Abnormal Behavior Detection Based on Smartphone Sensors

Dang-Nhac Lu[3](✉), Thuy-Binh Tran[2], Duc-Nhan Nguyen[2], Thi-Hau Nguyen[1], and Ha-Nam Nguyen[1]

[1] University of Engineering and Technology, Vietnam National University in Hanoi, Hanoi, Vietnam
{nguyenhau,namnh}@vnu.edu.vn
[2] Posts and Telecommunications Institute of Technology, Hanoi, Vietnam
tran.binh95@gmail.com, ducnhan@ptit.edu.vn
[3] Academy of Journalism and Communication, Hanoi, Vietnam
nhacld.di11@vnu.edu.vn

Abstract. There are a lot of applications were developed to take advance of smartphone sensors for utilizing the personal services such as health-care, walk-counting, routing etc. Users behavior analysis is attracted a lot of researches interested with various approaches. We proposed a novel framework to detect the abnormal driving behavior using smartphone sensors. It named Abnormal Behavior Detection System (ABDS). The system keep track the driver activities during he's trip based on smartphone sensors. The Practice Swarm Optimization (PSO) algorithm is used to automatically select suitable features extracted from sensors data. The oriented accelerometer is used to detect activity. The abnormal behavior is collected and labeled then detection by Artificial Neural Network (ANN). The implementation shown the promising results in case of seven activities (stop, moving, acceleration, deceleration, turn left, turn right and U-turn) with 86.71% accuracy.

Keywords: Activity recognition · Behavior recognition · Detecting behavior PSO algorithm

1 Introduction

The mobile phone is indispensable device in modern life and there is a lot of applications using sensor signals [1] for human activity analysis or behavior recognition. Recently, researchers concerned much about personal data analysis based on collected sensors data with various approaches [2]. Behaviors can be defined as sequences of primitive activities and it can be repeated time by time. Sometime it can be called complex activities. Driving behavior system is meaningful with traffic participant and defined by any activity analysis technical based on set of values such as: distances, gaps [3], time, angle [4] and velocity [5]. Hence, it could be help for recognizing the harmful activities when they are moving with their smartphone.

P. Cong Vinh et al. (Eds.): ICCASA 2017/ICTCC 2017, LNICST 217, pp. 195–204, 2018.
https://doi.org/10.1007/978-3-319-77818-1_19

The accelerometer is the most commonly sensor for reading motion signals and utilize in various application [6–8]. The smartphone sensors signal is time series data, which can be easy to collect but difficult to analysis. The quality of analysis depended on devices quality, environment conditional and sensitive applying model. In some cases, feature extraction technical is applied for human activity recognition, driving behavior problem [9, 10].

Vavouranakis et al. [11] proposed method to recognize driving behavior by smartphone sensor. However, the device is fixed in car and reoriented data by sensor fusion method, mobile coordinate system be reoriented by its coordinate system. The windowing technical utilize with 5 s on accelerometer data. Then, abnormal behavior are predicted by thresholds of x and y-axis accelerometer values. The 12 distinguish events about six safe and six unsafe behaviors deployed by their method.

Li et al. [4] developed system for detected dangerous driving behavior. It gathers accelerometer signal with ground truth position on taxi. The yaw angles is estimated by transformation matrix converter between vehicles coordinate and smartphone coordinate system and helping them to detect behavior on manual dangerous driving behavior set which define by accelerometer value threshold and 90% accuracy was received by their experiment.

Xu et al. [5] detected human behavior rules base on accelerometer with Fourier transform take 1 s to 8 s point for analysis and calculated velocity from accelerometer.

The one of challenges with driving behavior recognition using accelerometer is signal quality in difference devices. Following, analysis technical and models used for abnormal behavior recognition, which are complex and difficult. Hence, our problems is detecting user activity while they are moving, then the sequence of activity corresponding to their trip is background for system predicts and announce abnormal behavior.

The ABDS is divided into four parts: firstly, it collects label data, analysis and extract suitable features subset by PSO. Secondly, it predicts seven activity by some classification algorithms as Random Forest (RB), Naïve Bayes (NB), k-Nearest Neighbor (KNN) and Support Vector Machine (SVM). Finally, it predicts abnormal driving behavior by ANN. The experiment on collected data set with various driving types = {walking, bicycle, motorbike, bus, car} obtained the promising results with safe and unsafe behaviors compare to traditional methods.

2 The Proposed Framework

Our proposed method, named ABDS framework, is presented in Fig. 1. The system is consisting of four steps: firstly, the label data collected from each volunteer and features selection aim to predefine input value for predict activities. The raw data is converted into a set of features and then PSO are applied to select the suitable subset feature for driving activities recognition. Secondly, data with the best features subset is used for classifying and online recognition activity on smartphone. Finally, the abnormal driving behaviors are detected by ANN model which is trained in previous step.

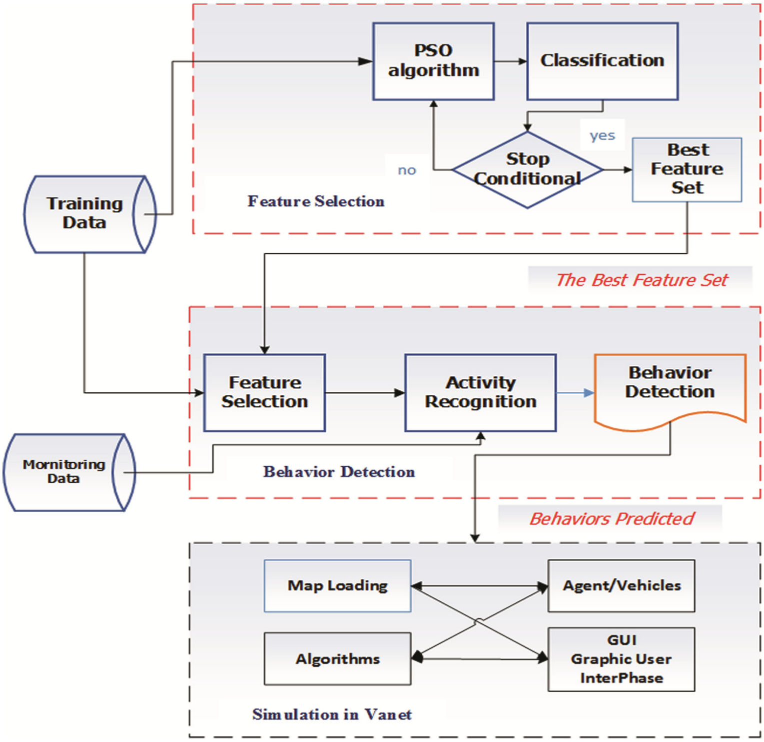

Fig. 1. The proposed framework (ABDS)

2.1 The Feature Selection

The Feature Set

In the phase 1, signal data label obtain from smartphone on their pocket, handbag, or in hands, etc. while they are moving. Hence, the orientation and signal value is frequent changing. Our paper suggest an approach to preparing data for classifier by collected and transform data base one windowing technical and feature extraction. The set of features is constructed by data sequences that were extracted and calculated from time-based, power-based and frequency-based domain data. It is a base for dynamic and suitable selected features system with complex activity. An approach to solve noisy accelerometer data is reoriented. We use accelerometer, gyroscope and magnetometer sensors to transform accelerometer data from the smartphone coordinate system to the Earth coordinate system [12]. Considering that, a (x, y, z) is data point in coordinate system then earth coordinate system of a′(x′, y′, z′) by R matrix and it is computed by function below:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = R \begin{pmatrix} x \\ y \\ z \end{pmatrix} \quad (1)$$

Following, directly analyze with amount raw sensor data is needed a lot of time or memory space. There are any features was extracted by time series technical analysis but, it depends on goal, environment, condition of problems and no method is enough good for all issues. We propose several types of features from instance in three domain above. The windowing technical is usually choice in time series data then it also apply to calculate value of features from root mean square, sample correlation coefficient, cross-correlation, vertical and horizontal accelerometer energy of window signal, energy of M coefficient Fourier values, Signal magnitude area, average Energy of X, Y, Z axis, and the entropy of signal. These total 21 features apply for detection in system and is shown in Table 1.

Table 1. The suggestion feature set for system

The features	Variable name
Root mean square (RMS)	X_{rms}
Correlation coefficient	$CorreCo_{xy}$, $CorreCo_{xz}$, $CorreCo_{yz}$
Cross-correlation	$Cross_{xy}$, $Cross_{xz}$, $Cross_{yz}$
Signal magnitude area	*SMA,*
The accelerometer energy of windows	*Ev, Eh*
Statistical value: mean, variance, standard deviation	*sM, sV, sSD*
The energy of M coefficient Fourier	*EM*
Average energy of X, Y, Z axis	E_x, $E_{y,}$ E_z
The entropy	H, H_x, H_y, H_z

The Training Model

There are two approach to classify data as offline and online training. The offline method in advance model, which compute on personal computer or server then client to send input and parameters of model. The online method implements computation, recognition on smartphone. The offline method has more propitious conditional and resources. However, it depends on linking and services. Nowadays, hardware and devices quality is more improved. So that, we use online training method on smartphone and assess by some appropriate algorithm such as RF, NB, SVM, KNN, which applied in researches in this field and have shown appropriate accuracy. The WEKA tool has used and integrated in ABDS for classification and recognition. Experiment in this paper indicated that, RF is appropriate and higher accuracy. This algorithm will be applied to optimize feature set.

Optimization Feature Set Using PSO Algorithm

In fact, any approaching chose several kind of feature suitable with data and problem in their field. The selected features is usually via experiment and no method agree to all problem. Hence, we suggest using PSO algorithm to select suitable features for improving prediction accuracy base on wrapper method. The PSO was introduced by Eberhart and Kennedy [13]. In PSO, each potential solution is corresponding to particle and assumption that, $x = [x_1, x_2, \ldots, x_D]$ with $X_i = (X_1, X_2, \ldots, X_D)$ are features at particle i^{th} and the x_k^i is particle position; the v_k^i is particle velocity; the p_k^i is the best individual particle position; p_k^g is the best swarm position; c_1, c_2 are cognitive and social parameters; r_1, r_2 is random numbers between 0 and 1. The PSO algorithm is express below (Fig. 2):

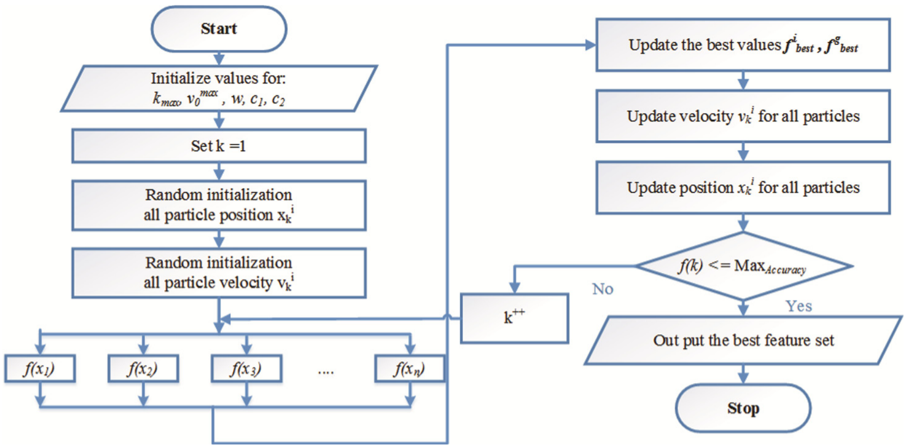

Fig. 2. The feature selection using PSO algorithm

Where

$$x_{k+1}^i = x_k^i + v_{k+1}^i \tag{2}$$

And:

$$v_k^i = v_k^i + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (g_k^i - x_k^i) \tag{3}$$

When phase one finished, the best of subset feature is chosen and utilizing to predict activity from online accelerometer signal sensors data.

2.2 Abnormal Behavior Analysis

The definition context safety or not depend on realities issue and opinions. The repeating activities usually reflect abnormal driving behaviors. It is also belonging personality of user habit. Hence, ABDS use k-series activity aim to predict abnormal driving behavior via accelerometer sensors signal. The system is also monitoring and predicting behavior at status of vehicle on real time. When systems has detected current driving activity a_c then combined with k − 1 previous activity to instance consist k linear activity as $(a_{c-k-1}, \ldots, a_{c-1}, a_c)$. In fact, abnormal behaviors have realized after one or several complex activity, which are abnormal and repeating. Hence, series activity in instance is basic to predict them. The problems affect to prediction accuracy is value of k and personal habit.

The abnormal behavior training dataset is build up from series activity while they are driving on sleeping, drunk and frequency swing with high velocity. The clustering technical with k-means clustering algorithm is used to set of k linear activity into three class and the label of abnormal behavior instance number i is shown by $S_i(S_{i_1}, S_{i_2}, \ldots, S_{i_k}, l_i)$. It indicated that, abnormal behavior has built up from sequence basic activity. The ANN algorithm is applied by some research in human activity and behavior recognition system. The neurons will be received inputs from other neurons. The value of each input is determined by a weight associated with them. The sum of input weights computed and value output is according to its transfer function. The neurons in a layer do not interconnect with each other, but interconnect with neurons in other layers. Neural networks can have one or more layers between input and output layers. The typical ANN is consisting of input layer, hidden layers and output layer that is expressed in Fig. 3.

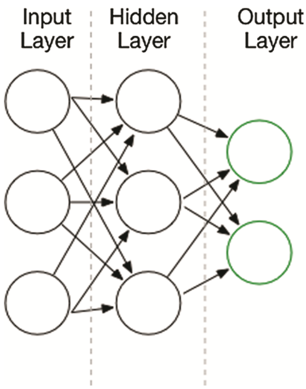

Fig. 3. Artificial Neural Network structure

The series monitoring activity is used to predict abnormal behavior in Fig. 4.

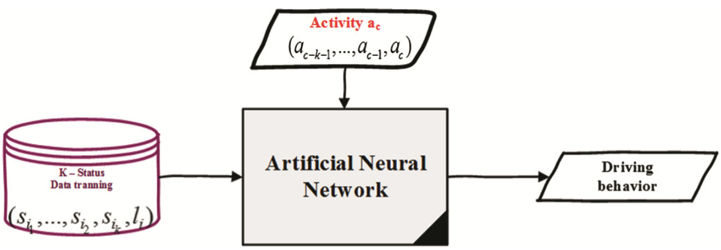

Fig. 4. Abnormal Behavior Detection

2.3 Monitoring Application

The training data set collects by any difference subjects with advanced supposed conditional. However, each user might have different in habits. Therefore, the prediction accuracy may be fall down when the system used by another or new users. Okeyo et al. [15] developed the idea to incrementally update the training data set by utilizing real-time feedbacks from users. As the system provides the activity, behaviors prediction, user can confirm the right of the results. The newly instance data labeled, which correcting from users is then added to the training data set. It is really meaningful with abnormal behavior, which happening and depend on user habit, complexity when user is moving. Specially, characteristic behavior of difference users will be recognize and update. The idea is express in Fig. 1 and some the interfaces of ABDS system is shown in Fig. 5.

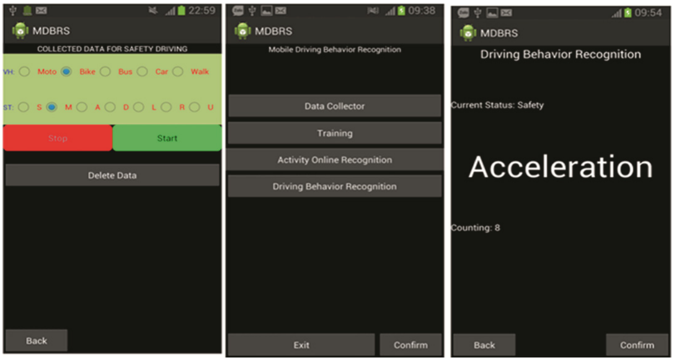

Fig. 5. The interfaces of ABDS

3 Experiment and Results

3.1 Experiment Environment

We implemented ABDS on the Android Operating System from 4.0 to 5.0 platform. The dataset with activity labels collected by 20 subjects when they are driving by walking, bicycle, motorbike, bus and car. They freely carry a Samsung galaxy S4, Quad-core 1.6 GHz Cortex-A15 processor, 2 GB of Ram, 2600 mAh battery, Android 4.2.2 Jelly Bean OS. The sevens activity recognition are {stop, moving, acceleration, deceleration, turn left, turn right and U-turn}. The Weka tool is used for deploying on our framework to predict the vehicle status. The classification was used such as Random Forest, KNN, Naive Bayes, SVM. In each case, the default setting is used by setting parameter of algorithms. We also used 10-fold cross validation for evaluating the accuracy of each classification algorithm.

3.2 The Collected and Processing Data

In this paper experiment, signal data is collected from three types of sensors as acceleration, gyroscope and magnetic sensor signal with 50 Hz frequency. These sensor returns x, y, and z coordinates values at point. The raw data stream is first cut out one seconds at the starting point, and one seconds at the end point, cause these periods time are usually redundant. Then, split into a window by 4 s size and the overlapping time is 50% of window size. We collected at least 200 samples for each activity from subjects. The training data set for behavior recognition also improved by users during their trips. It contained meaningful habit characteristic of users.

We have chosen the walking and motorbike for collecting abnormal driving behavior. With the abnormal driving behavior on training dataset, we use the k-means clustering algorithm with k = 3 base on series activity of users, reflecting to three label of abnormal driving behavior such as sleeping driving, drunk and frequency swing by high velocity. After that, the training dataset with normal and abnormal labeled is used for recognizing driving behavior.

3.3 The Abnormal Behavior Analysis Results

In this experiment, we deploy on about 3500 sample; the system will build up model for subjects to predict activity and abnormal behaviors base on two choosing feature method. The result when ABDS deploy with traditional on 21 features and using PSO to select features, it shows in Fig. 6.

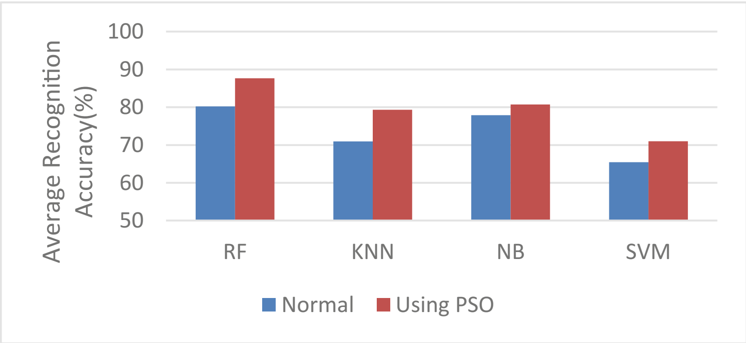

Fig. 6. Activity recognition accuracy of algorithms using PSO and traditional

The Fig. 6 is shown the results between two method select features, the average of recognition accuracy when user uses PSO is always higher. With RF is max as 87.66% and SVM is min with 71%. It indicates that, the RF algorithm is suitable in ABDS system.

The Fig. 7 is shown the average activity recognition accuracy by RF on normal method using 21 features and using PSO algorithm for optimization with the best feature subset, which selected by PSO. It indicated that, the accuracy of the abnormal activity are lower than normal, specially abnormal turn left and turn right activity is lowest.

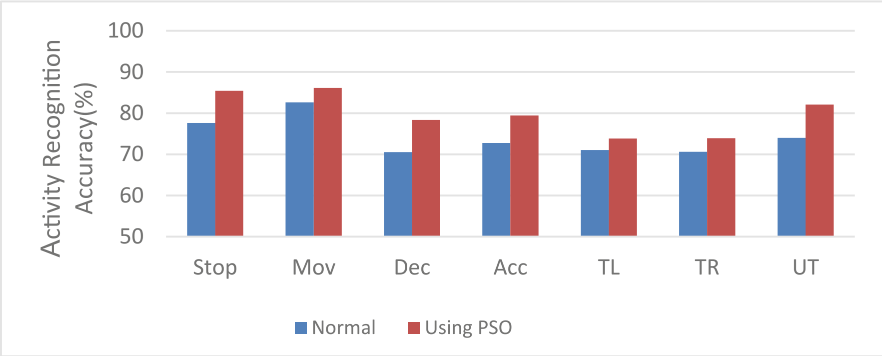

Fig. 7. The activity recognition by Random Forest algorithm

Thereafter, we are collected a behavior training dataset, which contain 300 abnormal behavior instances aim to detect current abnormal behavior base on activity. Through experiments, we chose k = 6 with 6 linear activity are built for each instance. The parameters value of ANN is default setting with behavior detecting accuracy is up to 86.71%.

4 Conclusion and Future Works

In this paper, we proposed a flexible framework to predict current driving behavior base on smartphone sensor, when user moving, dynamic changing position and direction. Besides, our proposed framework also using PSO to select suitable features. Following, ABDS detect vehicle activity and this is basic for recognition driving behavior using ANN. It utilizes and simulates on transportation dartboard using Vanet simulator. In the experiments, ABDS can achieve on average 86.71% accuracy for predicted driving behavior. Furthermore, Random Forest classifier is a promising one for our framework. In the future, we are planning to further improve the current framework to increase accuracy and integrated with any solutions in traffic simulation system.

Acknowledgments. This work has been supported by Vietnam National University, Hanoi (VNU) under project No. QG.17.39.

References

1. Reyes-Ortiz, J.-L., Oneto, L., Sama, A., Parra, X., Anguita, D.: Transition-aware human activity recognition using smartphones. Neurocomputing **171**, 754–767 (2016)
2. Gomes, J.B.R., Krishnaswamy, S., Gaber, M.M., Sousa, P.A., Menasalvas, E.: MARS: a personalised mobile activity recognition system. In: 2012 IEEE 13th International Conference on Mobile Data Management (MDM), pp. 316–319. IEEE, July 2012. https://doi.org/10.1109/MDM.2012.33

3. Kusuma, A., Liu, R., Montgomery, F.: Gap acceptance behavior in motorway weaving sections. In: Proceedings of the Eastern Asia Society for Transportation Studies, vol. 9 (2013)
4. Li, F., Zhang, H., Che, H., Qiu, X.: Dangerous driving behavior detection using smartphone sensors, pp. 1902–1907 (2016)
5. Xu, H., Zhang, L., Zhai, W.: Detection of human movement behavior rules using three-axis acceleration sensor. In: Jin, D., Lin, S. (eds.) Advances in Multimedia, Software Engineering and Computing Vol. 1. Advances in Intelligent and Soft Computing, vol. 128, pp. 647–652. Springer, Heidelberg (2011). https://doi.org/10.1007/978-3-642-25989-0_103
6. Jain, A., Kanhangad, V.: Exploring orientation and accelerometer sensor data for personal authentication in smartphones using touchscreen gestures. Pattern Recogn. Lett. **68**, 351–360 (2015)
7. Kalra, N., Bansal, D.: Analyzing driver behavior using smartphone sensors: a survey. Int. J. Electron. Electr. Eng. **7**(7), 697–702 (2014)
8. Ferrer, S., Ruiz, T.: Travel behavior characterization using raw accelerometer data collected from smartphones. Procedia - Soc. Behav. Sci. **160**, 140–149 (2014)
9. Bayat, A., Pomplun, M., Tran, D.A.: A study on human activity recognition using accelerometer data from smartphones. Procedia Comput. Sci. **34**, 450–457 (2014)
10. Yu, J., Chen, Z., Zhu, Y., Chen, Y., Kong, L., Li, M.: Fine-grained abnormal driving behaviors detection and identification with smartphones. IEEE Trans. Mob. Comput. **16**(8), 2198–2212 (2017)
11. Vavouranakis, P., Panagiotakis, S., Mastorakis, G., Mavromoustakis, C.X., Batalla, J.M.: Recognizing driving behaviour using smartphones. In: Batalla, J.M., Mastorakis, G., Mavromoustakis, C.X., Pallis, E. (eds.) Beyond the Internet of Things. IT, pp. 269–299. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-50758-3_11
12. Lu, D.-N., Nguyen, T.-T., Ngo, T.-T., Nguyen, T.-H., Nguyen, H.-N.: Mobile online activity recognition system based on smartphone sensors. In: Akagi, M., Nguyen, T.-T., Vu, D.-T., Phung, T.-N., Huynh, V.-N. (eds.) ICTA 2016. AISC, vol. 538, pp. 357–366. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-49073-1_39
13. Eberhart, R., Kennedy, J.: A new optimizer using particle swarm theory. In: 1995 Proceedings of the Sixth International Symposium on Micro Machine and Human Science, MHS 1995, pp. 39–43 (1995)
14. Liu, Z., Wu, M., Zhu, K., Zhang, L.: SenSafe: a smartphone-based traffic safety framework by sensing vehicle and pedestrian behaviors. Mob. Inf. Syst. **2016**, 1–13 (2016)
15. Okeyo, G., Chen, L., Wang, H., Sterritt, R.: Dynamic sensor data segmentation for real-time knowledge-driven activity recognition. Pervasive Mob. Comput. **10**, 155–172 (2014)