Accelerometer based transportation mode recognition on mobile phones

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***Abstract*—Recognizing the transportation modes of people's daily living is an important research issue in the pervasive computing. Prior research in this field mainly uses Global Positioning System (GPS), Global System for Mobile Communications (GSM) or their combination with accelerometer to recognize transportation modes, such as walking, driving, etc. In this paper, we will introduce transportation mode recognition on mobile phones only using embedded accelerometer. In order to deal with uncertainty of position and orientation of mobile phone, acceleration synthesization based method and acceleration decomposition based method are introduced. Performance comparison indicates that acceleration synthesization based method outperforms acceleration decomposition based method. We will discuss the factors affect the recognition accuracy of acceleration decomposition based method and present potential improvements.**

Keywords-transportation mode recognition; accelerometer; acceleration synthesization; acceleration decomposition

I. INTRODUCTION

With the advance in functionality and capability, mobile phone acts as not only a communication tool, but also a service platform to bridge the applications and the end user. It is being integrated with kinds of physical and virtual sensors to capture the user's real-time situational information, such as location, activity, etc. In this paper, we focus our attention on the mobile phone based transportation mode recognition.

Transportation mode recognition can reflect one's life pattern, help us to understand the user's behavior and facilitate context-aware service providing. There has been some research work concerning mobile phone based transportation mode recognition using Global Positioning System (GPS), Global System for Mobile Communications (GSM) or their combination with accelerometer. Zheng et al. [1] propose a supervised learning based approach to automatically infer transportation mode from raw GPS data. In [2], Mun et al. propose a GSM and WiFi based method to infer people's mobility states. Troped et al. [3] combine the GPS and accelerometer to predict five activity modes, including walking, jogging/running, bicycling, inline skating and driving an automobile. In [4], GPS and GSM are combined with map matching to recognize the transportation modes in a coarse-grained way.

However, for GPS based recognition, poor reception of GPS information and heavy energy consumption bring trouble to real implementation; for GSM based recognition, it needs long time to observe the change of cell information and the recognition accuracy is often low. Comparatively, accelerometer based recognition is more acceptable because: 1) the accelerometer consumes much less energy than GPS [5]; 2) the accelerometer needs a little starting time; 3) the accelerometer can obtain sensor data all the time; 4) this method does not depend on any external equipments and will not affected by different deployment of cell towers.

As to the accelerometer based transportation mode recognition on mobile phones, one problem should be solved beforehand is that, in real applications, it is hard to determine the position and orientation of mobile phone because the user can place his mobile phone at any places he would like to, such as in his hand, in the trouser pocket, in the bag, etc. In [6], Reddy et al. propose to recognize transportation modes using the combination of GPS and accelerometer. At there, the acceleration features are extracted from the series of acceleration magnitude, which is the value of acceleration synthesization of three axes. In [7], Mizell shows the accelerometer signal averages over a reasonable time period can produce a good estimate of the gravity related component. Then, the gravity vector estimate in turn enables estimation of the vertical component and the magnitude of the horizontal component of dynamic acceleration caused by user. In [8], Yang uses above two methods to recognize user's physical activities and demonstrates that acceleration decomposition based method performs a little better than acceleration synthesization based method.

In this paper, these two methods are used to recognize user's transportation modes in daily life. Their performances will be compared and the factors affect the recognition accuracy of acceleration decomposition based method will be discussed.

II. FEATURE EXTRACTION

A. Acceleration Synthesization

Accelerometer detects and transforms changes in capacitance into an analog output voltage, which is proportional to acceleration. Linear model can be used to calibrate the accelerometer and map output voltages into acceleration along three axes, a_x, a_y, a_z. As a_x, a_y, a_z are the orthogonal decompositions of real acceleration, the magnitude of synthesized acceleration can be expressed as $a = \sqrt{a_x^2 + a_y^2 + a_z^2}$.

B. Acceleration Decomposition

For a chosen sampling interval, the gravity component on each axis can be estimated by averaging all the acceleration measurements in the interval on that axis [7].

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Then, the vertical acceleration vector V corresponding to gravity is estimated as $V = (V_x, V_y, V_z)$, where V_x, V_y and V_z are averages of all the acceleration measurements on those respective axes for the sampling interval.

At a given point in the sampling interval, the dynamic component of the acceleration measurements is $d = (a_x - V_x, a_y - V_y, a_z - V_z)$, which is caused by the user's motion rather than gravity. Then, the projection P of d upon the vertical axis is $P = \left(\frac{d \bullet V}{V \bullet V}\right)V$. As a 3D vector is the sum of its vertical and horizontal components, we can compute the horizontal component of dynamic acceleration by vector subtraction, as $h = d - P$. Then, magnitude of the vertical component and magnitude of the horizontal component of dynamic acceleration at each point can be computed.

C. *Acceleration Feature Extraction*

The length of sliding window is set as 8 seconds without overlap between consecutive windows. In each sliding window, first 256 sample points are used to calculate acceleration features. This size enables fast computation of FFTs for calculating some features.

For acceleration synthesization based method, following 11 features are extracted from magnitude series of synthesized acceleration: mean, standard deviation, mean crossing rate, third quartile, sum and standard deviation of frequency components between 0~2 HZ, ratio of frequency components between 0~2 HZ to all frequency components, sum and standard deviation of frequency components between 2~4 HZ, ratio of frequency components between 2~4 HZ to all frequency components, and spectrum peak position.

For acceleration decomposition based method, above 11 features are extracted from magnitude series of vertical component and magnitude series of horizontal component, respectively. In addition, the correlation coefficient between these two series is also included, totally 23 features.

III. EXPERIMENTS AND ANALYSIS

A. *Data Collection*

The Nokia N82 mobile phone is used as the experimental platform. It is embedded with a tri-axial accelerometer, whose sensitivity is programmed from $-2g$ to $+2g$, where g is the gravitational acceleration and is set as $g = 9.8$. The sampling rate of accelerometer is set to approximately 35 HZ by calling Nokia Python S60 sensor module over Symbian platform.

Six transportation modes are included in our experiments. They are stationary, walking, riding bicycle, taking bus, driving car and taking subway. Stationary means the volunteer has no obvious movement during data collection. Each of these six transportation modes is performed by seven volunteers. During data collection, the volunteer can place the mobile phone at any place he would like to, such as in the hand, in the trouser pocket, in the bag, etc.

For the collected sensor data, no noise filtering is carried out. Totally, the amount of data collected across seven volunteers is more than 12 hours. With the collected sensor data, totally 5544 samples of six transportation modes are obtained. There are 821 samples for riding bicycle, 1067 for taking bus, 878 for driving car, 976 for stationary, 799 for taking subway and 1003 for walking.

B. *Performance Comparison*

Decision Tree (DT) J48, k Nearest Neighbor (kNN) and Support Vector Machine (SVM) provided by WEKA toolkit [9] are used to compare the performance of these two methods. 10-fold cross-validation is used for testing. Before classification, all features are normalized. For each classifier, all default parameters predefined by WEKA toolkit are used and k is set as 5 for kNN classifier.

Experimental results for different feature sets are listed in Table I, where 'vertical features' are the features extracted from magnitude series of vertical component, 'horizontal features' are extracted from magnitude series of horizontal component. 'Decomposition features' include all features extracted from magnitude series of vertical component and horizontal component. 'Selected decomposition features' refer to the features after feature selection using WEKA toolkit. 'Synthesization features' are extracted from magnitude series of synthesized acceleration, and 'selected synthesization features' refer to the features after selection.

From Table I we can see that 1) 'vertical features' and 'horizontal features' have similar capability to recognize these six transportation modes; 2) in general, acceleration synthesization based method obtains higher recognition accuracy than acceleration decomposition based method; 3) DT obtains the highest recognition accuracy for 'selected synthesization features'.

Table II and Table III show the confusion matrix of DT classifier for 'selected decomposition features' and 'selected synthesization features', respectively. These classification results indicate that, for all transportation modes, acceleration synthesization based recognition is more accurate than acceleration decomposition based recognition, especially for taking bus, driving car and taking subway. For example, of 1067 samples of taking bus, acceleration synthesization based method recognizes 622, but acceleration decomposition based method only recognizes 438.

TABLE I. RECOGNITION RESULTS FOR DIFFERENT FEATURE SETS

Feature set	DT	kNN	SVM
Vertical features	56.87 %	55.66 %	52.09 %
Horizontal features	56.17 %	57.11 %	49.71 %
Decomposition features	60.71 %	60.57 %	58.96 %
Selected decom. features	60.43 %	60.03 %	57.12 %
Synthesization features	61.42 %	69.88 %	61.42 %
Selected synth. features	70.73 %	69.93 %	58.33 %

From the rationale of acceleration decomposition introduced in subsection 2.2, we can see that acceleration decomposition based method is based on the assumption that accelerometer signal averages over a reasonable time period can produce a good estimate of the gravity. If the gravity estimation is not accurate enough, the recognition accuracy will be decreased. Figure 1 presents the gravity estimation of all samples for six transportation modes. It shows that although most gravity estimations are located near 9.8, gravity estimation error of many samples is a little large, especially for walking.

TABLE II. CONFUSION MATRIX OF DT FOR 'SELECTED DECOMPOSITION FEATURES'

Labeled	**Recognized results**					
	Biking	***Busing***	***Driving***	***Stationary***	***Subway***	***Walking***
Biking	594	121	22	14	22	48
Busing	134	438	204	112	147	32
Driving	29	190	481	64	109	5
Stationary	24	107	63	623	154	5
Subway	17	167	123	163	304	25
Walking	43	26	4	8	12	910

TABLE III. CONFUSION MATRIX OF DT FOR 'SELECTED SYNTHESIZATION FEATURES'

Labeled	**Recognized results**					
	Biking	***Busing***	***Driving***	***Stationary***	***Subway***	***Walking***
Biking	664	65	22	9	24	37
Busing	70	622	119	85	147	24
Driving	16	115	631	56	59	1
Stationary	14	107	69	657	121	8
Subway	32	136	57	138	417	19
Walking	33	16	7	6	11	930

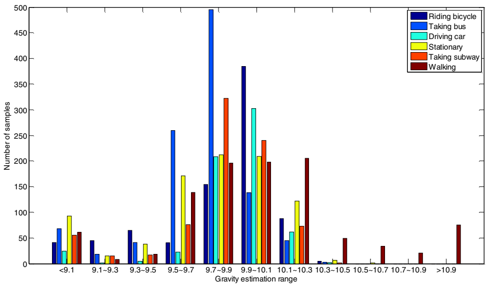

Figure 1. Gravity estimation of all samples for six transportation modes

The reasons for gravity estimation error may lie in 1) the length of sliding window is not long enough; 2) the sample rate is not high enough. Normally, the more intensive one activity or transportation mode is, the longer the window length and the higher the sample rate should be; 3) position or orientation change of mobile phone (not caused by user's activities or moving); 4) errors from accelerometer calibration. That is, the sensitivity and offset parameters for axes are not accurate; 5) real acceleration exceeds the measurement range of the accelerometer.

From the raw sensor data, we find that the signal characters of taking bus, driving car, stationary and taking subway are relatively stable and similar with each other, but the signal characters of riding bicycle and walking are distinct. Experimental results in Table II and Figure 1 demonstrate that the degradation caused by gravity estimation error is comparatively obvious for transportation modes whose signal characters are stable and similar with each other. One potential solution to distinguish these modes is to detect the difference of vibration characters of different vehicles, which needs high sample rate and more computation cost.

IV. CONCLUSION

Accelerometer based transportation mode recognition on mobile phones is introduced in this paper. In order to deal with uncertainty of position and orientation of mobile phone, acceleration synthesization based method and acceleration decomposition based method are compared and experimental results demonstrate that 1) the acceleration synthesization based method outperforms the acceleration decomposition based method for recognizing six typical transportation modes; 2) gravity estimation error degrades the performance of acceleration decomposition based method. Possible improvements to reduce the gravity estimation error include choosing appropriate window length, presetting high sample rate, preprogramming large measurement range, calibrating accelerometer accurately, etc.; 3) gravity estimation error will decrease the recognition accuracy especially for transportation modes whose signal characters are stable and similar with each other, such as taking bus, driving car, stationary and taking subway. In our future work, we will continue our research to reduce gravity estimation error and employ vibration characters of different vehicles to recognize transportation modes with similar signal characters.

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