A Novel Mobile Online Vehicle Status Awareness Method Using Smartphone Sensors

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Abstract. In this paper, we proposed an efficient method with flexible framework for vehicle status awareness using smartphone sensors, so called Mobile Online Vehicle Status Awareness System (MOVSAS). The system deployed while users to put their smartphones in any position and at any direction. In our proposed framework, principal component analysis (PCA) algorithm is used to selected suitable features from set of combining features on time-base, power-based and frequency-based domain, which extracted from accelerometer sensor data. The classification model using Random Forest (RF), Naïve Bayes (NB), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM) algorithms to deploy for awareness issues of vehicle status. The refining model is proposed using Artificial Neural Network (ANN) algorithm aim to improved accuracy prediction vehicle status results before. Training data sets, which are collected and the dynamic feedback also helping improved accuracy of system. A number of experiments are shown that the high accuracy of MOVSAS with vehicle kinds as bicycle, motorbike and car.

Keywords: Mobile online recognition · Vehicle status · Smartphone sensors analysis

1 Introduction

The vehicle awareness and prediction play an important role in various applications such as energy estimation, safety, healthcare, transportation, social networking, etc. [1]. This problem has the potential to impact our daily lives through extracting useful information from raw sensor data. There were many methods to understand smartphone sensors data, the most common method is using the windowing technique. For example, John J. Guiry et al. [1] used the windowed sensor data samples from phone and chest device to recognize six activities. The time domain and frequency domain are two modes used for sample analysis. The activity is inferred from the data window of one second and the frequency domain is also used to analyze sensor signals every fifteen seconds with accuracy of 98%. In the fact that, its high accuracy is resulted by the fixed position of

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the subjects' phones that is in their trouser pocket. Consequently, the recorded sensor signal is more stable.

With proposed recognition system at run-time, Jiahui Wen et al. [2] suggested a method which combines a basis classifier with graphical model. They used the five-second sliding window with 50% overlap to segment the streaming data. However, they did not describe details of the features *data instances*. The assessments were employed with several existed data sets such as smartphone dataset [3], sensor activity dataset [3], UCI HAR dataset, Opportunity dataset. This paper also suggested an extra assessment model for run-time system.

In the paper of sensor-based classification, Sang et al. [4] proposed a method to recognize daily activity of a user. The data was collected from smartphones placed in users' pocket. They extracted the features from the sensor signals: auto regressive coefficient, fractal dimension, mean and standard deviation. However, they did not explain the compatible features and their results obtained from this feature set were not compared to the others. In another study, Zahid Halim et al. [5] have developed artificial intelligence techniques for driving safety and vehicle crash prediction. This data analysis included the weather conditions; the data was gathered in ten years from the vehicle sensors such as accelerometer, camera in different driving behaviors before accidents. In their study, intelligence techniques were commonly used for accident prediction problems. The classification accuracy using decision tree (DT) and ANN in this study is 95% and they are good algorithms for time series data and driving behaviors recognition.

The challenges on recognition using smartphone sensors are the noises in data, mising data, variety of signal quality from different sensors, and the change in smartphone position. Therefore, we propose a method to automatically select a set of features from each window of acceleration data when smartphone users are moving. The possible features are based on time domain and frequency domain. The principal component analysis is applied to the online choice of suitable features. Then, the system uses one of classifier algorithms such as random forest, support vector machine, k-nearest neighbor and Naïve Bayes. In our framework, the refining model with ANN algorithm is used to improve the accuracy of vehicle status prediction. The feedback module will receive label then push this status information to data training set. In this paper, the different statuses including stop, moving, acceleration, deceleration on bicycle, motorbike and car are distinguished and the obtained results is outperformed.

2 The Mobile Online Vehicle Status Awareness System (MOVSAS)

The Mobile Online Vehicle Status Awareness System (MOVSAS) consists of three modules. The data collector module is responsible for collecting labeled smartphone sensor data of each predefined vehicle status. The signal data is then preprocessed, and a set of representative features is extracted. The Principal component analysis (PCA) is used to select the features for training model [6]. In the online training module, a classifier detects the vehicle status of smartphone users and then the model is refined to improve the accuracy from the prior detection results. It uses the recent status S_t corresponding to the window w_t and combines with *k-1* linear statuses. The set of k features as $\left[S_{t-k-1}, \ldots, S_{t-1}, S_t\right]$ aims to correctly detect the status from training data, which is a set of instances including k statuses were collected. Based on the trained knowledge, the real time vehicle status of users is detected by the Monitoring module. The MOVSAS framework is shown in Fig. 1.

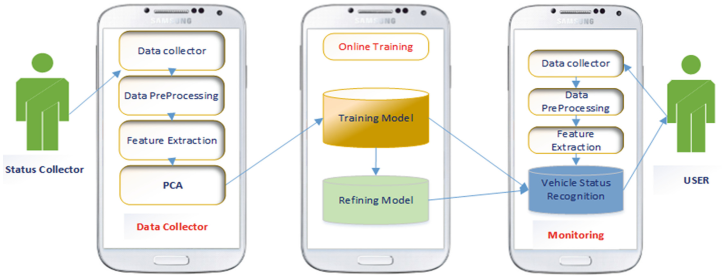

Fig. 1. The mobile online vehicle status awareness system framework

2.1 Data Preprocessing

The user information gained from smartphone sensors, especially accelerometer is very useful to recognize the vehicle status. However, while moving, the users might put their smartphones on their pocket, handbag, or in their hands, etc. As a result, the orientation of smartphones will be frequently changed. The approach to solve this issue is to transform accelerometer data from the smartphone coordinate system to the Earth coordinate system by relying on the additional data collected from magnetometer and gyroscope sensors as Fig. 2 that aims to reduce noise. For the details of this transformation, we refer readers to the work of Premerlani and Bizard [7]. Then the data is prepared for classification by a feature set based on time- and frequency domains. The PCA will be applied to select suitable features for classification.

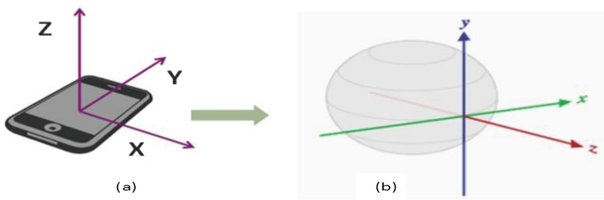

Fig. 2. The smartphone coordinate (b) the Earth coordinates

2.2 Using PCA for Feature Selection

The amount of raw data collected from smartphone sensors is various. Thus, directly analyzing such data would require a lot of either time or memory space. A popular approach to deal with this issue is to extract certain important features from such data and to select suitable features that would lead to an increase in the prediction accuracy.

In time domain, we have computed the features of accelerometer such as:

The root mean square (RMS) [8] of a signal x_i that represents a sequence of n discrete values $\{x_1, x_2, \ldots, xn\}$.

The sample correlation coefficient of axis x and y is computed by the equation below

$$\rho(x, y) = \frac{\mathrm{cov}(x, y)}{\sigma_x \sigma_y} \tag{1}$$

The cross-correlation is a measure to compare similarity between two waveforms and computed by the following equation:

$$CrossCorrelation(x, y) = \max_{d=1}^{n-1}\left(\frac{1}{n}\sum_{i=1}^{n} x_i y_{i-d}\right) \tag{2}$$

The SMA feature [9] is also calculated to distinguish between a resting state and vehicle status in a classification.

The vertical and horizontal accelerometer energy features of each time window are computed by the following equation.

$$E_v = \int_{t=t_0}^{T+t_o} |a_v| dt, \quad and \quad E_h = \int_{t=t_0}^{T+t_o} |a_h| dt \tag{3}$$

where a_v, a_h are respectively vertical and horizontal acceleration values, and T is the interval of integration with $a_v(t) = a_z(t), a_h(t) = \sqrt{a_x^2(t) + a_y^2(t)}$.

Thus, in time-domain, we have extracted thirteen features as CorreCoxy, CorreCoxz, CorreCoyz, Crossxy, Crossxz, Crossyz and Xrms, SMA, Ev, Eh and Mean [10], Variance [11], Standard deviation [12] in each data samples window.

For the frequency domain features, we compute Short Time Fourier Transform on the nth window including N samples $[x_n, x_{n+1}, \ldots, x_{n+N-1}]$ as following:

$$X(n, k) = \sum_{m=0}^{N-1} x[n + m].w[m].\exp\left(-j(2\pi/N).k.m\right) \tag{4}$$

with k = 0, 1,…, N-1 and $w[m]$ as window function.

The Energy of M coefficient Fourier is computed by the below formula:

$$E_M = \sum_{m=1}^{M} |X(m)|^2 = \sum_{m=1}^{M} X(m).X^*(m) \quad (5)$$

Because that, Z axis data capability different in vehicle status so that average Energy of Z axis (E_Z) also computed as:

$$\bar{E} = \frac{2\sum_{m=2}^{N/2} |X(m)|^2}{N} \quad (6)$$

Finally, the Entropy is computed with below formula:

$$H = -\sum_{m=1}^{N} p_m \log_2 \left(p_m\right) \; with \, p_m = \frac{|X(m)|}{\sum_{m=1}^{N} |X(m)|} \quad (7)$$

Thus, we have three features in frequency domain from Eqs. (5, 6 and 7) as E_M, E_Z and H and sixteen features for our system.

An interesting approach that uses PCA for building up a set of features for activity, behavior, vehicle status recognition problems using smartphone sensor [6] has applied to choose suitable features for classification with higher accuracy.

2.3 Online Training Model

Classification is an important step in data mining problem, especially in recognition problem with smartphone sensors class. The most commonly used classifiers are decision tree, KNN, SVM and NB algorithms [13]. In practice, a classifier firstly needs to be trained by using labeled vehicle status database (called training data). There are two training approaches such as the online training method which is performed on smartphones. On the other hand, the offline training is deployed in advance, usually on a local machine. Most of studies use the offline training method because of the computational cost reduction on smartphones. Nonetheless, the modern smartphones have much better computational capacity. This advances of smartphones allows us to implement the online training in our MOVSAS in Fig. 1.

In problems of the activity or behaviors or vehicle status recognition using smartphone sensor or wearable sensor data collected from any position, the prediction accuracy is usually of from 70% to 90% [7, 14]. Hence, our paper proposes a refining model using ANN algorithm on smartphone to improve the status prediction results. The training data for this collected by set of tubes includes k statuses. The tube is assigned a label by user and could be updated by the monitoring module. The value k also affects to the processing time of system. By experiment on stop, moving, acceleration, deceleration statuses, we chose the value k of 4. The method and processes of the refining model is shown in Fig. 3.

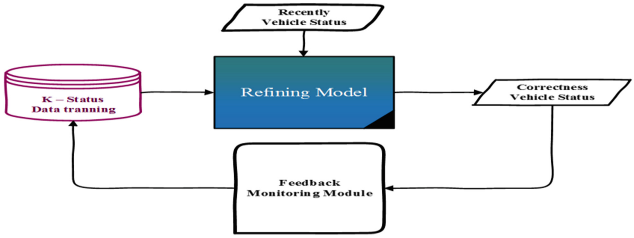

Fig. 3. The refining model for awareness vehicle status

In the traditional vehicles status recognition framework, the training data set is usually fixed and prepared in advance. Since each user might have different, characteristics and habits, for example one might drive faster than others. As a consequence that, the prediction accuracy might fall down when the system is used for another users. Gomes et al. [15] proposed an idea to incrementally update the training data set by using real-time feedbacks from users. We implement this approach in MOVSAS as following: the system provides the corresponding vehicle status prediction in each data window. Then, the user need to confirm the correctness of the result. If the prediction is correct, the data window label based on the correct prediction results is assigned to the training dataset. Continuously, it also assigns label to the tube including k status for data training of refining model. The challenge here is efficient processing with additional information.

3 Experiment and Results

3.1 Experiment Environment

We deploy MOVSAS on the Android from 4.0 to 5.0 platform. The labels of vehicles status database were collected by 30 subjects when they were driving a bicycle, motorbike and by 20 subjects on car. They freely carried 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. The set of vehicle status for recognition is {stop, moving, acceleration, deceleration}.

3.2 Data Collection

In our experiment, signal data collected from three types of sensors as acceleration sensor, gyroscope sensor and magnetic sensor. Each sensor returns three values corresponding to x, y, and z coordinates. The raw data stream is first cut out one seconds at the beginning, and 3 s at the end as these periods time are usually redundant. Then, the data is segmented into a number of windows of 6 s; the overlapping time is one second. We collected 3500 samples for each status from subjects about in two months. The training data set for refining classifier is collected by each subject and it contains characteristic vehicle status.

3.3 The Accuracy of Vehicle Status Awareness

The Weka tool integrated in framework for prediction. In each case, the default setting is used. We also used 10-fold cross validation technical for classification. In the first scenario (S_1), MOVSAS predicts vehicle status with traditional method which do not use user feedbacks, PCA and refining model. In the second scenario (S2), MOVSAS predicts vehicle status utilize PCA, refining model and user feedbacks to enhance the prediction accuracy. The obtained results are expressed in Table 1.

Table 1. The prediction accuracy(%) of MOVSAS with scenario S_1 and S_2

	Random forest		KNN		Naïve Bayes		SVM	
	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
Stop	83.00	94.10	76.00	81.00	78.00	83.00	71.25	75.65
Moving	78.65	90.85	69.19	76.00	63.15	65.15	52.00	69.52
Deceleration	74.19	86.15	63.00	74.35	60.00	71.16	57.80	61.78
Acceleration	78.66	87.75	69.16	73.86	63.00	73.45	66.25	69.75
Average	78.63	***89.71***	67.59	***76.30***	66.04	***73.19***	61.83	***69.18***

As shown in Table 1, the prediction accuarcy is clearly improved when PCA, refining model and user feedbacks are applied in most of cases. Especially for the case of predicting moving status by SVM, the accuracy is increased by 17.52%. These improvements highlight the effectiveness of the PCA and refining model strategy used by MOVSAS. The RF algorithm is the most suitable for our MOVSAS framework since it always offers higher accuracy compared with the other classifiers, i.e. KNN, Naïve Bayes, and SVM. The accuracy of scenario S_2 can be up to 94.10% when Random Forest classifier is used. The accuracy for detecting deceleration status is lower than that of others. The reason is due to misinterpreting some similar patterns such as slowly moving, slowing acceleration and deceleration. We note that our MOVSAS framework allows detecting the current vehicle status in the condition that their smartphones may put at any position and in any direction.

3.4 The Processing Time

In scenarios, they usually require additional time for processing such information. We counted and compared the time for prediction on S_1, S_2. The experiment result shows the average time to detect each type of vehicle status by MOVSAS. The Random Forest spends the least time for detecting vehicle status as comparing to KNN, Naïve Bayes, and SVM. The average processing time is of 2.75 s for detecting the status using RF and maximum of 3.75 s using SVM.

4 The Conclusion and Future Work

In this paper, we proposed a flexible framework, called MOVSAS, for detecting current vehicle status when the smartphones are randomly placed in any position and at any direction. Morever, our proposed framework uses PCA to select suitable features and refining model. Following, the real-time feedbacks from users are used to increase the prediction accuracy. In the experiments, MOVSAS can achieve on average 89.71% accuracy for detecting four predefined vehicles status, i.e. Stop, Moving, Acceleration, and Deceleration on bicycle, motorbike and car. Furthermore, RF classifier is a promising one for our framework. In the future, we are planning further improving the current framework to either increase prediction accuracy or reduce the processing time.

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