A classification of accelerometer data to differentiate pedestrian state

Pichaya Prasertsung
School of Information, Computer, and Communication Technology, SIIT, Thammasat University
Pathumthani, Thailand
m5822040043@studentmail.siit.tu.ac.th

Teerayut Horanont
School of Information, Computer, and Communication Technology, SIIT, Thammasat University
Pathumthani, Thailand
teerayut@siit.tu.ac.th

Abstract — **This research is motivated through the demand to create routing in indoor environment based on activity recognition approach. A model to discriminate between walking, climbing up stair, and climbing down stair is introduced. Data was collected from a group of participants performing walking up stairs, walking down stairs, and walking on normal path inside the building. 35 features are considered in order to build a model. The classification is carried out using support vector machine (SVM) using leave one person out cross validation method. From this study, a combination of features extracted from raw accelerometer data and filtered data can be used to improve a classification result. Based on this dataset, a combination of features extracted from body acceleration data and raw accelerometer data itself, provides accuracy up to 85.73% outperform other combination data.**

Keywords — activity recognition; accelerometer data; signal processing; SVM;

I. INTRODUCTION

Smartphone has gained a lot of interest to be used as activity monitoring due to its potential for activity recognition [1]. Sensors in smartphone (i.e. accelerometer, gyroscope, magnetometer, and barometer) provide sufficient data to enable physical activity recognition [2]. Various researchers successfully identify activities by classifying data gathered from smartphone sensors [2]. Accelerometer and gyroscope are preferable sensors for physical activity monitoring such as walking, running, sleeping and etc. In addition, these 2 kinds of sensor are also used to support pedestrian navigation where GPS are unavailable [3].

This research introduces activity recognition model in order to generate indoor routing based on activity recognition approach. A model for separating pedestrian state, which are walking up stair, walking down stair, and walking on flat path, is introduced. A classification result can be used to generate routing map in indoor environment. The result can be fused with indoor map to provide an alternative walking path in indoor environment. For example, provide a routing path avoiding walking up stair to elderly pedestrian. The rest of this paper is organized as following. The next section provides information about previous researches on activity recognition. Section 3 describes about methodology used to classify each activities including data collection, pre-processing data, features collection, and features evaluation. Result and evaluation are described in section 4. Conclusion and discussion about future work can be found in the last section.

II. RELATED WORK

Human Activity Recognition has been studied for many years. This filed can be applied with many applications in order to solve human-centric problems such as daily life monitoring for healthcare [4] , personal biometric signature, and navigation [2]. For past 10 years, many researchers successfully extract simple activities such as walking, running, from wearable sensors data. Activities can be recognized with fairly high accuracy using a single tri-axial accelerometer [4]. Multiple features are purposed ranged from common statistical features to frequency domain features such as energy of entropy [5].

Applying appropriate data preparation technique before classification increases the accuracy of activity recognition [6]. Various kinds of filter can be applying to raw accelerometer data in order to reduce sudden change or isolate the noise. In [6] states that after applying low pass filter and high pass filter to raw accelerometer data can achieving overall F-measure above 93%. In [7] researchers also used similar technique by applying low pass filter to raw accelerometer data and isolate body acceleration by subtracting low pass filtered data from raw accelerometer data. Then the body acceleration is used for features construction. Features can be chosen from different criteria. As stated in [8], for separating between walking and climbing stair, the correlation between axes can be used because more than one dimension is involved in climbing stair while only one dimension is involved in walking.

From the study in [7], six activities, which are dancing, walking up stair, walking down stair, fast walking, slow walking, and running are extracted from accelerometer data. Smartphone is used as a tool to collect data. Various classification resources are combined in order to improved classification accuracy. By combining MP, LogitBoost, and SVM, this combined model provides the best accuracy at 91.15%.

Previous researchers also purposed a method to increase performance of activity recognition by combining data from numerous sensors. In [9], a combination of accelerometer data

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and gyroscope data can improves the overall true positive rate. In [10], activity recognition performance can be increased upward to 82.00% using a combination of accelerometer and gyroscope data fused by Kalman filter. The result is better than a classification of raw data itself and a combination of accelerometer and gyroscope data fused by complementary filter. However, computational cost for extracting features from accelerometer data and gyroscope data fused by Kalman filter is greater than computational cost of extracting features from data collected from one sensor with no combination.

In this paper, an alternative way to increase activity recognition performance by using only accelerometer data is purposed. A method to increase activity recognition accuracy by combining filtered data extracted from raw accelerometer data is reported. Methodology and result can be found in the next section.

III. METHODOLOGY

There are 4 common tasks in sensor based activity recognition, which are data collection, pre processing, data segmentation, feature selection, and classification as illustrate in figure 1. Detail of each task can be found in sub section respectively.

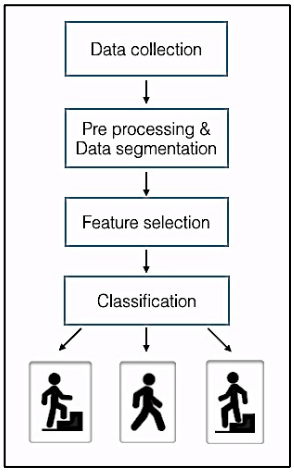

Fig. 1. Activity recognition process

A. Data collection

Accelerometer data is gathered from 5 participants, age range from 23 – 33 and have no medical record on gait behaviors. All participants perform walking up stair, walking down stair, and walking along the path in the building. The first 4 participants perform walking in the same route in the same building while the remaining participant was asked to perform the same activities in a different building. In each activity, participants perform walking with 3 different speeds for 3 times. The walking speed includes slow, normal, and fast. All participants are required to save data immediately after finish performing the activity. Then, participants repeatedly continue perform other activities until finish all tasks. Data is saved in the different files to avoid mislabeling. The remaining participant is required to do additional task, which is walking upstairs walking downstairs, and walking along normal path while smartphone is placed in his pocket. Data is collected via application in an android smartphone, LENOVO Vibe X3. Smartphone is mounted on waist on each participant as illustrated in figure 2.

Fig. 2. Smartphone is placed in the bag mounted on a participant waist.

Raw accelerometer data is obtained from a tri-axial accelerometer at rate of 100 Hz. Since accelerometer is sensitivity to orientation. Obtained data is wildly vary for the same activity when smartphone is placed at different position as shown in Figure 3, which shown a graph of raw accelerometer data for walking along flat path activities while smartphone is mount on a participant waist and in pocket. In this research, we consider only data obtained while position of smartphone is in a bag.

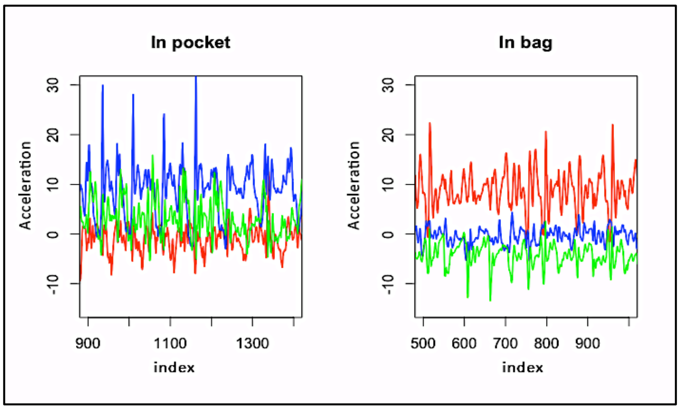

Fig. 3. Raw accelerometer data while smartphone is placed in bag mounted to waist and in pocket.

B. Pre processing

Raw accelerometer data obtained from smartphone contain both motion acceleration and gravity component as shown in figure 4. Therefore, gravity elimination is needed in order to identify information corresponding to actual motion and to obtain a reference axis that can be used to represent data in an orientation independent way.

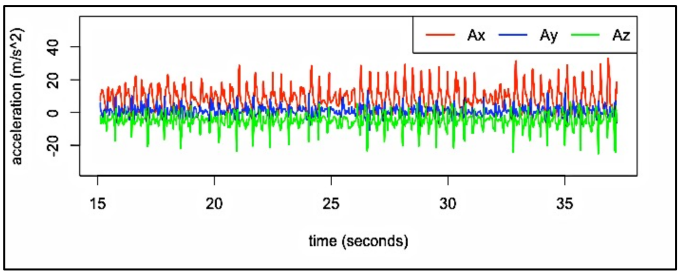

Fig. 4. A comparison of raw accelerometer data and body acceleration.

Refer to [11], the optimal cutoff frequency for excluding gravity component is range from 0.1 – 0.5 Hz. Hence, the 2nd order butterworth low pass filter with cutoff frequency at 0.5 Hertz is passed through raw accelerometer data. Gravity component is removed by subtracting the filtered data from raw accelerometer data as in equation (1).

$$A_{BA} = A - A_L \tag{1}$$

Where A_{BA} is body Acceleration, A is raw accelerometer data, and A_L is filtered data. A comparison of raw accelerometer data and body acceleration are shown in figure 5

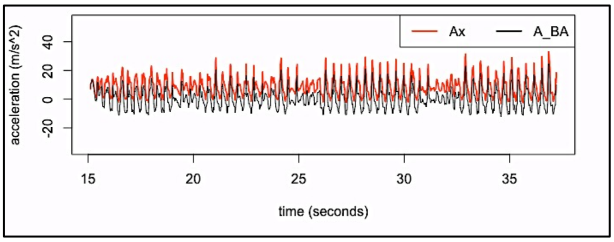

Fig. 5. A comparison of raw accelerometer data and body acceleration.

Before feature construction, data is segmented using sliding window overlapping technique with a window size of 128 samples corresponding to 1.28 seconds with 50% overlapping (64 samples or 0.64 seconds). Features are extracted from each portion as explained in the following section.

C. Features selection and features evaluation

Given A_{xyz} refer to total accelerometer data. A_x, A_y, and A_z refer to acceleration along x-axis, y-axis, and z-axis respectively. Based on previous studies in [5], [7], and [12], purposed features are listed as following.

TABLE I. PURPOSED FEATURES

Features name	***Definition***	***Abbreviation***
Mean	Average value in each window	mean
Variance	The average of the squared differences from the Mean.	var
Correlation	A correlation between different axis (x-y, x-z, y-z)	cor
Standard deviation	A measure of the spread of values within each window	sd
Max	The maximum value in each window	max
Min	The minimum value in each window	min
Range	Difference between maximum value and minimum value in each window	range
RMS	Root mean square	rms
Number of peak occurrence	Average number of occurrence of peak in each window	peak
Elapse time between consecutive local peak	The different of time between consecutive local peak in each window	elapseT
Average Energy	The sum of the square discrete FFT component magnitudes of the signal in window.	energy

Noted that each features is applied to all axis (x-axis, y-axis, and z-axis) and total acceleration of accelerometer data. Total acceleration is computed from equation (2).

$$A_{xyz} = \sqrt{x^2 + y^2 + z^2} \tag{2}$$

Recursive Feature Elimination approach is used for selecting the most relevant features. A recursive feature selection with Cross Validated (10 fold) is applied to the dataset. A Random Forest algorithm is used on each iteration in order to evaluate the model. After applying this approach, 35 relevant features are selected as displayed in table II. Noted that X, Y, Z, and XYZ indicated axis that the data is applied to, which corresponded to x axis, y axis, and z axis respectively.

TABLE II. RELEVANT FEATURES

Features name	***Abbreviation***
Correlation	corXZ, corXY, corYZ
Max	maxX, maxY, maxZ, maxXYZ
Elapse time between consecutive local peak	elapseTY, elapseTX, elapseTZ
Range	rangeX, rangeY, rangeZ
Min	minZ, minx, minY, minXYZ
Variance	varXYZ, varZ, varX
Standard deviation	sdXYZ, sdZ, sdX
Mean	meanZ, meanY, meanXYZ, meanX
RMS	rmsZ, rmsX, rmsY, rmsXYZ
Peak	peakZ, peakY, peakX
Average Energy	energyXYZ

By applying only 10 features, accuracy above 90% can be archived as illustrate in figure 6. However, applying 35 features provide the best accuracy for separating each activity at 96.26% with kappa 94.01%. Hence, these 35 features will be extracted from A, A_{BA} and A_L in order to construct a model.

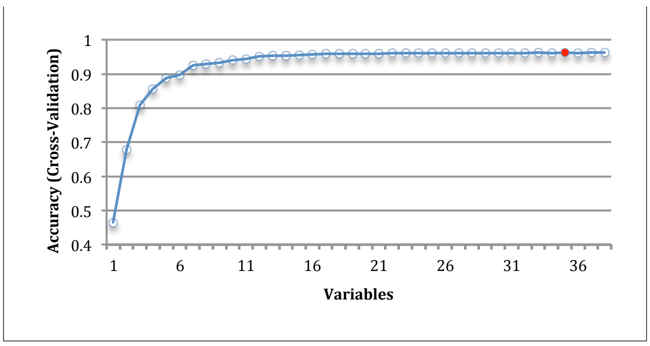

Fig. 6. Features comparison

IV. Classification

Obtained data was labeled as 3 types for supervised learning classification problem, which are

- **up** - walking up stair
- **down** - walking down stair
- **flat** - walking on flat path

Data from 4 participants is used for training dataset while the remaining is used as testing dataset. SVM is used to evaluate performance of the model. Table III and IV shows confusion matrix when applying training data and testing data to the model respectively.

TABLE III. CONFUSION MATRIX WHEN APPLYING TRAINING DATA

Prediction \ *Reference*	*down*	*flat*	*up*
down	**1610**	9	51
flat	96	**3705**	61
up	113	41	**1834**

TABLE IV. CONFUSION MATRIX WHEN APPLYING TESTING DATA

Prediction \ *Reference*	*down*	*flat*	*up*
down	**167**	45	120
flat	0	**869**	3
up	34	256	**69**

From result in table III and IV, obtained accuracy from training data is 95.07% while the accuracy after applying testing data is dropped to 70.70%. Figure 7 shows F-measures of each activity for training data and testing data. F-measure is a measure that combines precision and recall as in equation (3)

$$F - measure = 2 \times \frac{(precision \times recall)}{(precision + recall)} \quad (3)$$

Hence, high precision and recall indicate good performance for each activity.

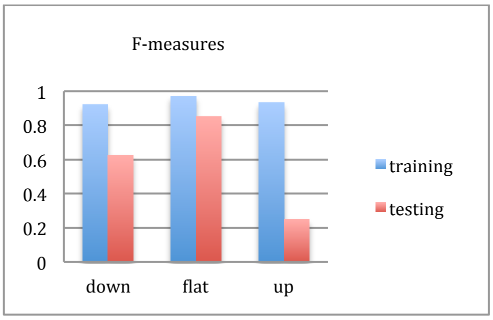

Fig. 7. Accuracy comparison when applying training data and testing data to a model

In order to increase recognition performance, we further investigate the signal by combining features extracted from A, A_{BA}, and A_L which are $A + A_L$, $A + A_{BA}$, and $A + A_{BA} + A_L$. The accuracy are shown in table V.

TABLE V. CLASSIFICATION ACCURACY WHEN APPLYING TRAINING DATA AND TESTING DATA TO EACH MODEL

Signal	*Accuracy for training data*	*Accuracy for testing data*
A	97.04%	78.12%
A_L	98.90%	14.17%
A_{BA}	95.07%	70.70%.
$A + A_{BA}$	95.86%	**85.73%**
$A + A_L$	97.81%	62.08%
$A_{BA} + A_L$	**99.81%**	60.63 %
$A+ A_{BA} + A_L$	96.86%	66.85%

Based on this dataset, using SVM classification, a combination between A and A_{BA} of testing data provides the best accuracy among others at 85.73%. F-measures comparison between each combination of signal are shown in figure 8.

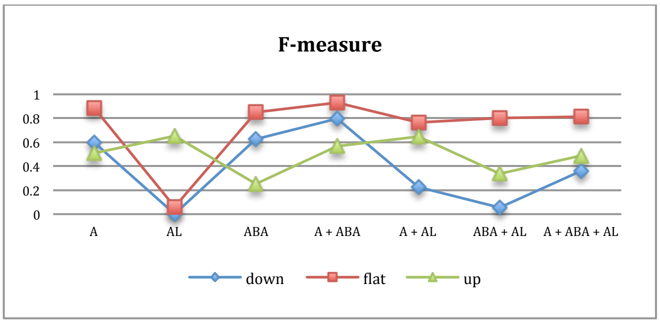

Fig. 8. F-measure comparison on combination of each signal

V. Conclusion

This study presents a model to differentiate pedestrian state focusing on walking up stair, walking down stair, and walking along normal path. A classification result from features extracted from body acceleration provides high accuracy up to 95.07% for training data but the accuracy is drop to 70.70% when applying testing data. In order to increase classification result performance, a combination of features extracted from raw accelerometer data and body acceleration can be used. A combination of features extracted from both signal can provides accuracy up to 95.86% on training data and 85.73% on testing data using SVM classification. In conclusion, features extracted from filtered accelerometer data can be used to fuse with features extracted from raw accelerometer data in order to increase classification result of activity recognition.

VI. Future Work

This model can be implemented in smartphone and integrated with indoor map. Step length estimation will be added for better turn-by-turn navigation such as telling the number of steps instead of distances in meter. This can be integrated with other indoor navigation technologies such as

Bluetooth and iBeacon for better indoor navigation. For further development plan, we plan to collect data from users when smartphone is not in the fixed position in order to evaluate the model. After that, we are going to implement this model in smartphone to classify walking activities in real time. Data from more users will be collected. Real time activity recognition function as mention above will be implemented in indoor navigation application for provide optional routing to user based on their profile and preference automatically.

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