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Accelerometry Based Classification of Walking Patterns Using Time-frequency Analysis

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Abstract— **In this work, 33 dimensional time-frequency domain features were developed and evaluated to detect five different human walking patterns from data acquired using a triaxial accelerometer attached at the waist above the iliac spine. 52 subjects were asked to walk on a flat surface along a corridor, walk up and down a flight of a stairway and walk up and down a constant gradient slope, in an unsupervised manner. Time-frequency domain features of acceleration data in anterior-posterior (AP), medio-lateral (ML) and vertical (VT) direction were developed. The acceleration signal in each direction was decomposed to six detailed signals at different wavelet scales by using the wavelet packet transform. The rms values and standard deviations of the decomposed signals at scales 5 to 2 corresponding to the 0.78–18.75 Hz frequency band were calculated. The energies in the 0.39–18.75 Hz frequency band of acceleration signal in AP, ML and VT directions were also computed. The back-end of the system was a multi-layer perceptron (MLP) Neural Networks (NNs) classifier. Overall classification accuracies of 88.54% and 92.05% were achieved by using a round robin (RR) and random frame selecting (RFS) train-test method respectively for the five walking patterns.**

I. INTRODUCTION

Monitoring and assessing daily activity play key roles in evaluation of the quality of life of those who have limited mobility, such as elderly people. Walking is one of the most common and important forms of human daily activity. Gait analysis entails measurement analysis and assessment of the biomechanical features that are associated with walking tasks. Significant technical and intellectual progress has been made in the area of gait analysis over the past few decades.

Accelerometry is a suitable method for measuring daily activity without constraining the subject and it has been proposed as a practical, inexpensive and reliable method for monitoring ambulatory motion in free-living subjects [1] [3]. The accelerometer output is correlated to energy expenditure, which is widely accepted as the standard reference for physical activities [5] [6] [7]. Measuring physical activity in elderly people is useful not only as an aid in assessing physical well-being and wellness but also as a means of ascertaining levels of appropriate daily exercise. However, precise evaluation using accelerometry requires classification of the different types of activities since the relationship between energy consumption and accelerometer output for a range of physical activity may not be easily expressed [1].

Classification of daily activities, including standing, sitting, stand-to-sit, sit-to-stand, lying, stand-to-lie, lie-to-stand and walking, has been done using a 25-dimensional feature vector extracted from acceleration signals combined with the Gaussian Mixture Models classifier by Allen et al. [3]. Also, similar problems have been examined by Makikawa et al. [8], Fahrehberg et al. [9], and Veltink et al. [10]. For a more precise evaluation, the data must be classified into different types of walking, identifying the relationships between energy consumption and acceleration for each walking type. These relationships during walking on a flat surface (i.e. a corridor) may not be the same for walking up or down a stairwell or a slope.

For gait data that is of finite duration, non-stationary or nonlinear, Fourier analysis is of limited use [11]. Wavelet analysis may be a better alternative in such a situation. The use of wavelets as an analysis tool, as a data smoothing procedure and as a dimension reduction/feature extraction tool in biomechanics and gait analysis has escalated in the past decade [12].

When the problem to be studied is non-linear or complex, neural network based classifiers and other artificial intelligence techniques have the potential to offer a better choice in some circumstances [14] [15] and are becoming increasingly popular in gait research. Most of the work in the area has utilized artificial neural networks for gait pattern classification and recognition tasks including categorization of normal and pathological gaits [16]. Aminian et al. estimated the incline and the speed of walking by using two artificial neural networks [17]. The inputs consisted of 10 parameters that characterize the walking types between two heel-strikes. However, few (i.e. Sekine et al. [1] [2] and Nyan et al. [13]) have tried to investigate the problem of classifying various walking patterns in greater detail.

In this paper, time-frequency analysis is applied to triaxial accelerometric data to characterize and differentiate between flat walking and inclined walking (either on steps or on a uniform slope).

II. METHODS

A. The Sensor Device

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

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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.

B. Data Collection

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.

C. Feature Extraction

Features were extracted from the raw triaxial accelerometer data to form a more useful and robust representation. A window size of 128 samples ($\approx$ 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. Moreover, a window size of 128 samples enabled fast computation of discrete Fourier transforms (DFT) used for some of the features in this study.

Wavelet Packet Decomposition: Walking is predominantly a low frequency activity and, as such, many Fourier coefficients representing high frequency signal content have very low amplitude. These low amplitude coefficients can be discarded without significant loss of information [18]. Most useful information closely related to the impact acceleration is contained in the band below 17 Hz [1]. Moreover, frequencies greater than 0.25 Hz enables us to effectively separate body acceleration (BA) and gravity acceleration (GA) components [19].

To facilitate wavelet packet decomposition as shown in Fig. 1, the frequency band of 0.39 – 18.75 Hz signal, therefore, was our prime interest in this study. This approximated the 0.25 – 17 Hz signal band as detailed above. A fifth-order Daubechies wavelet was used in wavelet decomposition applied to the acceleration signal with decomposition at six levels. While it was difficult to distinguish the walking patterns in either time or frequency domain alone, the time-frequency representation offered new insight.

The 33 dimensional features that we developed based on the time-frequency domain analysis can be generalized as follows:

- The sum of squared wavelet coefficients from level 2 to 6 corresponding to 0.39 – 18.75 Hz as depicted by the shaded boxes in Fig. 1, were calculated for anterior-posterior (AP), medio-lateral (ML) and vertical (VT) axes

$$E_{AP/ML/VT} = \sum_{j=2}^{6} ||aD_j||^2 + ||dA_3||^2 + ||dD_3||^2; \quad (1)$$

- The standard deviations of the acceleration signal at level 2 to 5 corresponding to 0.78 – 18.75 Hz in three (*i.e. AP/ML/VT*) directions were obtained

$$STD_{AP/ML/VT} = std(aD_j)_{j=2,3,4,5}; \quad (2)$$

$$STD_{AP/ML/VT} = std(dA_3); \quad (3)$$

$$STD_{AP/ML/VT} = std(dD_3); \quad (4)$$

- ML acceleration is not significantly different between walking patterns [1], whereas the rms of the acceleration signal has been demonstrated to be a distinctive feature in past works [2]. The rms values were computed only in AP and VT directions at level 2 to 5 wavelet coefficients corresponding to 0.78 – 18.75 Hz

$$RMS_{AP/VT} = \sqrt{\frac{(aD_j)^2_{(j=2,3,4,5)}}{length(aD_j)_{(j=2,3,4,5)}}}; \quad (5)$$

$$RMS_{AP/VT} = \sqrt{\frac{(dA_3)^2}{length(dA_3)}}; \quad (6)$$

$$RMS_{AP/VT} = \sqrt{\frac{(dD_3)^2}{length(dD_3)}}; \quad (7)$$

where $E_{AP/ML/VT}$ represents the energy of wavelet coefficients of AP, ML and VT acceleration signal. $STD_{AP/ML/VT}$ gives the standard deviation of AP, ML and VT acceleration signal. $RMS_{AP/VT}$ calculates the root mean square values of AP and VT acceleration signals. aD_j, dA_3 and dD_3 are the wavelet coefficients of scales 2 to 6 corresponding to 0.39 – 18.75 Hz.

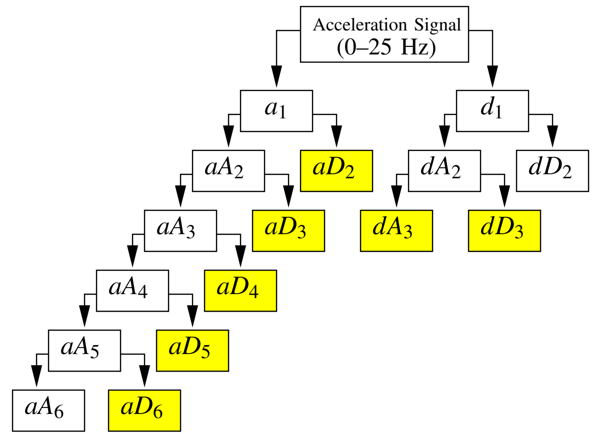

Fig. 1. Wavelet packet decomposition applied in the time-frequency domain analysis. The shaded boxes are the target frequency band signals for feature extraction.

D. Normalization

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

E. Classification Using Multi-layer Perceptron (MLP) Neural Networks (NNs)

The back-end classification was performed using a 3-multilayer perceptron neural network trained using back propagation. There were two hidden layers assigned with ten neurons on these hidden ones and one output layer with five neurons corresponding to the five classification outputs. The training and testing sequences of data were randomly selected either based on random frame selecting (RFS) or round robin (RR) train-test method. RFS and RR methods are stated in detail in section III. For an unknown sequence of data, the correct movement was then classified according to the output of MLP NNs that gave the highest likelihood score.

III. RESULTS AND DISCUSSION

A typical example of 2 seconds raw acceleration signal is shown in Fig. 2. Flat walking has more symmetrical acceleration waveforms in both AP and ML directions among the five walking patterns, which implied that the subject had roughly equal accelerations in the horizontal plane. The ML acceleration signals during walking down stairs showed that a significant impact appeared on both left and right sides of the body. The maximum acceleration in the vertical direction was regarded as heel-strike.

Overall classification accuracy rates of 92.05% using random frame selecting (RFS) train-test method and 88.54% using round robin (RR) train-test method were achieved for the five walking patterns.

The first experiment was conducted using RFS train-test method to determine the feasibility of the developed time-frequency domain features. In the RFS train-test experiment, 70% of data frames across all the five walking patterns were randomly selected as training data for the 3-layer MLP NNs and the other 30% as the testing data. These experimental results are presented in Table I.

As a comparison, Sekine et al. [1] and Nyan et al. [13] presented classification accuracies between walking on a stairway and walking on a flat surface with high classification rates of 98% among 20 male subjects and 99% among 22 subjects, respectively. However, only three types of walking patterns were examined with limited numbers of subjects. The energy expenditure in walking on paved ramps is also critical in our study. Our classification accuracy results were only a few percent lower than these other studies for descending and ascending stairs but our method involved significantly more complicated classification tasks.

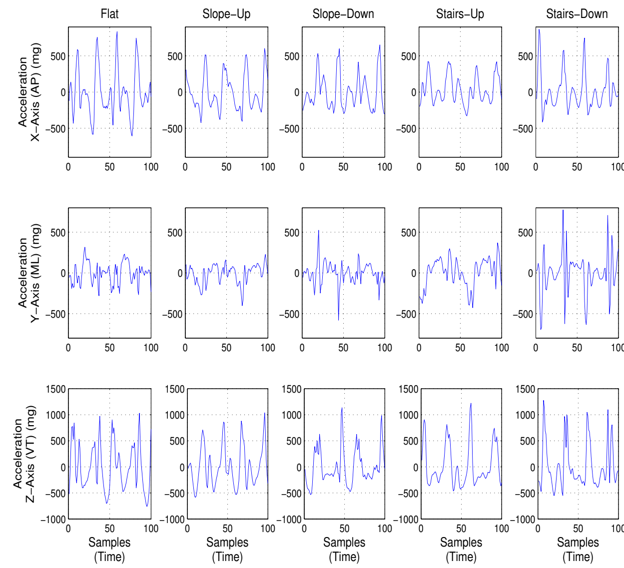

Fig. 2. A typical example of the triaxial acceleration signals in five types of walking (Subject No.30). The accelerations during flat-walking (1st column), slope-up (2nd column), slope-down (3rd column), stairs-up (4th column), stairs-down (5th column) are shown. The accelerations for anterior-posterior (AP), medio-lateral (ML) and vertical (VT) directions are shown in upper, middle and lower panels, respectively.

TABLE I

CLASSIFICATION ACCURACY (%) CONFUSION MATRIX FOR THE FIVE WALKING PATTERNS STUDIED USING THE MLP NNS CLASSIFIER OVER 52 SUBJECTS BY APPLYING THE RFS TRAIN-TEST METHOD BASED ON THE 33 DIMENSIONAL FEATURES.

Walking Activities	Flat	Slop-up	Slope-down	Stairs-up	Stairs-down
Flat	**95.94**	1.50	2.56	0	0
Slope-up	4.06	**89.10**	6.62	0.21	0
Slope-down	6.62	5.98	**87.39**	0	0
Stairs-up	0	0	0.21	**93.59**	6.20
Stairs-down	0	0	0	5.77	**94.23**
Overall Accuracy	**92.05**				

The second experiment was used to validate the robustness of the features proposed in section II-C. In the RR test (validation) experiments, data from 52 subjects were divided into five groups, each containing 10–11 subjects. One of these five groups was allocated as a testing set and the rest used as a training set. Each trial was repeated five times, each time using a different group as the test set. The results of the above five trials were averaged as given in Table II.

Comparing Table I and II, as expected the overall classification accuracy decreased. Specifically, there was a 25.4% drop in the detection of slope-up walking. It was noted that variance of training or testing data sets were large for this movement. Also, the MLP NNs needed a large number of training patterns to reduce the error since the training and testing frames were from totally different subjects and blind to each other in the RR test processes.

A third experiment was performed to show the contri-

TABLE II

CLASSIFICATION ACCURACY (%) CONFUSION MATRIX FOR THE FIVE WALKING PATTERNS STUDIED USING THE MLP NNS CLASSIFIER OVER 52 SUBJECTS BY APPLYING THE RR TRAIN-TEST METHOD BASED ON THE 33 DIMENSIONAL FEATURES.

Walking Activities	Flat	Slop-up	Slope-down	Stairs-up	Stairs-down
Flat	**95.00**	0.56	4.33	0	0.11
Slope-up	12.28	**63.67**	23.94	0.06	0.06
Slope-down	1.67	0.78	**97.44**	0	0.11
Stairs-up	0	0	0.06	**91.39**	8.56
Stairs-down	0	0.28	4.50	0	**95.22**
Overall Accuracy	**88.54**				

bution of normalization process to overall accuracy. Table III shows that the MLP NNs was able to classify the five walking patterns with 14.4% to 18.7% more accuracy through applying the normalization process.

TABLE III

COMPARISON BETWEEN THE OVERALL CLASSIFICATION ACCURACY RATE WITH AND WITHOUT NORMALIZATION PROCESS.

	Overall Classification Accuracy (%)	
	the RFS test method	the RR test method
Without Normalization	77.65	69.83
With Normalization	92.05	88.54

We compared our classification method with previous attempts in our laboratory and by others. Allen et al. [4] showed that time-domain features were effective to classify a series of postures and movements. But, walking was not studied in great detail. Moreover, they had to apply an 8th order elliptic low pass filter with a cut-off frequency of 0.25 Hz in order to separate the BA and GA components. Sekine et al. [1] computed the features from three-dimensional accelerometry signals derived from a device located to the subject's back. Nyan et al. [13] made use of a garment-based detection system.

The advantages of our method are: (1) wavelet transforms enable us to select and analyze a frequency band of interest with optimal time-frequency localization, and (2) 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.

IV. CONCLUSION

An investigation has been conducted into the effectiveness of using time-frequency domain features for classification of walking activities from accelerometry data. It demonstrated that the normalization process was essential for walking pattern feature extraction to minimize the individual's variance.

Further work will investigate the extension of these methods to other daily activities and look to applying them in a practical home telecare system.

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