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The application of EMD in activity recognition based on a single triaxial accelerometer

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Abstract. Activities recognition using a wearable device is a very popular research field. Among all wearable sensors, the accelerometer is one of the most common sensors due to its versatility and relative ease of use. This paper proposes a novel method for activity recognition based on a single accelerometer. To process the activity information from accelerometer data, two kinds of signal features are extracted. Firstly, five features including the mean, the standard deviation, the entropy, the energy and the correlation are calculated. Then a method called empirical mode decomposition (EMD) is used for the feature extraction since accelerometer data are non-linear and non-stationary. Several time series named intrinsic mode functions (IMFs) can be obtained after the EMD. Additional features will be added by computing the mean and standard deviation of first three IMFs. A classifier called Adaboost is adopted for the final activities recognition. In the experiments, a single sensor is separately positioned in the waist, left thigh, right ankle and right arm. Results show that the classification accuracy is 94.69%, 86.53%, 91.84% and 92.65%, respectively. These relatively high performances demonstrate that activities can be detected irrespective of the position by reducing problems such as the movement constrain and discomfort.

Keywords: Activity recognition, accelerometer, empirical mode decomposition (EMD), adaboost

1. Introduction

Activity recognition aims to automatically distinguish different activities of humans that is one of the most interesting and challenging research areas. It is appealing for many domains because it has great advantages in automatic identification of human activities. One of the most meaningful applications is healthcare. Because activity recognition can be used to provide information about persons' routines, which contributes to daily activity monitoring and emergency detection, such as the fall from elders [1]. In addition, the development of activity recognition has been extended to the rehabilitation assessment of disease, such as the physical handicaps caused by the stroke or the Parkinsonism [2]. Other interesting applications include smart phones, tracking system and sport training. Nowadays, many approaches applied in recognizing activities are majorly classified into

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three categories [3], 1) the method based on computer vision; 2) the method based on acoustic and ambient sensor; 3) the wearable sensor-based method such as kinematic sensors. In all approaches, due to the smaller, lighter and wireless devices, wearable sensors encompass a persuasive potential in these fields. They can be even worn in clothes which cause little noise and can be applied in most of real life conditions.

Accelerometer is convenient and multifunctional which is one of the most common sensors utilized in current activity monitors. The velocity, trajectory information and inclination information with respect to the reference planes all can be provided by it. Shyamal Patel, et al. chose six accelerometers to classify the rehabilitation stage of different stroke patients through operating certain motions [4]. Juan Cheng combined accelerometers with the surface electromyography to detect the fall [5]. Bao and Intile [6] utilized five biaxial accelerometers, worn on different parts of the body, to classify 20 different activities of daily living. While in above-mentioned papers, results were achieved by more than one sensor and sensors were always positioned in different areas. In fact, the number and placement of sensors are vital factors to the classification accuracy. More information will be provided by the larger number and multiple placements, while the cost, discomfort and operation difficulty will also increase. So several studies about utilizing one accelerometer for activity recognition have been proposed.

A survey about features used in the activity recognition based on accelerometers was carried out by Figo, et al. [7]. Features could be classified into three different domains, such as the time domain, the frequency domain and the discrete representation domain. The most frequently used features in the activity recognition with a single-accelerometer including the mean, the standard deviation, the entropy, the energy and correlation. The most popular sensor location for a single accelerometer is on waist because it is near the centre of the trunk and can better represent human movement. Khan, et al. used a single triaxial accelerometer to distinguish different activities of daily living [8, 9]. In [8], a triaxial accelerometer was attached to the chest of the user in a particular orientation and was able to classify fifteen activities with an average accuracy of 97.9%. However, when the system was tested with the sensor at five different positions, the accuracy of the system was reduced to 47%. In [9], a new system was proposed which detected activities irrespective of five different positions of the sensor with an accuracy of 94.4%. But the distribution of sensors was not very extensive, they still concentrated on the trunk. In the above papers, the non-linear and non-stationary of signals were not considered, features were all extracted from the traditional signals. So the sensors were more concentrated in one certain area, and the accuracy was low in some positions.

In this paper, considering the non-linear and non-stationary of accelerometer data, a novel method based on the empirical mode decomposition (EMD) is proposed for the feature extraction. The EMD acts as an adaptive non-linear filter, decomposing the signal into a number of intrinsic mode functions (IMFs). Besides five traditional features, additional features are extracted from the IMFs. Five normal activities can be classified by a single accelerometer based on this method.

2. Methods

2.1. Data acquisition

The data was downloaded from the public database: http://groupware.les.inf.puc-rio.br/har. The wearable device of data collection comprised a tri-axial ADXL335 accelerometer connected to an ATmega328 V microcontroller. From the database, it was known that the sampling rate was 8 Hz. The accelerometer was positioned in the waist, left thigh, right ankle and right arm respectively. Before the collecting all sensors were calibrated on top of a table in the same position. In order to keep the same orientation in each position, the Y axis of all sensors were kept vertical to the ground in a positive direction. The specific description about the setup can be found in the website mentioned above. The data was collected from four subjects: two men and two women. They were all adults and healthy, between 20 years old and 80 years old. All five activities: sitting, standing, sitting down, standing up and walking were completed and needed to be classified [10].

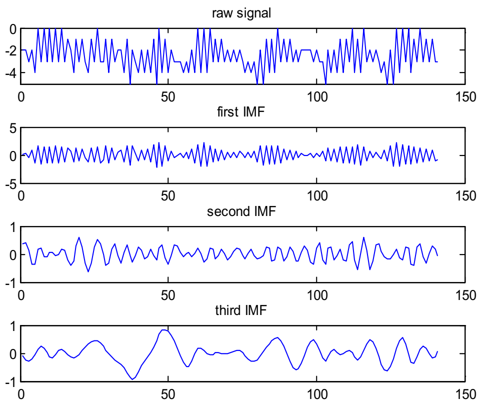
2.2. Traditional features extraction

Feature extraction is a significant procedure in all pattern recognition applications. The essential nature of the data can be extracted by the procedure and the problem of the curse of dimension will be alleviated. Generally speaking, every normal activity such as sitting down and standing up could be completed in 2.5 s, 2.5 s could be regarded as one cycle. In order to get continuous and more information, the time window is chosen as 5s (40 points) and an overlap of 2.5 s (20 points) which contains approximately two cycles.

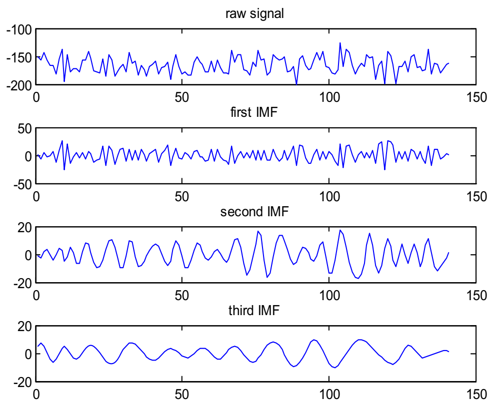
Five popular features were extracted from each window: the mean value, the standard deviation, the entropy, the energy and the correlation coefficients between X and Z axis, Y and Z axis [11-13]. As an example, Figure 1 shows the raw accelerometer signal along with the first three IMFs for the X axis of different movements ((a) the sitting, (b) the walking). From the first row of Figure 1, the mean and the range of fluctuation between sitting and walking can be observed completely different. The standard deviation can reflect the volatility of the signal. Movement complexity can be depicted by the energy. While the entropy is useful in differentiating between signals corresponding to different activities with similar energy values, such as sitting down and standing up. The correlation is used in measuring the strength and direction of a linear relationship between two time series [7].

2.3. Empirical Mode Decomposition

When recognizing the activities, actions are always repeated several times. Theoretically, the signal should be repetitive. Actually, from Figure 1, signals have the certain periodicity for each 50 points, but as a whole, the time sequence is still non-linear and non-stationary because of irresistible factors.



(a)



(b)

Fig. 1. The raw accelerometer signal along with first three IMFs for X axis of different movements, (a) the sitting movement and (b) the walking movement.

As a result, using algorithms that only assume the linearity and stationarity can be problematic. The EMD is a new method for processing non-stationary and non-linear signals [14]. The function of the EMD is stabilizing signals.

The EMD can be applied in any type of signal in the theory through decomposing the signal into finite number of IMFs. Each IMF contains local characteristics of original signals in different time scales. And a valid IMF is based on the following assumed conditions:

1. During the whole time range, the number of zero crossings and the number of local extreme values must be equal or differ by one at most.
2. In any moment, the average of the local maximum and the local minimum envelope must be zero.

These two conditions guarantee all maximum values of one IMF are positive and all minimum values are negative.

In this paper, the signal $x(t)$ decomposed according to EMD was the whole signal. And its local minimum value and local maximum value are firstly identified. The whole process of EMD is always called "shifting" vividly. Firstly, one upper ($\theta_{max}(t)$) and one lower ($\theta_{min}(t)$) envelope interpolating between successive local maximum values and local minimum values respectively (always via the cubic spline interpolation) are created and used to calculate the running mean $m(t)$:

$$m(t) = \frac{\theta_{max}(t)+\theta_{min}(t)}{2} \tag{1}$$

Then, the detail $d(t)$ is extracted by subtracting the mean from the signal:

$$d(t) = x(t) - m(t) \tag{2}$$

The detail $d(t)$ could be regarded as a new signal. However, if negative local maxima and positive local minima exist, $d(t)$ is not a valid IMF. The shifting needs to take place until a valid IMF is got [11].The whole process will be repeated until the final residual is a monotonic function (or specific number of IMFs utilized by user has been extracted). Figure 2 demonstrates the process of shifting.

As a result, $x(t)$ is finally decomposed into some IMFs with a residual term.

$$x(t) = \sum_{\mathrm{i}} IMF_i(t) + \gamma(t). \tag{3}$$

Figure 1 depicts accelerometer signals of sitting and walking along with the corresponding first three IMFs for the activity. The change of the time series can be clearly observed, the IMF is becoming more and more smooth and periodic. Especially the third IMF of Figure 1(b), it is almost stable compared with the traditional signal. So the mean value and standard deviation of first three IMFs are computed as additional features.

2.4. Classification

In this paper, a classifier named AdaBoost is employed. It is an iterative algorithm. The core idea is gathering different weak classifiers to form a strong classifier. In each iteration, every sample is given a weight which would be modified due to the classification correctness of the sample and the total accuracy in last classification. The new data with the modified weight would be used in the next weak classifiers. The final strong classifier would be made up of the several trained weak classifiers. The individual classifier can be weak, but the final model can be proven to be a strong classifier provided

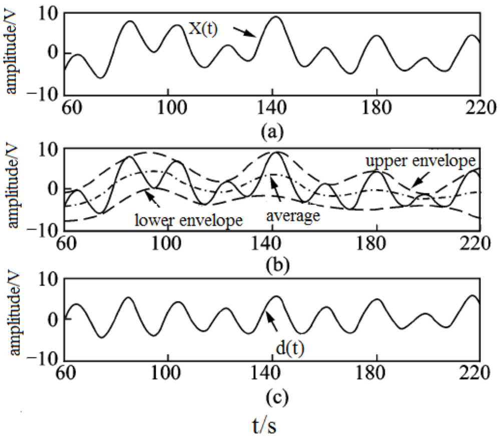


Fig. 2. The specific procedure of EMD, (a) the original signal x(t), (b) the upper envelope and lower envelope of x(t), the average of two envelopes and (c) the detail d(t).

Table 1

The average accuracy and standard deviation based on different feature sets and sensor positions

Features/Sensor	1	2	3	4
five traditional features	93.46±8.34%	84.48±11.78%	91.02±7.85%	88.57±11.60%
five traditional features+EMD	94.69±7.72%	86.53±14.83%	91.83±7.50%	92.65±9.85%
Khan[9]	89.39±8.83%	73.47±27.42%	88.98±9.64%	84.90±10.67%

each one is slightly better than random guessing [15].

Here the weak learner was a simple classifier based on thresholds. The classifier was transformed based on the voting principle aiming to distinguish multiple classes.

3. Results

A single sensor was positioned in the waist, left thigh, right ankle and right arm respectively. So the data from each position was chosen to classify five activities (sitting, standing, sitting down, standing up and walking) respectively as well. Every activity data from each position for simulation was 2000 points from four subjects. Since the size of data is large, the half is enough to build a model with strong generalization ability. So half of the each activity data was randomly selected as the training set, the rest was acted as the test set. All computation was completed on Matlab R2013a and the processor type was 3.50-GHz Intel Xeon E5-2637.

Firstly, only five traditional features mentioned above were extracted from the raw data. Then the EMD was conducted, the mean value and standard deviation were calculated from first three IMFs. The method presented in [9] was also implemented in the comparison. The sensor positioned in the waist, left thigh, right ankle and right arm was successively given the number 1, 2, 3, 4. Table 1 shows the average accuracy of five motions based on various features.

From Table 1, it is found that our proposed method obtains the highest accuracy and the relatively lower standard deviation. The application of the EMD makes up the deficiency of traditional features. The effectiveness of the EMD is remarkable. Our result is also better than that achieved from the method in [9] which demonstrated the accuracy independent from the accelerometer's position. The accuracy of each sensor is relatively high, even on the arm when our activities are all about foot. Thus it is reasonable to conclude that a single accelerometer independent from the position can be used in normal activities recognition under our algorithm.

4. Discussion

Our results suggest that the effectiveness of the EMD in activity recognition based on one accelerometer irrespective of the placement. In the area of activity recognition by using the accelerometer, the number and the placement are key factors to the experiment. They have great influences on the cost and the comfort level of subjects. Our algorithm reduces the problems successfully. Our findings show that the sensor 1 always provides the highest accuracy. Since the waist is in the center of our body, it can reflect movement better. Because the sensor on the arm is the most volatile, so it's easy to find that the accuracy of the sensor 4 increases the most after tranquilization from the EMD. Comparing to the method mentioned in [9], our method has a great advantage in the accuracy. At the same time, the accuracy of each sensor is approximate and the stability is better as well.

5. Conclusion

In this paper, a novel method for activity recognition is proposed. Considering the non-linear and non-stationary of accelerometer signals, the EMD acted as an adaptive non-linear filter is introduced to stabilize signals. Additional features extracted from the IMFs make up the disadvantage of traditional features. A single triaxial accelerometer positioned in a wider range, such as the waist, left thigh, right ankle and right arm, is utilized to classify five activities of daily living: sitting, standing up, sitting down, standing up and walking. The highest accuracy in Table 1 illustrates the effectiveness of the EMD. Although one accelerometer is enough to recognize five normal activities, it still need another activity to enrich experiment. Positions can be changed to improve the convenience, such as the wrist, chest and so on. More features and/or other classifier will be tried in order to improve the classification accuracy. In the future work, other wearable sensors like the surface electromyography will also be adopted to realize more functions.

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