A Survey on Human Activity Recognition based on Temporal Signals of Portable Inertial Sensors

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Abstract. In recent years, automatic human activity recognition has drawn much attention. On one hand, this is due to the rapid proliferation and cost degradation of a wide variety of sensing hardware, which resulted in the tremendous explosion of activity data. On the other hand there are urgent growing and pressing demands from many application areas such as: in-home health monitoring especially for the elderly, smart cities, safe driving by monitoring and predicting driver's behavior, healthcare applications, entertainment, assessment of therapy, performance evaluation in sports, etc. In this paper, we introduce a detailed survey on multiple human activity recognition (HAR) systems which use portable inertial sensors (Accelerometer, Magnetometer, and Gyro), where the sensor's produced temporal signals are used for modeling and recognition of different human activities based on various machine learning techniques.

Keywords: human activity recognition, machine learning, Inertial Measurement Unit, accelerometer, gyroscope

1 Introduction

Automatic recognition of human activities has become a very substantial research topic. A wide range of computer applications depend mainly on *human activity recognition (HAR)* in their work such as monitoring patients and elderly people, surveillance systems, robots learning and cooperating, and military applications. The idea of automatic HAR system depends on collecting measurements from some appropriate sensors which are affected by selected human motion attributes. Then, depending on these measurements, some features are extracted to be used in the process of training activity models, which in turn will be used to recognize these activities later.

Based on the data acquisition paradigm, HAR systems can be divided into two categories: surrounding fixed-sensor systems and wearable mobile-sensor systems. In the first category, the required data are collected from distributed sensors attached to fixed locations in the activity environment (where users activities are monitored) such as surveillance cameras, microphones, motion sensors, etc. Alternatively, the sensors are attached to interactive objects in order to detect the type of interaction with them, such as a motion sensor attached to the cupboard doors or microwave ovens (to detect opening and/or closing), or on water tap to feel turning it on or off, and so on. Although this method can detect complex actions efficiently, it has many limitations due to its fixed nature.

In the wearable based systems, the measurements are taken from mobile sensors mounted to human body parts like wrists, legs, waist, and chest. Many sensors can be used to measure selected attributes of human body motion, such as accelerometers, gyroscopes, compasses, and GPSs. Or to measure phenomena around the user, such as barometers, magnetometers, light sensors, temperature sensors, humidity sensors, microphones, and mobile cameras. On the contrary of the fixed-sensor based systems, wearables are able to measure data from the user everywhere, while sleeping, working, or even traveling anywhere since it is not bounded by a specific place where the sensors are installed. Also, it is very easy to concentrate on directly measuring data of particular body parts efficiently without a lot of preprocessing that are needed, for example, in fixed depth cameras. However, carrying and installing a lot of sensors, wires, and power supplies mounted to the user may be uncomfortable and annoying. A comprehensive review on the use of wearables in the medical sector can be found in [34].

During the recent few years, there has been a tremendous evolution in the manufacturing of mobile devices. Particularly mobile phones, tablet PCs, and smart watches. All such devices contain various types of sensors, such as acceleromters, barometers, gyroscopes, microphones, GPS, etc. The evolution of the Internet of Things and ubiquitous sensing have encouraged mobile device manufacturers to provide more types of sensors and improve the accuracy and efficiency of the existing ones. Smart phones have also become more and more popular. Recent statistics show that the total number of smartphone subscribers reached 3.9 billion in 2016 and is expected to reach 6.8 billion by 2022 [1]. Other statistics show that in some countries, the percentage of smart phone subscribers reaches 88% of the population [35]. Therefore, the disadvantages of wearable mobile-sensors of being intrusive, uncomfortable, and annoying have vanished to a great extent, making this method of on-board sensing from smart devices very suitable for HAR data acquisition.

Many kinds of attributes can be measured using wearable sensors [26]. These include: (i) environmental data such as barometric pressure, temperature, humidity, light intensity, magnetic fields, and noise level, (ii) vital health signs such as pulse, body temperature, blood pressure, and respiratory rate, (iii) location data which are typically identified by longitudes and latitudes using GPS sensors, and (iv) body limbs motion such as acceleration and rotation of body parts like arms, legs, and torso using accelerometers and gyros. For the purpose of activity recognition, the latter type of attributes have proven to represent human motion accurately, where some methods depending only on acceleration measurements have achieved very high accuracy [8,20]. However, it is very difficult to extract the pattern of motion from acceleration raw data directly because of high frequency oscillation and noise. So, feature extraction techniques should be applied on the raw data before using it. Many types of features can be extracted from acceleration data: (1) time-domain features like mean and variance [21], (2) frequency-domain features like Fourier transform, discrete cosine transform, and wavelet transform, and (3) applying dimensionality reduction techniques like PCA and LDA [8].

An essential function of HAR systems is to provide a general model for each activity. The activity models are mostly generated based on the features extracted from training data using supervised machine learning techniques. Thus, the role of machine learning techniques in HAR systems is to build general models to describe each activity and use these models to detect or classify the target activities later. Many classification techniques are used such as support vector machine (SVM), random forests, C4.5 decision trees, hidden Markov models (HMM), k-nearest neighbor (KNN), Bayesian networks, and artificial neural networks (ANN) [12,44].

Among all wearable sensors, accelerometers are considered as the most used sensors in HAR systems [12]. Being small-sized, inexpensive, and embedded in most of smart mobile devices has encouraged many researchers to use acceleration in their work. Compared to cameras, accelerometers are more suitable for HAR systems, it is very difficult to fix a camera to monitor a user everywhere; also mounting the camera to the user's body is very annoying and uncomfortable. From the privacy point of view, it is not acceptable nor convenient by many people to be monitored all the time. As well, the videos or images collected using cameras are very sensitive to many environmental conditions like lighting and surrounding barriers. However, accelerometers can be easily mounted to users or embedded into many devices such as smart phones and/or smart watches which are naturally carried by many users everywhere most of the time. Also acceleration data preserve user privacy and are not affected by any outside conditions.

2 Related Work

Sensors locations and count are very important issues that have to be taken into consideration while designing an accelerometer-based HAR system. As seen in Table 1, many settings have been studied through the previous work. Regarding the locations of wearable sensors, different body locations have been used from feet to chest. However, the relevance of the selection to activities plays an important role in specifying the sensor's location. For example, ambulation activities (such as walking, running, jumping, etc) can be detected efficiently using a chest or waist mounted sensor [20,37,16]. Whereas, non-ambulation activities (such as brushing teeth, combing hair, eating, etc) can be classified more efficiently using a wrist-worn sensor [22,8]. This makes using more than one sensor in different body locations a good idea for improving accuracy for both ambulation and non-ambulation activities [13].

Accelerometer sampling frequency is also an important parameter. Maurer et al. [31] and Yan et al. [43] studied the effect of different sampling frequencies on the classification accuracy. Maurer et al. [31] found that the accuracy stabilizes between 15 to 20Hz and not considerably improved on higher sampling rate. Yan et al. [43] studied sampling frequency from the energy saving point of view. They found that there is a an activity specific tradeoff between consumed energy and classification accuracy based on sampling frequency. So, they introduced a smart adaptive method which changes the sampling frequency in real-time based on the type of activity.

There are mainly two approaches to HAR: threshold-based and machine learning-based. HAR systems which are threshold-based don't require any training processes, however, they can be used to classify relatively small number of activities compared to systems which are based on machine learning techniques. The majority of HAR systems use supervised classification algorithms in order to classify the relevant activities as shown in Table 1 making use of the ability of learning algorithms to detect and discriminate between different hidden patterns of activities.

Several kinds of activities have been considered by HAR systems. These include: ambulation activities, daily activities, fitness activities, and industrial activities. However, most of the studied HAR systems concentrate on ambulation activities as shown in Table 2, because such activities are regularly performed by almost all people. Ambulation activities are also easy to recognize because of having many repetitive motions and having the same patterns everywhere for any subject. The effectiveness of any HAR system depends not only on the recognition accuracy but also on the number and types of activities which can it recognize. According to Table 1, the number of activities for developed HAR systems widely vary, starting from only 2 or 3 activities to more than 20 activities. However, the average recognition accuracy is affected by the count and the diversity of the types of considered activities.

Raw acceleration data can not be used directly to recognize human activities. It is generally hard getting the same acceleration values for the same activity twice even if the activity is performed by the same person. Thus, to measure the similarity between acceleration time series, preprocessing have to be applied first to extract more informative features which can substitute the raw data. Table 3 summarizes the selected features for our related work. Two common types of features can be extracted from acceleration data (and generally from any time series): time domain features and frequency domain features. Frequency domain features are avoided in many studies, especially those assuming limited computing resources or requiring real-time recognition, to avoid the costly computation overhead required to transform the signals from the time domain to the frequency domain using fast Fourier transform (FFT). Time domain feature represent more the values of the acceleration, whereas the frequency domain features usually reflect the periodicity in the signal. As seen in Table 3, the most popular time domain features are mean, standard deviation, correlation,

Table 1: Related work classified by sensors (type, count, location), sampling rate, learning method, number of activities, and average accuracy (A: Accelerometer, M: Magnetometer, G: Gyroscope).

Reference	Used Sensors			No. of Sensors	Sensors Location	Sampling Rate (HZ)	Learning Method/Algorithm	No. of Activities	Accuracy (%)
	A	M	G						
[29]	X			2	Hip left and right sides	256	Multilayer perceptron	4	90
[27]	X		X	2	Waist, front trouser pocket	5	Threshold-based	5	86.7
[36]	X			1	Waist	50	Multiple classifiers	8	84
[19]	X			1	Waist	45	Threshold-based	12	90.8
[31]	X			6	Wrist, waist, necklace, trouser pocket, shirt pocket, bag	50	Decision Trees Naive-Bayes	6	88
[18]	X			12	Ankles, knees, elbows,shoulders, wrists, hip left and right sides	92	Multiple Eigenspaces combined with SVM	8	88.3
[17]	X			1	different locations (clothes pocket, waist belt,and trouser pocket)	100	SVM	4	97.21
[37]	X			1	Waist	14	Multilayer perceptron	9	95.5
[11]	X			1	Chest	50	Threshold-based	3	81.25
[23]	X			3	Hip, dominant ankle, non-dominant thigh	50	AdaBoost, SVM, RLogReg	7	88.2
[16]	X			1	Trouser pocket	100	SVM	4	97.5
[47]	X			2	Foot, waist	150	Feed forwarn NN, HMM	4	89.7
[22]	X			1	Wrist	100	KNN	5	92.2
[46]	X			1	Waist	1	SVM	6	82.8
[20]	X			1	Chest	20	Feed-forwarn NN	15	97.9
[24]	X			1	Trouser pocket	20	Decision trees (J48), logistic regression, neural network	6	91.7
[28]	X			1	Thigh	250	SVM	5	99
[9]	X			1	Wrist	33	C4.5, neural network	5	94.1
[13]	X		X	9	Wrists, arms, thighs, ankles, waist	50	Hierarchical clustering, K-means, decision trees	25	93.3
[48]	X			1	Right thigh	20	Feed Forwarn NN, HMM	8	85
[25]	X			1	Chest	50	C4.5	3	92.6
[43]	X			1	Waist	100,50, 16,5	J48 adaptive decision tree	10	87
[33]	X			1	Torso	40	Threshold-based	6	100
[10]	X			2	Dominant wrist, ankle	30	K-NN probabilistic neural network	7	96
[42]	X		X	7	Waist, wrists, right arm, left thigh, ankles	30	Bayesian Sparse representation-Based	14	87.7
[3]	X			1	Waist	50	MC-HF-SVM	6	89
[45]	X		X	1	Waist	100	K-NN, naive Bayes, SVM	9	95.2
[2]	X			1	Waist	80	Stochastic Approximation classifier	2	94.5
[38]	X			3	Chest, right thigh,left ankle	25	HMM	12	91.4
[8]	X			1	Right wrist	32	GMM, GMR	8	68.7
[39]	X			1	Trouser pocket	1	Hierarchical-SVM	4	98.5
[4]	X			1	Trouser pocket	20	KNN	6	99.4
[14]	X			2	Abdomen,right thigh	50	Threshold-based, Random Forest	4	98.85
[32]	X	X	X	1	Right shoe	100	KNN	20	77
[6]	X			3	Wrist, chest, foot	100	Neural network	14	89.7
[7]	X		X	3	Chest, left crus, right thigh	50	Neuro-fuzzy classifier	7	97.2
[40]	X			1	Back mounted	50	KNN	5	95.6
[21]	X			1	Wrist	32	Neural network	7	91
[30]	X			1	Wrist	20	Template-matching-based	22	80
[41]	X			3	Chest,dominant wrist, dominant ankle	100	Back propagation neural network	12	93.7
[15]	X		X	1	dominant wrist	50	Random forests	14	80
[5]	X		X	1	dominant wrist	50	LSTM	31	97

and variance. While the most popular frequency domain features are energy and entropy.

3 Conclusion

A review of HAR systems which uses temporal signals generated from portable inertial sensors has been introduced. Types of HAR systems according to data acquisition paradigms, types of attributes, and sensors' types, counts and locations have been presented. Moreover, various machine learning algorithms which are used with HAR systems have been stated. Finally, some important related proposed systems are illustrated.

References

1. Ericsson Mobility Report on The Pulse of The Networked Society. Tech. rep., Ericsson (11 2016), https://www.ericsson.com/assets/local/mobility-report/documents/2016/ericsson-mobility-report-november-2016.pdf
2. Alshurafa, N., Xu, W., Liu, J.J., Huang, M.C., Mortazavi, B., Sarrafzadeh, M., Roberts, C.: Robust human intensity-varying activity recognition using stochastic approximation in wearable sensors. In: Body Sensor Networks (BSN), 2013 IEEE International Conference on. pp. 1–6. IEEE (2013)
3. Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J.L.: Energy efficient smartphone-based activity recognition using fixed-point arithmetic. J. UCS 19(9), 1295–1314 (2013)
4. Arif, M., Bilal, M., Kattan, A., Ahamed, S.I.: Better physical activity classification using smartphone acceleration sensor. Journal of medical systems 38(9), 95 (2014)
5. Ashry, S., Elbasiony, R., Gomaa, W.: An lstm-based descriptor for human activities recognition using imu sensors. In: Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics - Volume 1: ICINCO,. pp. 494–501. INSTICC, SciTePress (2018)
6. Basterretxea, K., Echanobe, J., del Campo, I.: A wearable human activity recognition system on a chip. In: Design and Architectures for Signal and Image Processing (DASIP), 2014 Conference on. pp. 1–8. IEEE (2014)
7. Braojos, R., Beretta, I., Constantin, J., Burg, A., Atienza, D.: A wireless body sensor network for activity monitoring with low transmission overhead. In: Embedded and Ubiquitous Computing (EUC), 2014 12th IEEE International Conference on. pp. 265–272. IEEE (2014)
8. Bruno, B., Mastrogiovanni, F., Sgorbissa, A., Vernazza, T., Zaccaria, R.: Analysis of human behavior recognition algorithms based on acceleration data. In: Robotics and Automation (ICRA), 2013 IEEE International Conference on. pp. 1602–1607. IEEE (2013)
9. Chernbumroong, S., Atkins, A.S., Yu, H.: Activity classification using a single wrist-worn accelerometer. In: Software, Knowledge Information, Industrial Management and Applications (SKIMA), 2011 5th International Conference on. pp. 1–6. IEEE (2011)
10. Chuang, F.C., Wang, J.S., Yang, Y.T., Kao, T.P.: A wearable activity sensor system and its physical activity classification scheme. In: Neural Networks (IJCNN), The 2012 International Joint Conference on. pp. 1–6. IEEE (2012)

Table 2: Related work classified by tested activities.

Ref.	Walking	Stairs (Up/Down)	Sitting	Standing	Running	Lying	Jumbing	Other
[29]	X	X						X
[27]	X	X	X	X				
[36]	X	X		X	X			X
[19]	X		X	X		X		X
[31]	X	X	X	X	X			
[18]	X	X	X	X				X
[17]	X				X		X	X
[37]	X		X	X	X	X		X
[11]	X				X			X
[23]	X	X	X	X	X	X		X
[16]	X				X		X	X
[47]	X	X			X			
[22]								X
[46]	X		X	X		X		X
[20]	X	X	X	X	X	X		X
[24]	X	X	X	X	X			
[28]	X		X	X	X			X
[9]	X		X	X	X	X		
[13]	X	X	X	X		X	X	X
[48]	X		X	X		X		X
[25]	X		X		X			
[43]	X	X	X	X				X
[33]	X	X				X		
[10]	X	X	X	X	X			X
[42]	X		X	X		X	X	X
[3]	X	X	X	X		X		
[45]	X	X	X	X	X		X	
[2]	X				X			
[38]	X	X	X	X		X		
[8]	X	X	X	X				X
[39]	X		X	X	X			
[4]	X	X	X	X	X			
[14]			X			X		X
[32]	X				X			X
[6]	X	X	X	X	X	X	X	X
[7]	X	X	X	X	X	X		
[40]	X				X		X	X
[21]	X	X	X	X				X
[30]	X				X			X
[41]	X	X	X	X	X	X		X
[15]	X	X	X	X		X		X
[5]	X	X	X	X	X			X

Table 3: Accelerometer data classified by extracted features.

Ref.	Time Domain												Frequency Domain		Other
	Mean	Standard Deviation	Correlation	Variance	RMS	Mean Crossing Rate	Zero Crossing Rate	Normalized Signal Magnitude Area (SMA).	Interquartile Range	Minimum	Maximum	Median	Energy	Entropy	
[29]															X
[27]		X													X
[36]	X	X	X										X		
[19]								X							X
[31]	X	X		X	X	X	X								X
[18]	X			X											
[17]															X
[37]															Raw data
[11]	X							X							
[23]	X		X	X									X	X	
[16]															X
[47]	X														
[22]	X	X	X							X	X	X			X
[46]										X	X				
[20]	X	X	X					X							
[24]	X	X													X
[28]	X			X					X			X			X
[9]	X	X	X	X						X			X	X	X
[13]	X	X			X										X
[48]	X			X											
[25]	X	X	X	X	X								X		X
[43]	X			X									X	X	X
[33]	X										X				X
[10]		X											X	X	X
[42]	X	X	X	X	X	X	X		X			X			X
[3]	X	X	X					X						X	
[45]	X	X	X	X	X	X	X	X				X	X	X	X
[2]	X	X	X	X	X	X	X		X			X			X
[38]															Raw data
[8]															Raw data
[39]					X										X
[4]	X	X	X		X			X	X	X	X	X		X	X
[14]															X
[32]	X														
[6]	X	X										X	X	X	X
[7]	X	X					X					X	X	X	X
[40]															X
[21]	X			X		X									X
[30]	X			X	X					X	X		X	X	
[41]															X
[15]			X												
[5]													X		X

11. Chung, W.Y., Purwar, A., Sharma, A.: Frequency domain approach for activity classification using accelerometer. In: Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE. pp. 1120–1123. IEEE (2008)
12. Cornacchia, M., Ozcan, K., Zheng, Y., Velipasalar, S.: A survey on activity detection and classification using wearable sensors. IEEE Sensors Journal 17(2), 386–403 (2017)
13. Ghasemzadeh, H., Jafari, R.: Physical movement monitoring using body sensor networks: A phonological approach to construct spatial decision trees. IEEE Transactions on Industrial Informatics 7(1), 66–77 (2011)
14. Gjoreski, H., Kozina, S., Gams, M., Lustrek, M.: Rarefall—real-time activity recognition and fall detection system. In: Pervasive Computing and Communications Workshops (PERCOM Workshops), 2014 IEEE International Conference on. pp. 145–147. IEEE (2014)
15. Gomaa, W., Elbasiony, R., Ashry, S.: Adl classification based on autocorrelation function of inertial signals. In: Machine Learning and Applications (ICMLA), 2017 16th IEEE International Conference on. pp. 833–837. IEEE (2017)
16. He, Z., Jin, L.: Activity recognition from acceleration data based on discrete consine transform and svm. In: Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on. pp. 5041–5044. IEEE (2009)
17. He, Z., Liu, Z., Jin, L., Zhen, L.X., Huang, J.C.: Weightlessness feature—a novel feature for single tri-axial accelerometer based activity recognition. In: Pattern Recognition, 2008. ICPR 2008. 19th International Conference on. pp. 1–4. IEEE (2008)
18. Huynh, T., Schiele, B.: Towards less supervision in activity recognition from wearable sensors. In: Wearable Computers, 2006 10th IEEE International Symposium on. pp. 3–10. IEEE (2006)
19. Karantonis, D.M., Narayanan, M.R., Mathie, M., Lovell, N.H., Celler, B.G.: Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE transactions on information technology in biomedicine 10(1), 156–167 (2006)
20. Khan, A.M., Lee, Y.K., Lee, S.Y., Kim, T.S.: A triaxial accelerometer-based physical-activity recognition via augmented-signal features and a hierarchical recognizer. IEEE transactions on information technology in biomedicine 14(5), 1166–1172 (2010)
21. Kilinc, O., Dalzell, A., Uluturk, I., Uysal, I.: Inertia based recognition of daily activities with anns and spectrotemporal features. In: 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA). pp. 733–738. IEEE (2015)
22. Koskimaki, H., Huikari, V., Siirtola, P., Laurinen, P., Roning, J.: Activity recognition using a wrist-worn inertial measurement unit: A case study for industrial assembly lines. In: Control and Automation, 2009. MED'09. 17th Mediterranean Conference on. pp. 401–405. IEEE (2009)
23. Krishnan, N.C., Panchanathan, S.: Analysis of low resolution accelerometer data for continuous human activity recognition. In: Acoustics, Speech and Signal Processing, 2008. ICASSP 2008. IEEE International Conference on. pp. 3337–3340. IEEE (2008)
24. Kwapisz, J.R., Weiss, G.M., Moore, S.A.: Activity recognition using cell phone accelerometers. ACM SigKDD Explorations Newsletter 12(2), 74–82 (2011)

25. Lara, O.D., Labrador, M.A.: A mobile platform for real-time human activity recognition. In: Consumer Communications and Networking Conference (CCNC), 2012 IEEE. pp. 667–671. IEEE (2012)
26. Lara, O.D., Labrador, M.A.: A survey on human activity recognition using wearable sensors. IEEE Communications Surveys & Tutorials 15(3), 1192–1209 (2013)
27. Lee, S.W., Mase, K.: Activity and location recognition using wearable sensors. IEEE pervasive computing 1(3), 24–32 (2002)
28. Mannini, A., Sabatini, A.M.: On-line classification of human activity and estimation of walk-run speed from acceleration data using support vector machines. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE. pp. 3302–3305. IEEE (2011)
29. Mantyjarvi, J., Himberg, J., Seppanen, T.: Recognizing human motion with multiple acceleration sensors. In: Systems, Man, and Cybernetics, 2001 IEEE International Conference on. vol. 2, pp. 747–752. IEEE (2001)
30. Margarito, J., Helaoui, R., Bianchi, A.M., Sartor, F., Bonomi, A.G.: User-independent recognition of sports activities from a single wrist-worn accelerometer: A template-matching-based approach. IEEE Transactions on Biomedical Engineering 63(4), 788–796 (2016)
31. Maurer, U., Smailagic, A., Siewiorek, D.P., Deisher, M.: Activity recognition and monitoring using multiple sensors on different body positions. In: Wearable and Implantable Body Sensor Networks, 2006. BSN 2006. International Workshop on. pp. 4–pp. IEEE (2006)
32. Mortazavi, B., Nyamathi, S., Lee, S.I., Wilkerson, T., Ghasemzadeh, H., Sarrafzadeh, M.: Near-realistic mobile exergames with wireless wearable sensors. IEEE journal of biomedical and health informatics 18(2), 449–456 (2014)
33. Naranjo-Hernández, D., Roa, L.M., Reina-Tosina, J., Estudillo-Valderrama, M.A.: Som: a smart sensor for human activity monitoring and assisted healthy ageing. IEEE transactions on biomedical engineering 59(11), 3177–3184 (2012)
34. Patel, S., Park, H., Bonato, P., Chan, L., Rodgers, M.: A review of wearable sensors and systems with application in rehabilitation. Journal of neuroengineering and rehabilitation 9(1), 21 (2012)
35. Poushter, J.: Smartphone ownership and internet usage continues to climb in emerging economies (2016), http://www.pewglobal.org/2016/02/22/smartphone-ownership-and-internet-usage-continues-to-climb-in-emerging-economies
36. Ravi, N., Dandekar, N., Mysore, P., Littman, M.L.: Activity recognition from accelerometer data. In: Aaai. vol. 5, pp. 1541–1546 (2005)
37. Song, S.k., Jang, J., Park, S.: A phone for human activity recognition using triaxial acceleration sensor. In: Consumer Electronics, 2008. ICCE 2008. Digest of Technical Papers. International Conference on. pp. 1–2. IEEE (2008)
38. Trabelsi, D., Mohammed, S., Chamroukhi, F., Oukhellou, L., Amirat, Y.: An unsupervised approach for automatic activity recognition based on hidden markov model regression. IEEE Transactions on Automation Science and Engineering 10(3), 829–835 (2013)
39. Weng, S., Xiang, L., Tang, W., Yang, H., Zheng, L., Lu, H., Zheng, H.: A low power and high accuracy mems sensor based activity recognition algorithm. In: Bioinformatics and Biomedicine (BIBM), 2014 IEEE International Conference on. pp. 33–38. IEEE (2014)
40. Wilson, J., Najjar, N., Hare, J., Gupta, S.: Human activity recognition using lzw-coded probabilistic finite state automata. In: Robotics and Automation (ICRA), 2015 IEEE International Conference on. pp. 3018–3023. IEEE (2015)

41. Xu, H., Liu, J., Hu, H., Zhang, Y.: Wearable sensor-based human activity recognition method with multi-features extracted from hilbert-huang transform. Sensors 16(12), 2048 (2016)
42. Xu, W., Zhang, M., Sawchuk, A.A., Sarrafzadeh, M.: Co-recognition of human activity and sensor location via compressed sensing in wearable body sensor networks. In: Wearable and Implantable Body Sensor Networks (BSN), 2012 Ninth International Conference on. pp. 124–129. IEEE (2012)
43. Yan, Z., Subbaraju, V., Chakraborty, D., Misra, A., Aberer, K.: Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach. In: Wearable Computers (ISWC), 2012 16th International Symposium on. pp. 17–24. Ieee (2012)
44. Ye, L., Ferdinando, H., Seppänen, T., Huuki, T., Alasaarela, E.: An instance-based physical violence detection algorithm for school bullying prevention. In: 2015 International Wireless Communications and Mobile Computing Conference (IWCMC). pp. 1384–1388. IEEE (2015)
45. Zhang, M., Sawchuk, A.A.: Human daily activity recognition with sparse representation using wearable sensors. IEEE journal of Biomedical and Health Informatics 17(3), 553–560 (2013)
46. Zhang, S., McCullagh, P., Nugent, C., Zheng, H.: Activity monitoring using a smart phone's accelerometer with hierarchical classification. In: Intelligent Environments (IE), 2010 Sixth International Conference on. pp. 158–163. IEEE (2010)
47. Zhu, C., Sheng, W.: Human daily activity recognition in robot-assisted living using multi-sensor fusion. In: Robotics and Automation, 2009. ICRA'09. IEEE International Conference on. pp. 2154–2159. IEEE (2009)
48. Zhu, C., Sheng, W.: Motion-and location-based online human daily activity recognition. Pervasive and Mobile Computing 7(2), 256–269 (2011)