Activity Recognition from Accelerometer Signals Based on Wavelet-AR Model

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***Abstract*—In this paper, a new Wavelet-AR feature for activity recognition from a tri-axial acceleration signals has been proposed. We use Wavelet Transform to decompose the raw accelerometer signals and obtain the decomposed singnals that can efficiently discriminate the different activities. After that we build autoregressive（AR）model for the decomposed signals and extract the AR coefficients as features for activity recognition. As a consequence, Multi-class Support Vector Machines is uesed to distinguish different human activities. The average recognition results for four activities using the proposed Wavelet-AR features are 95.45%, which are better than traditional features. The results show that Wavelet-AR feature obvious discriminates different human activities and it can be extract as an effective feature for the recognition of accelerometer data.**

Keywords-Tri-axial accelerometer; Activity recognition; Wavelet-AR model; Feature extraction; Support Vector Machines

I. INTRODUCTION

Context awareness is a central issue in ubiquitous and wearable computing. Accurate recognition and tracking of human activities is an important goal of ubiquitous computing. In recent years, a new kind of technology that recognizes users' daily activity has emerged due to the rapid development of MEMS accelerometer technology. For example, several activities such as ambulation, typing, talking were distinguished in [2] with five small bi-axial accelerometers. In [3] and [4], daily activities of standing, walking, climbing up/down stairs and brushing teeth, were analyzed based on the data collected from accelerometers. Compared with activities recognition based on visual analysis, it has a number of advantages, including the simplicity of device, long-term monitoring, and conveniences for integration into handheld devices and so on.

As activity recognition can be formulated as a typical classification problem and just like many pattern recognition problem, features extraction plays a crucial role during the recognition process. The choice of good features is a fundamental step in statistical pattern recognition and a highly problem dependent task. In general, most of the attempts to extract features from acceleration date can be classified into two categories, say, time-domains features and frequency-domains features. Traditional widely used time domains features are mean [1~3], variance or standard deviation [1,2], energy [1,2,4], entropy [2], correlation between axes [1,2,4] and so on. The most popular frequency-domains features are FFT coefficients [1] and DCT coefficients [7]. Although using frequency-domains features could obtain much hight accuracy, they require much high components to discriminate different activities. Hence it will increase computation and do not suitable for real time application. As the time-domains features can be easily extracted in real time, they are more popular in many practical acceleration activity recognition systems. Moreover, the autoregressive model of time-series was presented to recognize human activity from a tri-axial accelerometer data in [5].

In this paper, an efficient method for high-accuracy activity recognition based on the Wavelet Transform (WT), the autoregressive (AR) model and Support Vector Machine (SVM) is presented. Since the usefull information for activity recognition locates in some specifically signals frequency band, Wavelet Transform are used to decompose signals to different frequency band. After that, the decomposed signals that can efficiently represent the features of signal patterns are easily obtained and then AR model is built and the AR coefficients are chosen as the input features of the SVM classifier. Classification of four human daily activities produces encouraging results. The block diagram of our proposed activity recognition system is shown in Figure 1.

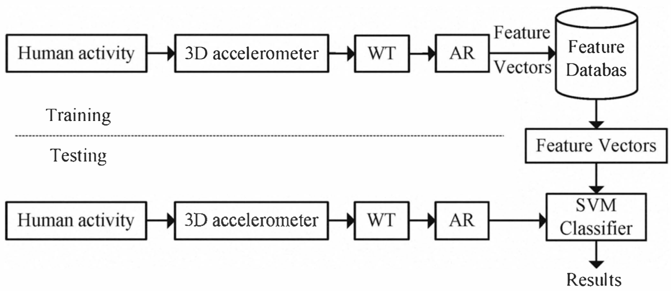
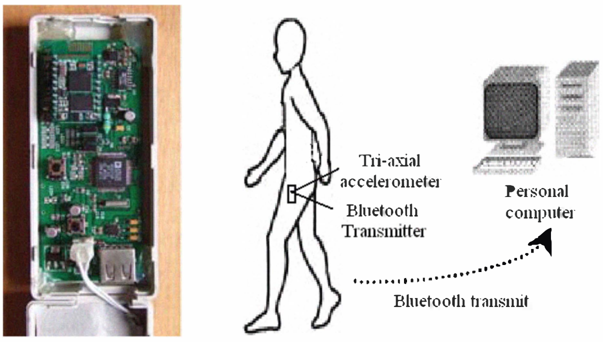


Figure 1. Overview of our system

The remainder of this paper is organized as follows: In section II, we introduce the data collection. Section III presents the detailed information about the feature extraction. Section IV introduce classification method and experiment results is given in section V. Finally, conclusions are given in section VI.

II. DATA COLLECTION

The diagram of our experimental setup is shown in Fig.2. We used a tri-axial accelerometer ADXL330 manufactured by Analog Devices, which is capable of sensing accelerations from –3.0g to +3.0g with tolerances within 10%. The output signal of the accelerometer is sampled at 100 Hz. The data generated by the accelerometer was transmitted to a personal computer wirelessly over Bluetooth. We collected four daily used activities: jumping, still, running and walking. In order to achieve robustness with regard to sensor position, subjects put the accelerometer in their trousers pocket when collecting the data. As we don't fix the sensor with the body, it may move randomly in the pocket (such as rotation) and therefore produces more variations among different collectors. Eleven persons (night male and two female) were asked to perform each activity about one minute. The activities were performed in two rounds over different days. The subjects keep standing still five seconds while every activity start and stop. Figure 3 shows an example of raw data.



(a) (b)

Figure 2. (a) Data collection apparatus (b) Diagram of experimental setup

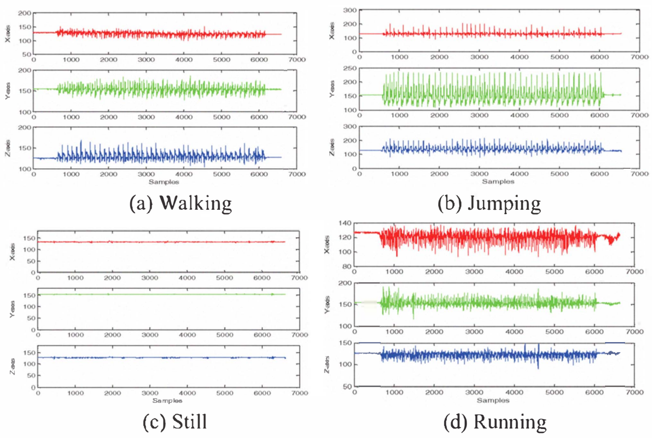


Figure 3. Examples of raw accelerometer signals for different activities

III. FEATURE EXTRACTION

Feature extraction is the elementary problem in the area of pattern recognition. For activity recognition task, extraction of effective gesture features is a very important step which will greatly improve the performance of the activity recognition system. In this paper, we proposed an effective feature extraction method from acceleration data based on Wavelet-AR model and the detail is presented as follows.

A. *Wavelet Transform theory*

A discrete wavelet transform uses a set of basis functions to decompose a signal into the detailed signals and the approximate signals of the original signal. Wavelet decomposition can be realized by the following Mallat Algorithm [6]:

$$\left.\begin{aligned} C_k^0 &= f \\ C_k^j &= \sum_n C_n^{j-1}\bar{h}_{n-2k} \\ d_k^j &= \sum_n C_n^{j-1}\bar{g}_{n-2k} \end{aligned}\right\} (k = 0,1,\cdots,N-1) \qquad (1)$$

Where f is the signal to be analyzed, with length N, c_k^j and d_k^j being scaling coefficients and wavelet coefficients under scale j; $\bar{h}_n$ and $\bar{g}_n$ being the pulse response of conjugate mirror filters.

Recursive applications of the above Mallat algorithm led to the decomposition of the signal into a matrix of sequences [8], as shown in Fig.4 (here three scale decomposition is adopted). The shadowed part is filled with zeros.

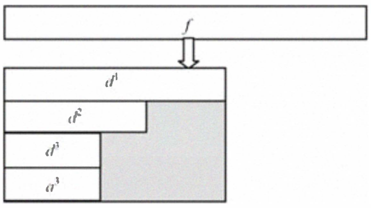


Figure 4. Wavelet analysis and its coefficients matrix

In wavelet analysis, different basis functions may be suitable for different signals, and appropriate selection of the wavelet basis for signal representation can result in maximal benefits. One simple way is to choose a basis available after some comparison, although such a result is not optimal. In this experiment, Daubechies 3 wavelet was selected by comparing the decomposition level required while keeping the energy as much as possible.

Sun M et al [9] reported that the major energy band for daily activities is 0.3–3.5 Hz. In other words, changes in activities are characterized mainly by low-frequency of signal. Thus, it's reasonable to use the low-frequency component, which includes activities information, can discriminate the different activities efficiently. We decompose the original signals into three level using Daubechies 3 wavelet and obtain wavelet coefficients of node d(3,0) which represents the low-frequency of signal. In general, the useful signal usually lies in low-frequency, while the noise and random dithering usually lies in high-frequency. Thus the low-frequency of decomposed signals are also insensitive to noise.

B. *AR model representation*

Auto-Regression (AR) model is expressed as the following difference equation [10]:

$$x(n) = -\sum_{k=1}^{p} a(k) * x(n-k) + u(n) \quad (2)$$

where $x(n)$ is the random signal to be processed, the input $u(n)$ is assumed to be a white noise signal and p is the model order. The selection of the model order in AR model is a critical problem, too low an order is a smoothed estimation, while too large an order causes spurious peaks and general statistic instability. We use the methods proposed by Akaike [11] to determine the model order p, which aims to minimize the following Akaike information criterion (AIC) function:

$$AIC(k) = N \ln \hat{\rho}_k + 2k \quad (3)$$

where $\hat{\rho}_k$ is the estimate of the white noise variance for the k th order AR model.

Once the order of AR model has been determined, the AR coefficients $a_1 \cdots a_n$ can be estimated by an auto-correlation method, known as the Yule-Walker equations:

$$\begin{bmatrix} r_x(0) & r_x(1) & \cdots & r_x(p) \\ r_x(1) & r_x(0) & \cdots & r_x(p-1) \\ r_x(2) & r_x(1) & \cdots & r_x(p-2) \\ \vdots & \vdots & \cdots & \vdots \\ r_x(p) & r_x(p-1) & \cdots & r_x(0) \end{bmatrix} \begin{bmatrix} 1 \\ a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} \sigma^2 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (4)$$

It can be proved that matrix in (4) is hermitian and toeplitz. And the Levinson-Durbin algorithm [10] can be used to solve the equations. In this paper, the 5-order AR coefficients are extracted from each of the three axes of the decomposed accelerometer signals, giving a total of 15 features.

IV. CLASSIFICATION

The classification algorithm we used is Support Vector Machine (SVM) [12]. SVM has become one of the most popular classification methods in Machine Learning field in recent years. As SVM was originally designed for binary classification, it cannot deal with multi-class classification directly. The multi-class classification problem is usually solved by decomposition of the problem into several two-class problems. We used One-versus-One Strategy (OVO), where a set of binary classifiers are constructed using corresponding data from two classes. While testing, we used the voting strategy of “Max-Wins” to produce the output.

Five-fold cross-validation [2] was used for classifier assessment. The data was randomly divided into 5 groups with the same number of samples for different classes. The classifier was built ten times. Each time one group in turn was excluded from the training and used solely as a test set. The cross-validated classification result is the average of the ten testing results.

Since the training dataset is relative limited here, generalization capability of the classifier is more important for recognition. We also use the leave-one-subject-out validation test [2] to evaluate the classifiers’ ability to recognize unacquainted actions. Classifiers were trained on activity data for all subjects except one. The classifiers were then tested on the data for only the subject left out of the training data set. This process was repeated for all subjects. In other words, the recognized are subject-independent.

V. EXPERIMENT RESULTS AND DISCUSSION

This section describes experiments with the developed activity recognition system. Features were extracted from the raw accelerometer data using a window size of 512 with 256 samples overlapping between consecutive windows. Feature extraction on windows with 50% overlap has demonstrated success in previous work [2].

In order to compare the performance of our new features against other traditional features, we carry out several experiments under same experimental conditions. As discuss above, the following kinds of traditional time-domains features (TF) were extracted from each axes of accelerometer: mean, standard deviation, energy and correlation between axes [4]. In [5], Four orders of autoregressive (AR) model accelerometer data is built and the AR coefficients are chosen as features.

For the first experiment, we carried out five-cross-validation procedure to validate the effectiveness of the proposed features against traditional TF and AR features. The recognition results of time-domain features, AR coefficients and wavelet-AR features are given in Table 1.

TABLE I. THE ACCURACY OF THE FIVE-CROSS-VALIDATED TEST

Method	run	still	jump	walk	average
TF	64.48	100	93.19	100	89.42
AR	80.69	100	90.05	98.29	92.25
Wavelet-AR	87.50	100	95.73	98.57	**95.45**

It can be seen from table I that accuracy using the proposed wavelet-AR features is higher than using traditional time-domains features and AR features. The average recognition results for time-domains features, AR features and wavelet-AR features are 89.42%, 92.25% and 95.45% respectively. Experimental results show that using wavelet transform we can obtain decomposed signals that can efficiently represent the features of signal patterns.

Secondly, we utilized a leave-one-subject-out cross-validation test. The results are shown in table II. From table II, we can also see that in this case classification accuracy of the Wavelet-AR features is still better than four traditional time-domains features and AR features. We notice that the average accuracy of the leave-one-subject-out test is lower than that of the five-cross-validated test, because the leave-one-subject-out test is subject-independent. As we known, the characteristics of the gait signals is unique for every person, therefore generalization capability based on leave-one-subject-out training is better than cross-validated training.

TABLE II. THE ACCURACY OF THE LEAVE-ONE-SUBJECT-OUT TEST

Method	run	still	jump	walk	average
TF	58.23	100	75.85	100	83.52
AR	69.03	100	81.53	96.87	86.86
Wavelet-AR	75.28	100	90.62	99.15	91.26

In order to find out which activities are relatively harder to be recognized, we analyzed the confusion matrices. Table III shows the aggregate confusion matrix for Wavelet-AR feature based on leave-one-subject-out validation. It can be seen that running is often confused with jumping and is in general hard to recognize. This result is reasonable, because the raw signals of running are similar to the jumping. (see Fig.3).

TABLE III. CONFUSION MATRIX FOR THE WAVELET-AR FEATURE

	run	still	jump	walk
run	265	0	55	32
still	0	352	0	0
jump	27	0	319	6
walk	0	0	3	349

VI. CONCLUSION

A new Wavelet-AR based feature for activity recognition from a tri-axial acceleration signals has been proposed in this paper. To recognize different human activities, we adopt multi-class support vector machines in our system. Our experimental results demonstrate that the average recognition result for four activities using the proposed Wavelet-AR features are 95.45%, which are better than traditional time-domains features and AR features. It is found from our study that the Wavelet-AR can provide sufficient discrimination between different types of human activity and provides a new choice of feature for activity recognition.

ACKNOWLEDGMENT

The authors would like to thank professor Jin Lianwen from SCUT for his revised advise. This paper is partially supported by the following research fundings: Science and Technology Plan of Guangdong Project (No. 2010B050900016), the Fundamental Research Funds for the Central Universities (No. 21609606).

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