature selection for activity recognition and its impact on system complexity and performance, which is crucial in developing smartphone-based activity recognition. Considering a trade-off between the performance and the computational complexity, we obtained an optimal feature which can solely distinguish static from dynamic activities. To achieve a fair evaluation, in an experimental study we recorded a data set with 10 users and 2 different smartphones, where users were instructed to perform different static and dynamic activities holding a smartphone in their hands. We selected a conventional feature set through an in-depth survey on

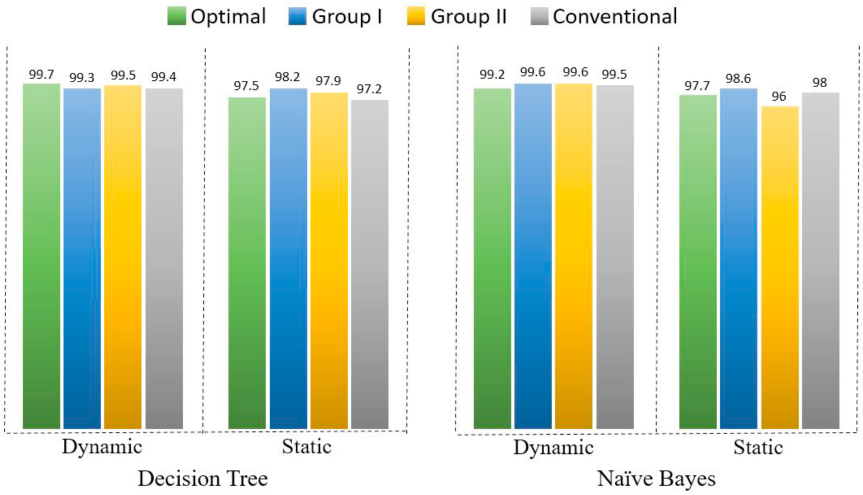

Fig. 4. Performance comparison of activity recognition for different feature sets using a decision tree and naïve Bayes classifiers.

the features that are commonly used in the state-of-the-art. Implementing a decision tree and Bayesian network, we compared activity recognition performance using optimal feature and conventional feature sets. The experimental evaluation demonstrated that replacing the conventional feature set with an individual optimal feature has only a negligible impact on the overall system performance, while it can significantly reduce the complexity of the activity recognition system.

In future work, we plan to extend the proposed approach to distinguish more activities, such as walking and going on the stairs.

Acknowledgements

The authors would like to acknowledge the support of the Centre for Artificial Intelligence, Robotics and Human-Machine Systems (IROHMS), operation C82092, part-funded by the European Regional Development Fund (ERDF) through the Welsh Government. In addition, the authors would like to thank Prof. Eckehard Steinbach from Technical University of Munich and Dr. Georg Schroth from NavVis Gmb. for their support during the collaborative research, and the participants of the data logging experiments.

References

[1] Akbari, A., Jafari, R., 2020. Personalizing activity recognition models with quantifying different types of uncertainty using wearable sensors. IEEE Transactions on Biomedical Engineering .

[2] Allen, F., Ambikairajah, E., Lovell, N., Celler, B., 2006. An adapted gaussian mixture model approach to accelerometry-based movement classification using time-domain features, in: 28th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society., pp. 3600–3603.

[3] Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J., 2012. Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine, in: Ambient Assisted Living and Home Care. Springer, pp. 216–223.

[4] Avci, A., Bosch, S., Marin-Perianu, M., Marin-Perianu, R., Havinga, P., 2010. Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey, in: 23rd Int. conf. Architecture of computing systems (ARCS), VDE. pp. 1–10.

[5] Banos, O., Galvez, J.M., Damas, M., Pomares, H., Rojas, I., 2014. Window size impact in human activity recognition. Sensors 14, 6474–6499.

[6] Bao, L., Intille, S., 2004. Activity recognition from user-annotated acceleration data, in: Pervasive Computing. Springer, pp. 1–17.

[7] Bayat, A., Pomplun, M., Tran, D.A., 2014. A study on human activity recognition using accelerometer data from smartphones. Procedia Computer Science 34, 450–457.

[8] Bidargaddi, N., Sarela, A., Klingbeil, L., Karunanithi, M., 2007. Detecting walking activity in cardiac rehabilitation by using accelerometer, in: 3rd Int. Conf. Intelligent Sensors, Sensor Networks and Information., IEEE. pp. 555–560.

[9] Biswas, D., Cranny, A., Gupta, N., Maharatna, K., Ortmann, S., 2014. Recognition of elementary upper limb movements in an activity of daily living using data from wrist mounted accelerometers , 232–237.

[10] Bourobou, S.T.M., Yoo, Y., 2015. User activity recognition in smart homes using pattern clustering applied to temporal ann algorithm. Sensors 15, 11953–11971.
[11] Bulling, A., Blanke, U., Schiele, B., 2014. A tutorial on human activity recognition using body-worn inertial sensors. ACM Computing Surveys (CSUR) 46, 33.
[12] Capela, N.A., Lemaire, E.D., Baddour, N., 2015. Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients. PLOS ONE , 1–18.
[13] Casale, P., Pujol, O., Radeva, P., 2011. Human activity recognition from accelerometer data using a wearable device, in: Pattern Recognition and Image Analysis. Springer, pp. 289–296.
[14] Catal, C., Tufekci, S., Pirmit, E., Kocabag, G., 2015. On the use of ensemble of classifiers for accelerometer-based activity recognition. Applied Soft Computing , 1–5.
[15] Chernbumroong, S., Cang, S., Yu, H., 2014. A practical multi-sensor activity recognition system for home-based care. Decision Support Systems 66, 61–70.
[16] Coskun, D., Incel, O.D., Ozgovde, A., 2015. Phone position/placement detection using accelerometer: Impact on activity recognition, in: IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), IEEE. pp. 1–6.
[17] Dehkordi, M.B., Frisoli, A., Sotgiu, E., Loconsole, C., 2014. Pedestrian indoor navigation system using inertial measurement unit. Sensor Netw Data Commun 3, 2.
[18] Dougherty, J., Kohavi, R., Sahami, M., 1995. Supervised and unsupervised discretization of continuous features, in: ICML, pp. 194–202.
[19] Fang, H., He, L., Si, H., Liu, P., Xie, X., 2014. Human activity recognition based on feature selection in smart home using back-propagation algorithm. ISA transactions 53, 1629–1638.
[20] Gao, L., Bourke, A., Nelson, J., 2014. Evaluation of accelerometer based multi-sensor versus single-sensor activity recognition systems. Medical engineering & physics 36, 779–785.
[21] Garcia-Ceja, E., Brena, R.F., Carrasco-Jimenez, J.C., Garrido, L., 2014. Long-term activity recognition from wristwatch accelerometer data. Sensors 14, 22500–22524.
[22] Guiry, J.J., van de Ven, P., Nelson, J., Warmerdam, L., Riper, H., 2014. Activity recognition with smartphone support. Medical engineering & physics 36, 670–675.
[23] Gupta, P., Dallas, T., 2014. Feature selection and activity recognition system using a single tri-axial accelerometer. IEEE Transactions on Biomedical Engineering 61, 1780–1786.
[24] Hache, G., Lemaire, E., Baddour, N., 2010. Mobility change-of-state detection using a smartphone-based approach, in: 2010 IEEE Int. Workshop on Medical Measurements and Applications Proceedings (MeMeA), IEEE. pp. 43–46.
[25] Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I., 2009. The weka data mining software: an update. ACM SIGKDD Explorations Newsletter 11, 10–18.
[26] Heinz, E., Kunze, K., Gruber, M., Bannach, D., Lukowicz, P., 2006. Using wearable sensors for real-time recognition tasks in games of martial arts-an initial experiment, in: IEEE Symp. on Computational Intelligence and Games, IEEE. pp. 98–102.
[27] Huynh, T., Schiele, B., 2005. Analyzing features for activity recognition, in: Proc. of the joint Conf. on Smart obj. and ambient inte.: innovative context-aware services: usages and technologies, ACM. pp. 159–163.
[28] Ibrahim, R.and Ambikairajah, E., Celler, B., Lovell, N., 2007. Time-frequency based features for classification of walking patterns, in: 15th Int. Conf. on Digital Signal Proc., IEEE. pp. 187–190.
[29] Ishimaru, S., Kunze, K., Kise, K., Weppner, J., Dengel, A., Lukowicz, P., Bulling, A., 2014. In the blink of an eye: combining head motion and eye blink frequency for activity recognition with google glass, in: Proceedings of the 5th Augmented Human International Conference, ACM. p. 15.
[30] Kaghyan, S., Sarukhanyan, H., 2012. Activity recognition using k-nearest neighbor algorithm on smartphone with tri-axial accelerometer. Int. Journal of Informatics Models and Analysis. Int. Scientific Society , 146–156.
[31] Karantonis, D., Narayanan, M., Mathie, M., Lovell, N., Celler, B., 2006. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Transactions on Information Tech. in Biomedicine 10, 156–167.
[32] Kerdjidj, O., Ramzan, N., Ghanem, K., Amira, A., Chouireb, F., 2020. Fall detection and human activity classification using wearable sensors and compressed sensing. Journal of Ambient Intelligence and Humanized Computing 11, 349–361.
[33] Khan, A.M., Lee, Y.K., Lee, S.Y., Kim, T.S., 2010. A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. IEEE Transactions on Information Technology in Biomedicine 14, 1166–1172.
[34] Khan, M., Ahamed, S.I., Rahman, M., Smith, R.O., 2011. A feature extraction method for realtime human activity recognition on cell phones, in: Proc. of 3rd Int. Symp. on Quality of Life Tech. Toronto, Canada.
[35] Kwapisz, J., Weiss, G., Moore, S., 2011. Activity recognition using cell phone accelerometers. ACM SIGKDD Explorations Newsletter 12, 74–82.
[36] Lester, J., Choudhury, T., Borriello, G., 2006. A practical approach to recognizing physical activities, in: Pervasive Computing. Springer, pp. 1–16.
[37] Liu, H., Motoda, H., 2012. Feature selection for knowledge discovery and data mining. volume 454. Springer Science & Business Media.
[38] Loconsole, C., Dehkordi, M.B., Sotgiu, E., Fontana, M., Bergamasco, M., Frisoli, A., 2016. An imu and rfid-based navigation system providing vibrotactile feedback for visually impaired people, in: International Conference on Human Haptic Sensing and Touch Enabled Computer Applications, Springer. pp. 360–370.
[39] Lu, J., Zheng, X., Sheng, Q.Z., Hussain, Z., Wang, J., Zhou, W., 2019. Mfe-har: multiscale feature engineering for human activity recognition using wearable sensors, in: Proceedings of the 16th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, pp. 180–189.
[40] Mathie, M., Coster, A., Lovell, N., Celler, B., 2003. Detection of daily physical activities using a triaxial accelerometer. Medical and Biological

Eng. and Computing 41, 296–301.

[41] Mitchell, E., Monaghan, D., O'Connor, N., 2013. Classification of sporting activities using smartphone accelerometers. Sensors 13, 5317–5337.

[42] Pei, L., Liu, J., Guinness, R., Chen, Y., Kuusniemi, H., Chen, R., 2012. Using ls-svm based motion recognition for smartphone indoor wireless positioning. Sensors 12, 6155–6175.

[43] Sheng, W., Du, J., Cheng, Q., Li, G., Zhu, C., Liu, M., Xu, G., 2015. Robot semantic mapping through human activity recognition: A wearable sensing and computing approach. Robotics and Autonomous Systems 68, 47–58.

[44] Siirtola, P., Röning, J., 2012. Recognizing human activities user-independently on smartphones based on accelerometer data. International Journal of Interactive Multimedia and Artificial Intelligence 1, 38–45.

[45] Susi, M., Renaudin, V., Lachapelle, G., 2011. Detection of quasi-static instants from handheld mems devices, in: Int. Conf. on Indoor Positioning and Indoor Navigation (IPIN), IEEE. pp. 1–9.

[46] Susi, M., Renaudin, V., Lachapelle, G., 2013. Motion mode recognition and step detection algorithms for mobile phone users. Sensors 13, 1539–1562.

[47] Tomlein, M., Bielik, P., Krátky, P., Mitrík, S., Barla, M., Bieliková, M., 2012. Advanced pedometer for smartphone-based activity tracking., in: HEALTHINF, pp. 401–404.

[48] Ward, J., Lukowicz, P., Tröster, G., 2005. Gesture spotting using wrist worn microphone and 3-axis accelerometer, in: Proc. of the joint Conf. on Smart objects and ambient inte.: innovative context-aware services: usages and tech., ACM. pp. 99–104.

[49] Ward, J., Lukowicz, P., Troster, G., Starner, T., 2006. Activity recognition of assembly tasks using body-worn microphones and accelerometers. IEEE Transactions Pattern Analysis and Machine Inte. 28, 1553–1567.

[50] Wu, W., Bui, A., Batalin, M., Au, L., Binney, J., Kaiser, W., 2008. Medic: Medical embedded device for individualized care. Artificial Intelligence in Medicine 42, 137–152.

[51] Yang, J., 2009. Toward physical activity diary: motion recognition using simple acceleration features with mobile phones, in: Proc. of the 1st Int. workshop on Interactive multimedia for consumer elec., ACM. pp. 1–10.

[52] Yang, J., Wang, J., Chen, Y., 2008. Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers. Pattern recognition letters 29, 2213–2220.

[53] Zappi, P., Lombriser, C., Stiefmeier, T., Farella, E., Roggen, D., Benini, L., Tröster, G., 2008. Activity recognition from on-body sensors: accuracy-power trade-off by dynamic sensor selection, in: Wireless Sensor Networks. Springer, pp. 17–33.