ACCELEROMETRY BASED CLASSIFICATION OF GAIT PATTERNS USING EMPIRICAL MODE DECOMPOSITION

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ABSTRACT

This paper describes accelerometry based classification of walking patterns. A feature extraction technique based on empirical mode decomposition (EMD) is proposed for the classification of unsupervised walking activities from accelerometry data. The front-end 20 dimensional features representing the gait patterns were obtained from the first three modes of decomposition of the acceleration data in anterior-posterior, medio-lateral, and vertical direction. The back-end of the system was a 64-mixture Gaussian Mixture Model (GMM) classifier. Overall classification accuracy of 96.02% was achieved for the five different human gait patterns including walking on flat surfaces, walking up and down paved ramps and walking up and down stairways.

Index Terms **—** feature extraction, gait classification, accelerometry, empirical mode decomposition, Gaussian Mixture Model.

1. INTRODUCTION

It is well-established that the level of daily physical activity is correlated with a person's health. Monitoring of physical activity has been used to assess energy expenditure in some activities of daily living. The amount of energy consumption due to daily physical activity is widely recognized as a major contributing factor in various disease processes including obesity, diabetes, hyperlipidemia, hypertension, cardio-vascular disease, and muscle wasting in elderly people. Therefore, such indices are of particular interest for preventive medicine, chronic disease management, rehabilitation management and health promotion programs.

Accelerometry has been proposed as a preferable method to detect the frequency and intensity of vibrational human motion [1]. Numerous previous studies have demonstrated the efficacy of accelerometry in evaluating daily physical activities by placing four to seven accelerometers at a subset of the thighs, wrists, arms, sternum, hips and lower legs [2-4]. Only a few studies have investigated the use of a single accelerometry device located at the waist [5, 6]. Employment of multiple wearable sensors brings a number of restrictions and uneasiness that possibly interfere with normal daily activities, though such a system is likely to provide a higher accuracy in terms of classifying motions and postures.

The correlation between the accelerometry and the energy expenditure is broadly accepted as the standard reference for daily physical activities [1, 7]. However, for a more precise assessment of energy expenditure, daily physical activity classification must be made for a range of unsupervised tasks, including different patterns of walking, since there are still some difficulties to quantify energy consumption of detailed ambulatory movements in terms of accelerometry data.

Gait classification has been applied to various supervised walking patterns. Aminian et al. classified walking uphill, downhill and on a flat surface using a neural network approach based on triaxial accelerometry data [8]. Sekine et al. and Nyan et al. managed to classify walking stairs-up, stairs-down and on a flat surface [9, 10]. In these cases walking was studied on a small group of subjects (5~11 subjects) and only for limited types (3) of walking patterns. Furthermore, gait was analyzed as either a linear and stationary or non-stationary signal [10, 11]. However, recent research in the area of biomechanics has led to the conclusion that gait is both non-linear and non-stationary [12]. Using basic signal characteristics, the results obtained from the use of a non-linear, non-stationary signal analysis algorithm named the empirical mode decomposition (EMD) for kinematics gait recognition are encouraging [13].

In this paper, we extend these previous studies by applying empirical mode decomposition (EMD) to the analysis of gait data from a single waist-mounted triaxial accelerometer to characterize and differentiate between flat walking and inclined walking (either on steps or on a uniform slope).

2. METHODS

2.1. The Sensor Device and Data Collection

The sensor device used in this study is a single, waist mounted triaxial accelerometer powered by a lithium polymer battery, which has the dynamic range of +/−6 g. The data from the sensor device with typical radio range of 100 m outdoor and 30 m indoor is transmitted using a Bluetooth class 1 radio. The sampling rate of the sensor device is 50 Hz per channel. The device is capable of measuring both static and dynamic accelerations. The acquired signal is the net result of the body acceleration due to movement of the subject, acceleration due to gravity, and other external forces and noise.

Five types of walking patterns were collected from 52 subjects. Among these 52 subjects (39 males, 13 females, aged 21 – 64 years, height ranged between 1.53 and 1.88 m, and weight between

42 and 94 kg). The five walking patterns were specifically walking flat, walking slope-up, walking slope-down, walking stairs-up and walking stairs-down. Each of these five walking patterns was performed by the 52 subjects, 10 times for each type of walking. The duration of each walking pattern ranged from 11 to 29 seconds.

2.2. Preprocessing and Feature Extraction

Normal gait is primarily a low frequency physical activity and, as such, many Fourier coefficients representing high frequency signal content have very low amplitude. The most useful information closely related to the impact acceleration is contained in the band below 17 Hz [9]. Therefore, the raw accelerometry data was low pass filtered first to suppress artifacts and preserve the useful bandwidth (i.e. 0~17 Hz).

Peng et al. recently concluded that gait is both non-linear and non-stationary [12]. For that reason, a non-linear, non-stationary signal analysis technique (namely EMD) was adopted. A window size of 128 samples (≈ 2.56 seconds) with half window length overlapping between consecutive windows was used. Preliminary data showed that a window with such length was able to capture a variety of walking patterns.

EMD is an intuitive signal-dependent decomposition of a time series into waveforms modulated in both amplitude and frequency [14]. That is, the basis of the expansion is generated in a direct, a posteriori, and adaptive way. Each signal $x(t)$ can be decomposed as follows:

$$x(t) = \sum_{i=1}^{n} c_i + r_n \tag{1}$$

where c_i is an intrinsic mode function (IMF) and r_n is the mean trend of $x(t)$ or residue.

For one IMF $c_i(t)$ in Eq. (1), its Hilbert transform is defined as

$$H[c_i(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{c_i(t')}{t - t'} dt' \tag{2}$$

With the above definition, an analytic signal can be expressed as

$$z_i(t) = c_i(t) + jH[c_i(t)] = a_i(t) e^{j\Phi_i(t)} \tag{3}$$

From Eq. (3), the instantaneous frequency (IF) is obtained with

$$IF_i(t) = \frac{1}{2\pi} \frac{d\Phi_i(t)}{dt} \tag{4}$$

A range of features were then extracted from both the $\mathrm{IMF}_{i\,(i=1,2,3)}$ and the analytic signals to form a more useful and robust gait representation. The details of IMFs can be referred in [14]. The EMD and feature extraction processes are illustrated as in Fig 1.

The number of IMFs for each subject varied from four to five due to inter-subject variability. Any mode beyond IMF_3 did not provide significant useful information in separating these five classes of walking. Therefore, only the first three modes of decomposition from each subject for all five walking patterns were chosen. Consequently, there existed three analytic signals and their corresponding instantaneous frequencies.

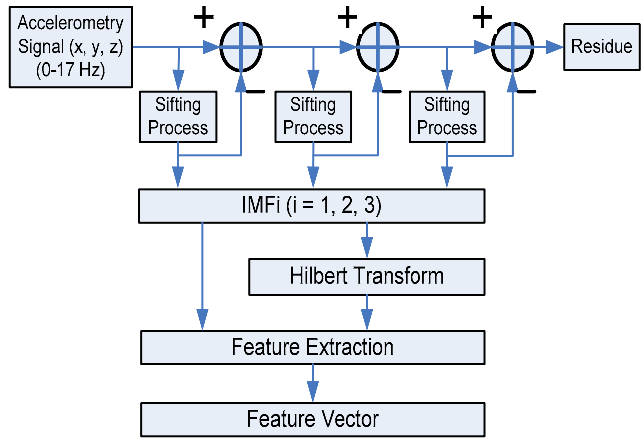

Fig.1. Feature extraction was done on both the intrinsic mode functions (IMFs) derived by the empirical mode decomposition and analytic signals from the Hilbert transformed IMFs.

Table I tabulates the derived and selected accelerometry gait features. 37 features were extracted initially which are rms of first three modes of IMFs, maximum amplitude of analytic signals, mean of IFs, weighted mean of IFs, and sum of the energy of the first three IMFs for three directions of acceleration as expressed in feature extraction column in Table I. 20 features were then selected from the total 37 ones based on the statistical analysis, referring section 2.4 for detailed explanation, as described in feature selection decision column in Table I.

TABLE I

GAIT FEATURES WERE EXTRACTED FROM THE EMPIRICAL MODE DECOMPOSITION AND HILBERT TRANSFORM AND FEATURES SELECTED

Set No	Feature Extraction	Feature Selection Decision
1	rms($IMF_{i\,(i=1,2,3),\,j(j=x,y,z)}$)	rms($IMF_{3,x}$, $\mathrm{IMF}_{3,z}$) discarded
2	max($a_{i\,(i=1,2,3),\,j(j=x,y,z)}$ (t))	max($a_{2,x}$, $a_{3,z}$) discarded
3	mean($IF_{i\,(i=1,2,3),\,j(j=x,y,z)}$)	mean($IF_{1,x}$,$IF_{2,y}$, $IF_{2,z}$,$IF_{3,z}$) discarded
4	$Weighted\_MIF(i,j) = \frac{\sum_{k=1}^{m} IF_{i,j}(k) a_{i,j}^2(k)}{\sum_{k=1}^{m} a_{i,j}^2(k)}$ (i=1, 2, 3) , j(j=x, y, z)	All discarded
5	$\sum_{k=1,i=1,2,3,j=x,z}^{m} IMF_{i,j}^{2}(k)$	Selected

2.3. Normalization Based on Flat Walking Features

Normalization or standardization of different types of walking data facilitates comparisons between different gait patterns by standardizing specific parameters. For a specific subject, the process involved normalizing each feature vector by the average of five seconds of data taken during flat walking activity for the same subject. That is, for an individual subject, subtract and divide by the priori knowledge of the same subject's walking flat features from the feature vectors of five walking patterns correspondingly as shown in Eq 5.

$$\hat{F} = \frac{F - mean(F_{flat\_walking})}{std(F_{flat\_walking})} \tag{5}$$

where $F_{flat\_walking}$ is the feature vector of walking flat; F is the feature vector of any walking pattern and $\hat{F}$ is the normalized feature vector of that corresponding gait pattern.

2.4. Feature Selection

Extracted features were evaluated after the normalization process based on visual and statistical analysis. One example of the statistical boxplot of the feature of maximum magnitude of the analytic signal from the IMF_2 is shown in Fig. 2.

The Fig. 2 depicts how each extracted feature was distributed across five different walking patterns whereas each box has lines at the lower quartile, median, and upper quartile values and the whiskers are lines extending from each end of the box to show the extent of the rest of the data. Outliers are plotted as the symbol of "+" beyond the ends of the whiskers. To have an effective discrimination capability, ideally the distribution of each feature would be less varied within each gait pattern and have minimum overlap between different types of walking.

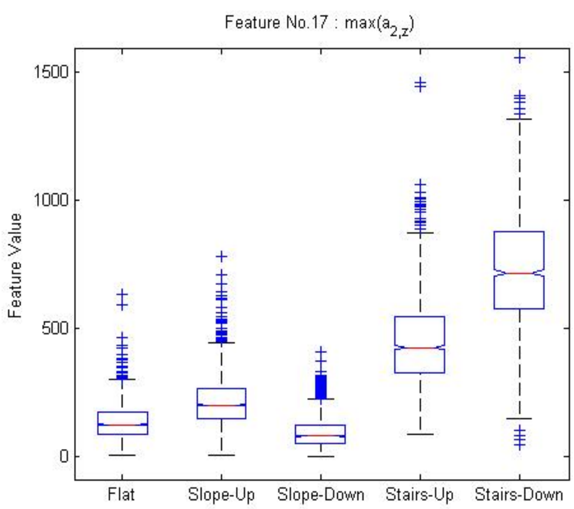

Fig.2. An example of the distribution of feature No. 17, max($a_{2,z}$), for walking flat, slope-up, slope-down, stairs-up and stairs-down

By way of a visual comparison across all such plots of feature distribution versus walking patterns, those features with less discrimination power were discarded.

As a result of the feature selection process, 20 dimensional features were finalized for classification as demonstrated in the third column of Table I. Specifically, nine dimensional features of set No. 4 with weighted mean instantaneous frequency of three analytic signals from three axes were totally removed because the amplitude weighting smeared out some distinctive characteristics of the absolute averaged IFs.

2.5. Classification

The back-end classification was performed using a Gaussian Mixture Model (GMM), which are parametric representations of a probability density function (PDF). A GMM was trained using an expectation maximization (EM) algorithm to model the PDF of the feature representation of each class. Considering the over fitting issues, 64 mixtures and 100 iterations were chosen for individual target classes. The GMM classifier has demonstrated success in previous work [5].

We performed a 10-fold cross-validation for the gait classification. In a 10-fold cross-validation, 52 subjects' data were randomly divided into 10 data sub-groups including 5 to 6 patients. Each sub-group was tested against the GMM trained using the remaining nine sub-group's data. The test results were then averaged over the 10 validation outcomes.

3. RESULTS AND DISCUSSION

Based on the selected 20 dimensional features extracted from the IMFs obtained by means of the EMD, overall classification accuracy of 96.02% was achieved for the five gait patterns using the 64-mixture GMM classifier.

Table II presents the classification accuracies of different types of walking activities in the format of a confusion matrix. It can be noted that walking stairs-down was classified with the highest accuracy of 98.81%. This intuitively makes sense since every subject essentially produced the largest magnitude of acceleration in the vertical direction (z-axis) for this type of gait pattern. On the other hand, walking flat was classified with the lowest accuracy of 92.30% because different subjects inherently tend to have their own manner of level walking resulting in large variance within this movement.

TABLE II
CLASSIFICATION ACCURACY (%) CONFUSION MATRIX FOR THE FIVE WALKING PATTERNS STUDIED USING THE GMMS CLASSIFIER OVER 52 SUBJECTS BASED ON THE 20 DIMENTIONAL FEATURES

Walking Activities	Flat	Slope Up	Slope Down	Stairs Up	Stairs Down
Flat	**92.30**	0	7.36	0	0.33
Slope-Up	0.64	**96.95**	0.53	1.88	0
Slope-Down	5.91	0	**93.76**	0	0.33
Stairs-Up	0	1.18	0	**98.27**	0.55
Stairs-down	0	0	0.27	0.92	**98.81**
Overall Accuracy	**96.02**				

As a comparison, Sekine et al. [9] and Nyan et al. [10] presented classification accuracies between walking on a stairway (up and down) and walking on a flat surface with high classification rates of 98% among 20 male subjects and 99% among 22 subjects, respectively. However, they only examined three types of walking patterns with limited numbers of subjects compared with our classification of five gait classes verified on 52 subjects' data.

A comparative study has been conducted on the performance of various features contributing to the overall classification accuracy with different numbers of features between before and after walking-flat feature normalization. The results of this experiment are illustrated in Fig. 3. After the feature selection decision was made, seven features were selected initially from the feature set No. 1 (as described in Table 1), then another seven features were selected from set No 2 combining with the initial seven features to obtain 14 features, and finally all 20 features were selected.

As plotted in Fig. 3, both the light and dark color bar plots demonstrate that the overall accuracy increases with increasing number of features. Moreover, comparing the dark color bars with the light ones, there was 10.08% to 14.54% improvement made by using the flat-walking feature normalization process. The comparison infers that the normalization process successfully minimizes the individual subject variance.

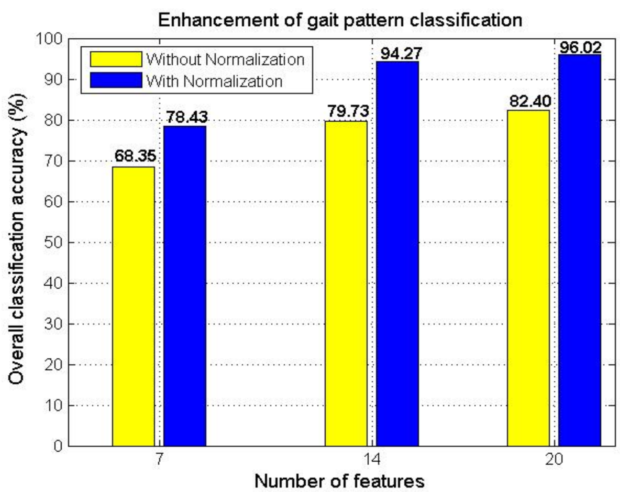

Fig.3. A comparison of overall gait pattern classification accuracy with different numbers of features before and after walking-flat feature normalization

Kuchi et al. applied EMD to the kinematic signals in gait recognition [13]. However, they applied 15 marker sensors around the body compared to only one sensor used in our experiments. Sekine et al. computed the features from three-dimensional accelerometry signals derived from a device located on the subject's back [9]. Nyan et al. made use of a garment-based detection system [10].

In our method, the classification approach covers a range of walking activities that directly impact metabolic energy expenditure. Hence it should be possible to more accurately derive estimates of energy expenditure through identification of the nature of the walking task.

4. CONCLUSION

A feature extraction technique based on empirical mode decomposition has been proposed for classification of walking activities from accelerometry data. Experiments demonstrated that the normalization process significantly diminished the individual's variance and enhanced the feature discrimination ability.

Further work will investigate the classification of different grades of up and down slope walking and the correlation between these activities and metabolic energy expenditure.

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