Human Activity Recognition with Smart Watch based on H-SVM

Tao Tang[1], Lingxiang Zheng[1]*, Shaolin Weng[1], Ao Peng[1] and Huiru Zheng[2]

School of Information Science and Engineering, Xiamen University, Xiamen, China[1]
School of Computing and Mathematics, University of Ulster, Jordanstown Campus, Shore Road, Newtown Abbey[2]
lxzheng@xmu.edu.cn

Abstract. Activity recognition allows ubiquitous wearable device like smart watch to simplify the study and experiment. It is very convenient and extensibility that we do study with the accelerometer sensor of a smart watch. In this paper, we use Samsung GEAR smart watch to collect data, then extract features, classify with H-SVM (Hierarchical Support Vector Machine) classifier and identify human activities classification. Experiment results show great effect at low sampling rate, such as 10 Hz and 5 Hz, which will give us the energy saving. In most cases, the accuracies of activity recognition experiment are above 99%.

Keywords: Human Activity Recognition; Smart Watch; H-SVM

1 Introduction

In the studies of human activity recognition, there are two main directions. One of them is based on vision sensors, which is not suitable for long-term monitoring in real life because of monitor environmental, equipment price and protection of privacy. The other is based on wearable sensors, which has been widely used because of low cost, small size and low energy consumption.

Mi Zhang did his study by wearing a device around his waist, this device is similar to a pager [1]. Piyush Gupta improved his study on the basis of Mi Zhang's study by wearing three devices around his waist. Thus, the accuracy of human activity recognition is higher [2]. Jennifer R. Kwapisz and his research group used a smart phone to instead of a sensor device to identify different activities in 2011. And his method has a praiseworthy recognition accuracy [3]. There is a higher accuracy of SVM than accuracies of other classification algorithms in Davide Anguital's paper [4]. However, the use of smartphones also has its limitations in the study of human activity recognition. It has different results when smartphones are placed in different pockets of clothes. Thus, the smartphones are putted into specified pockets in more and more studies [5]. Now it is so popular to do the study of activity recognition with home-made wrist-mounted devices [9]. Of course, it is very convenient and extensibility that we do study with the accelerometer sensor of a smart watch. In this paper, we use Samsung GEAR

*Corresponding author
Email address: lxzheng@xmu.edu.cn

smart watch to collect data, then extract features, classify with H-SVM classifier and identify human activities classification.

There is a high accuracy of human activity recognition by using home-made device. But it has no generalizability by using that device. By contrast, it is a lot easier for activity recognition by using smart phone. However, it has different experimental results when smartphones are placed in different pockets of clothes. The experiment conducted by smart watch [6-8], but its identification accuracy is not particularly high. James Amor shows the wonderful walking accuracies at high frequency and low frequency [7]. Our H-SVM algorithm performs better than James Amor's at low frequencies.

The remainder of this paper is structured as follows. Section 2 describes the methodology of H-SVM. Section 3 describes our experiments and results, including data collection, feature extraction and classification performance. Section 4 summarizes our conclusions and discusses areas for future research. Acknowledgement is described in Section 5.

2 Methodology

The proposed approach is illustrated in Figure 1. Raw data is collected with high sampling rate (50Hz) to extract features activity. And the H–SVM classifiers were applied to distinguish human activities [10].

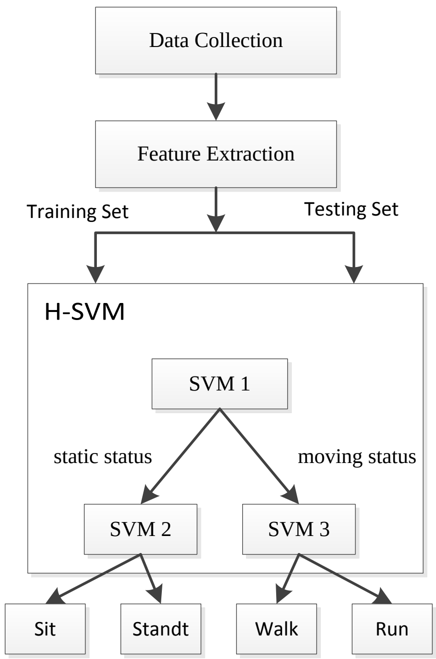


Fig. 1. The system of human activity recognition

2.1 Sampling Rate

The original frequency of human activities (sitting, standing, walking and running) are 50Hz.

2.2 Feature Extraction

Four features were extracted to recognize the user behaviors, including the motion acceleration in three axis X, Y and Z, and the RMS (root-mean-square) of the changes in acceleration. Three-axis acceleration are the features that reflected the human position. The three-axis acceleration changed during the transition between sitting and standing, so that it can be used for distinguishing sitting and standing. The root-mean-square of the changes in acceleration reflected the amplitude changes of human activities, the acceleration of movement changed significantly while very little during the static status, so it can be used for distinguishing movement and static. It can also be used for distinguishing running and walking because the amplitudes and the variations of the acceleration in running are larger than those in walking.

The root-mean-square value of the dynamic variation of acceleration can be calculated by equation (1).

$$acc_t = \sqrt{highX_t^{\ 2} + highY_t^2 + highZ_t^{\ 2}} \tag{1}$$

Where $highX_t$, $highY_t$ and $highZ_t$ are the changes of the acceleration in the three axis X, Y and Z at time t. acc_t is the root-mean-square value of the change of acceleration in the three axis at time t.

All the features are extracted from a time window and integrated by using the mean filter described in equation (2).

$$\alpha_t = \sum_{i=-b}^{b} (\alpha_{t+i})/(2\text{b}+1) \tag{2}$$

Where $2b+1$ is the width of the sliding time window, and α is X, Y, Z or acc_t.

After passing through the mean filter, a median filter with the time window of $2b+1$ (width), is applied to the features before being analyzed by the H-SVM.

2.3 Activity recognition

An H-SVM classification model was applied in the research to distinguish four activities (sitting, standing, walking, and running) in the daily living for identification and classification. Support vector machine (SVM) is a supervised learning algorithm. The basic SVM model is the probability of a binary classification. The H-SVM includes three basic SVM classifiers: SVM1, SVM2 and SVM3.

The SVM1 is used to distinguish static status and moving status based on acc_t. The SVM2 is used to distinguish standing and sitting activities according to X_t, Y_t and Z_t. The SVM3 is used to distinguish the walking and running activities based on acc_t.

3 Experiments and Results

3.1 Data Collection

We installed a data collection Application on Samsung GEAR Smart Watch. We collect raw data of acceleration sensor by sampling frequency of 50 Hz. Our experiments contains four motions, which are sitting, standing, walking and running. Original sampling frequency is 50Hz. We divided it into four kinds of sampling frequencies, 50 Hz, 25 Hz, 10 Hz and 5Hz in experiments. There are five volunteers participate in our experiments. The five volunteers are all males and age from 24 to 25. The five volunteers are numbered as A, B, C, D and E. Each motion of each person was sampled 4 minutes (240 seconds). To avoid the influence of extraneous data, each data set is removed its first 20 seconds and last 20 seconds. So each data set is 200 seconds.

3.2 Feature Extraction

Feature selection methods select the features, which are most discriminative and contribute most to the performance of the classifier, in order to create a subset of the existing features.

Although SVM are powerful neural computing methods, their performance is reduced by too many irrelevant features. Therefore, H-SVM feature selection methods are proposed. We consider an SVM feature selection approach for better system performance.

In this paper, we propose 4 attributes for human activity recognition:

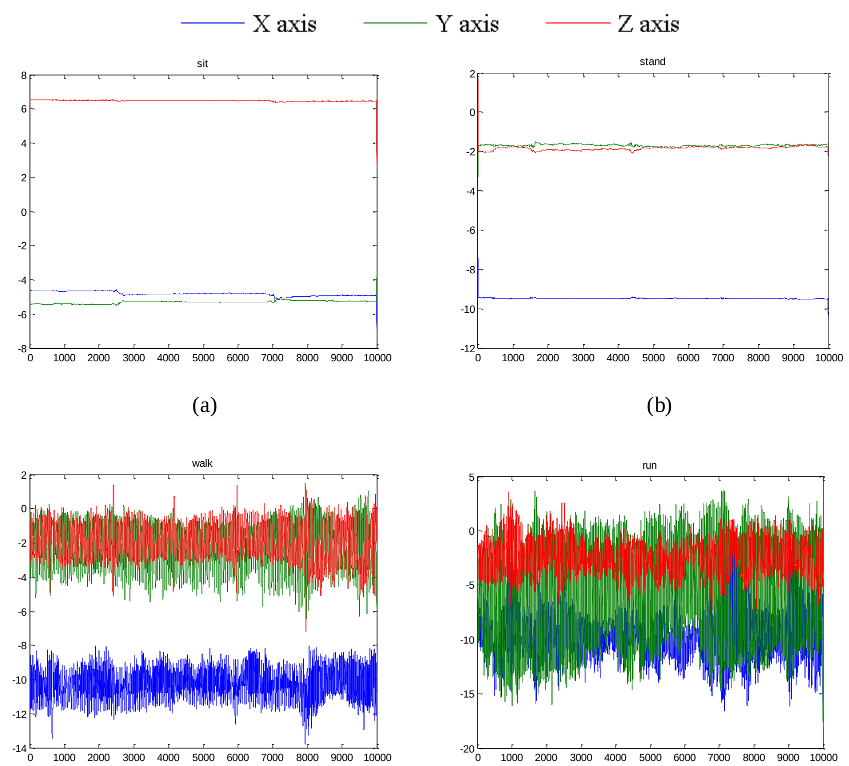
X axis : Filtered data of X axis

Y axis : Filtered data of Y axis

Z axis : Filtered data of Z axis

Root Mean Square (RMS) of Variation : RMS value of the change of accelerations in the three axis.

The filtered data of each axis are different between Fig 2(a) and Fig 2(b), so it can identify sitting and standing. The raw data are processed by mean filter and median filter. Figure 2 is the filtered data in 50 Hz.

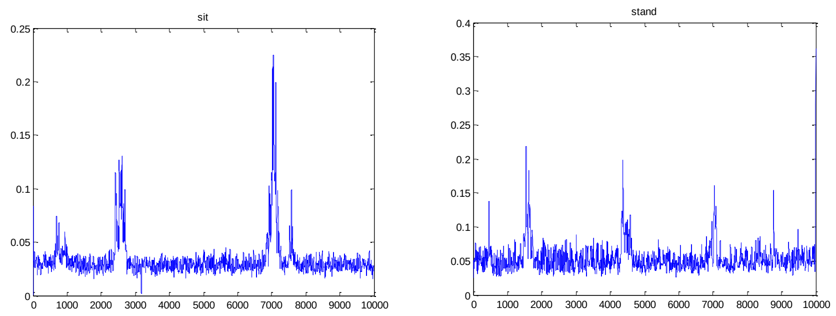


(a) (b)

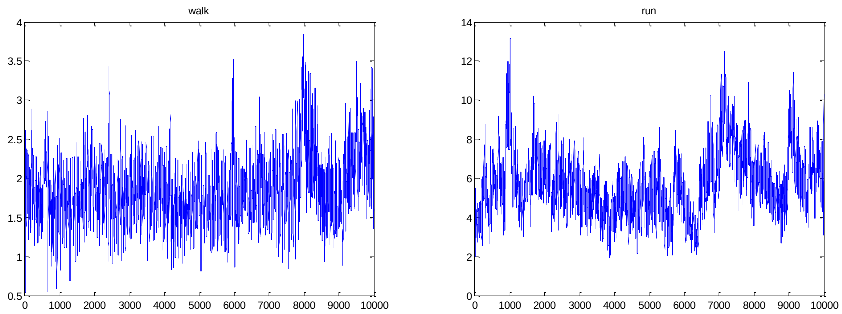
(c) (d)

Fig. 2. The filtered training data set in 50 Hz

RMS of variation value is almost the same between Fig 3(a) and Fig 3(b), but it has a huge difference between Fig 3(c) and Fig 3(d). Thus, this value can be used to distinguish walking and running. Figure 3 is the RMS of variation value of each motion in 50Hz.



(a) (b)



(c) (d)

Fig. 3. The RMS of variation value of training data set in 50Hz

3.3 Training Set and Testing Set

The data set of volunteer A is set as a training data set, while the data of other volunteers are set as a big testing data set.

3.4 Performances of Different Classifiers

The selected or reduced features that create feature sets are used as inputs for the classification and recognition methods. Following are a summary for the most widely used classification and recognition methods.

J48 : J48 are decision support tools using a tree-like model of decisions and their outcomes, and costs.

Decision Tables (DT) : Decision Tables serve as a structure which can be used to describe a set of decision rules and record decision patterns for making consistent decision.

Naive Bayes (NB) : Naive Bayes is a simple probabilistic classifier based on Bayes' theorem.

Support Vector Machine (SVM) : SVM is supervised learning methods used for classification.

We put the selected characteristic values into different classifiers. Table 1 shows the accuracies of different classifiers.

Table 1. Accuracies of Activity Recognition

	% of Records Correctly Predicted				
	H-SVM	**SVM**	**J48**	**NB**	**DT**
Sitting	99.31	24.90	100	2.28	90.60
Standing	98.49	16.25	81.93	0	4.34
Walking	98.99	87.51	83.48	86.04	87.79
Running	99.34	99.54	90.07	99.14	98.48
Overall	99.03	57.05	88.87	46.87	70.30

As can be seen from Table 1, the accuracies of SVM and NB are very low at the motion of sitting. And the accuracies of SVM, NB and DT are also low at the motion of standing. It can be seen in these attributes, H-SVM and J48 perform wonderful at each motion. On the whole, H-SVM algorithm performs the best between them.

3.5 Performances of Different Frequencies

To test the performance of H-SVM algorithm at different frequencies, we extract four different frequency from the raw data as 50 Hz, 25 Hz, 10 Hz and 5 Hz. Table 2 shows the classification accuracy of each motion at different frequencies.

Table 2. Accuracies of Activity Recognition based on H-SVM

	% of Records Correctly Predicted			
	50Hz	**25Hz**	**10Hz**	**5Hz**
Sitting	99.31	99.86	99.99	99.87
Standing	98.49	99.02	98.95	98.62
Walking	98.99	99.78	99.91	99.67
Running	99.34	99.90	99.64	99.85
Overall	99.03	99.64	99.62	99.50

As can be seen from Table 2, the accuracies of H-SVM performs very well at different frequencies. Even at the low frequency (5 Hz), this classifier can very easy to distinguish different motions, and its overall accuracy is above 99%.

4 Conclusions

In this paper, we present an activity recognition approach based on H-SVM. In our experiments, smart watch performs a good classification ability. Smart watch is not lost to other devices in the field of recognition activity. Experiment results show that H-SVM algorithm performs the best between many algorithms. At each motion, H-SVM almost has the highest classification accuracy between those algorithms. Experiment results show great effect at low sampling rate, such as 10 Hz and 5 Hz. In most cases, the accuracies of activity recognition experiment are above 99%. Future work will include more participants, especially elderly users and evaluating the proposed algorithm with data collected at real living environments.

5 Acknowledgement

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