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Gait episode identification based on wavelet feature clustering of spectrogram images

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Abstract—**Measurement of gait parameters can provide important information about a person's health and safety. Automatic analysis of gait using kinematic sensors is a newly emerging area of research. We propose a new approach to detect gait episodes using Neural Network and and clustering of wavelet-decomposed spectrogram images. Signals from a chest-worn inertial measurement unit (IMU) is processed using Explicit Complementary Filter (ECF) to estimate and track torso angle. Using the feature obtained from wavelet decomposition of spectrogram images, we use an Augmented Radial Basis Neural Network (ARBF) to classify walking episodes. Cluster centroids of ARBF are optimized using Rapid Cluster Estimation (RCE). A pilot study of 11 participants suggests that our approach is able to distinguish between walk and non-walk activities with up to 85.71% sensitivity and 91.34% specificity.**

I. Introduction

Measuring the frequency and length of walking activities are useful for monitoring health condition assessing treatment efficacy [1]. Passantino reported strong correlation between the chance of survival and changes in the distance walked for patients with chronic heart failure [2]. Walking is a complex process. It involves complex involuntary coordination of the limbs and torso [3]. Gait cadence (step rate) can be determined from small swings in torso angle in the sagittal plane due to the periodic shifting of moment of inertia that occurs on each phase [4].

Previousy Barralon has classified walk episode by calculating spectral energy from Short-time Fourier transform (STFT) and wavelet energy from Discrete Wavelet Transform (DWT) [4]. Barralon reported detection sensitivity of 78% and specificity of 68.7%. Bidargaddi uses similar approach using waist-worn accelerometer to distinguish walking from other high impact activities with 89.14% sensitivity and 89.97% specificity [1].

This research aims to develop more-accurate gait cycle analysis for ambulatory monitoring systems, such as those we are working on at University of Technology Sydney Centre for Health Technologies [5].

This paper describes a new approach for gait episode detection using signals from a chest-mounted IMU. It is divided as follows. Section II explains the development infrastructure. Section III describes the method. Section IV presents the data collection. Section V presents results and analysis, and Section VI provides conclusions.

II. Overview

This pilot study used a Shimmer MEMS kinematic module with a 9DoF daughterboard. The 9DoF board has a Freescale MMA7361 tri-axial accelerometer, a Honeywell HMC5843 magnetometer, and an InvenSense500 gyroscope.

Data collection and an Attitude Heading Reference System (AHRS) is run externally in J2SE running a custom driver, with 3-D visualization under jMonkey Engine. The IMU samples at 50 Hz [6]. We do algorithmic prototyping in MATLAB. The device is strapped on the participant's chest in a way that the torso angle can be observed directly from the pitch measurement. During walking, the frequency of torso-swing ranges from 0.6 to 2.5 Hz, [4, 7], so we sample data for processing at 20Hz.

III. Method

The method includes three processes: torso angle estimation, time-frequency signal processing, and spectrogram image processing. First, the orientation quaternion q of the sensor is estimated using the explicit complementary filter (ECF) [8] applied to measurements of angular velocity ω and acceleration a. Pitch information θ is calculated from the sensor orientation. The signal is then convolved with a digital band pass filter (bpf) with cutoff frequencies of 0.5Hz and 5Hz to yield θ_{bpf}. Autocorrelation is used to minimize noisy signals on θ_{bpf}. The Discrete Fourier Transform (DFT) is then be applied to the autocorrelated signal using Bartlett's method to extract the spectrogram $S(f,t)$. Overlapped spectrograms are averaged. The spectrogram image from 0Hz to 5Hz is cropped and transformed using discrete wavelet transform (DWT) to the third order using Haar wavelet. This image feature is used as the input to the Augmented Radial Basis Neural Network to classify whether the activity is walking or not walking. The learning process consists of the use of Rapid Centroid Estimation (RCE) to determine optimal cluster centroids for the training set. The block diagram describing the gait cycle classification algorithm can be seen in Figure 1.

A. *Torso Angle Estimation*

Torso angle is estimated using ECF applied to the information from the gyroscope and accelerometers [8]. Our initial tests suggest that the information provided by these two sensors is sufficient to estimate torso angle.

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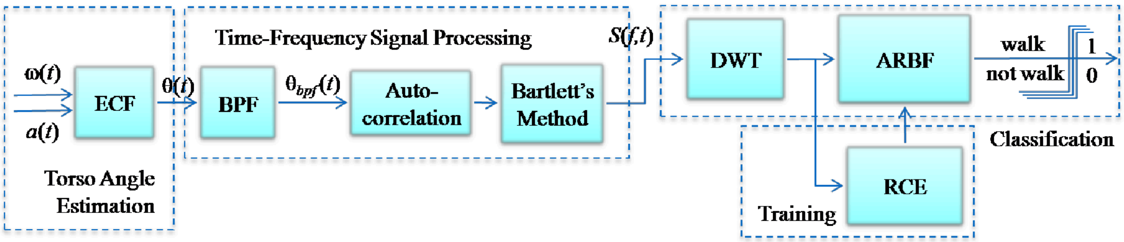

Figure 1. Block Diagram of the Gait Cycle Classification Algorithm

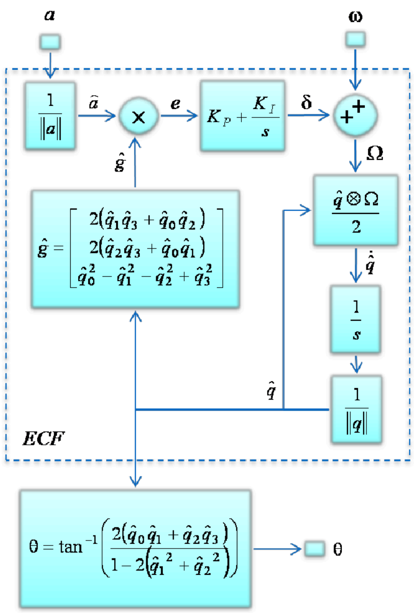

Figure 2. Block Diagram of the Torso Orientation Estimation Algorithm

The output of the rate gyroscope ω and normalized accelerometer reading $\hat{a}$ can be represented in vector form as in (1) and (2). The symbol ^ denotes a (1-norm) unit vector.

$$\omega = \begin{bmatrix} 0 & \omega_x & \omega_y & \omega_z \end{bmatrix}^T \tag{1}$$

$$\hat{a} = \begin{bmatrix} 0 & \hat{a}_x & \hat{a}_y & \hat{a}_z \end{bmatrix}^T \tag{2}$$

System attitude $\hat{q}$ is estimated by integrating $\dot{\hat{q}}$ (3). Rotation $\dot{\hat{q}}$ is evaluated using a simple quaternion product of the current estimate and the compensated gyroscope measurement (4). Innovation δ is updated using proportional-integral (PI) compensation (5). The proportional gain K_P corrects the attitude information by referring to gravity. The integral gain K_I corrects gyroscope bias. The error is the relative rotational discrepancy between the $\hat{q}$ estimate of the z-axis of the inertial frame and the gravitational reference from the accelerometer $\hat{a}$ (6-7).

$$\hat{q} = \int \dot{\hat{q}}\,dt \tag{3}$$

$$\dot{\hat{q}} = \frac{1}{2}\hat{q} \otimes (\omega + \delta) \tag{4}$$

$$\delta = K_P e + K_I \int e\,dt \tag{5}$$

$$e = \hat{a} \times \hat{v} \tag{6}$$

$$\hat{v} = \begin{bmatrix} 2(\hat{q}_1\hat{q}_3 + \hat{q}_0\hat{q}_2) \\ 2(\hat{q}_2\hat{q}_3 + \hat{q}_0\hat{q}_1) \\ \hat{q}_0^2 - \hat{q}_1^2 - \hat{q}_2^2 + \hat{q}_3^2 \end{bmatrix} \tag{7}$$

The orientation of the torso is then calculated using a quaternion to Euler angle transformation (8),

$$\theta = \tan^{-1}\left(\frac{2(\hat{q}_0\hat{q}_1 + \hat{q}_2\hat{q}_3)}{1 - 2(\hat{q}_1^{\,2} + \hat{q}_2^{\,2})}\right) \tag{8}$$

In (8), θ represents the pitch angle equivalent of the quaternion that corresponds to the torso angle as per the installed orientation of the sensor.

A block diagram describing the data flow of the torso orientation estimation algorithm is given in Figure 2.

B. Time-Frequency Signal Processing

On detection period T_d, which is set to happen every 20 samples, the time domain signal of torso angle is first filtered with a band pass filter. Autocorrelation is applied to the filtered signal to extract its fundamental frequency and reduce unwanted noise. The signal is transformed using Bartlett's method to estimate the power spectra.

A 4th order Butterworth filter with cutoff frequencies of 1 Hz and 5 Hz is used because of its perfectly flat frequency response within its pass band. Autocorrelation is used to extract fundamental frequency of a single tone signal based on its periodicity. This property is highly useful for gait parameter analysis where the gait-cadence frequency is of primary interest [9]. The waveforms before and after the time frequency signal processing are shown in Figure 3.

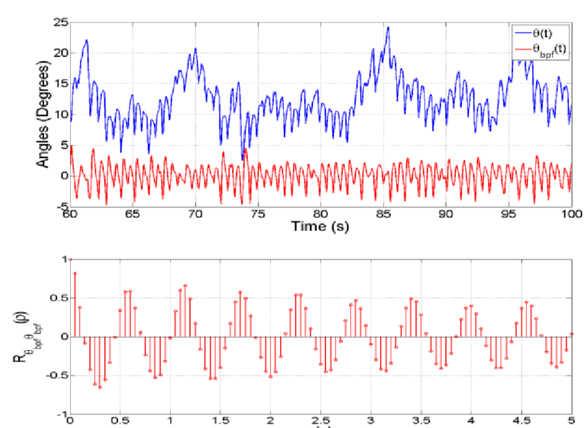

Figure 3. Torso angle θ and and its band passed filtered signal with respect to time during walk (top) and autocorrelation (bottom)

Spectrogram overlaps are averaged as more signals are collected over time. Blackman-Harris windows are used for each DFT transform. In this situation, Bartlett's method is preferable to that of conventional STFT because the spectrograms it produces are denser, more defined, and less noisy.

C. DWT Image Feature Extraction

Spectrogram image processing is exploited as a powerful signal processing method in many fields including speech processing [10] and biomedical engineering [11, 12]. Recent research by El-Gohary demonstrated the capability of spectrogram analysis using kinematic sensors to track tremors in Parkinson Disease patients in free-living conditions [12].

Each second the spectrogram image of 20 seconds before current activity is cropped (400 samples). The image resolution is exactly 128 by 400. 128 is the number of FFT bins used (0-10Hz). Since walking activity is characterized by frequency between 0.6 to 2.5Hz, we crop the image to 5Hz. The cropped image size is reduced to 64 by 400. DWT to the third order is applied to the cropped image. We use the approximation image coefficients from the resulting transform. The resulting image size is further reduced to 8 by 50. This approach effectively discretizes the 5Hz bandwidth to 8 levels. Frequency consistency in the first four level of the image is an important feature for describing walking cadence. These images are used for training and classification. DWT features of walking spectrogram can be seen in Figure 4. DWT features of non-walking spectrogram can be seen in Figure 5.

Figure 4. DWT features of walking signal from torso angle spectrogram

Figure 5. DWT features of non-walking signal from torso angle spectrogram

D. Swarm Rapid Centroid Estimation

Rapid Centroid Estimation (RCE) was recently proposed as a lightweight variant of Particle Swarm Clustering (PSC) [13, 14]. A comprehensive information on swarm strategy for RCE used in this paper can be read in [15]. The Swarm RCE is used to cluster the DWT features obtained from III.C. We encourage readers to refer to the original papers for comprehensive information on the algorithm and optimization strategies [13-15]. The results can be seen in Figure 6.

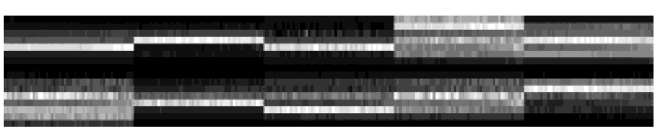

Figure 6. Cluster centroids of DWT features of torso angle spectrogram optimized with RCE

E. Augmented Radial Basis Function – Neural Network

Augmented Radial Basis Neural Network (ARBF-NN) or simply ARBF was proposed as a variant of RBF neural network. It has been used for the classification of head movement command using head-worn accelerometer [16] and classification of falls using waist-worn accelerometer [5].

The ARBF uses Gaussian radial basis kernel, and is highly dependent to the quality of centroids. The input to the RBF layer is the vectorized DWT feature image which dimension is 8*50 = 400. The dimension of the Gaussian kernel is then equal to 400. The output of the RBF layer is a vector where μ_n and σ_n correspond to cluster centroids and the standard deviation of each RBF node. In this paper the RBF centroids for ARBF are optimized using RCE (III.D). The MLP layer uses both sigmoid kernels in hidden and output layer. No normalization method is required for MLP because the RBF layer has already normalized the input signals from 0 to 1. The MLP layer is trained with resilient back-propagation. The configuration of ARBF can be seen in Figure 7.

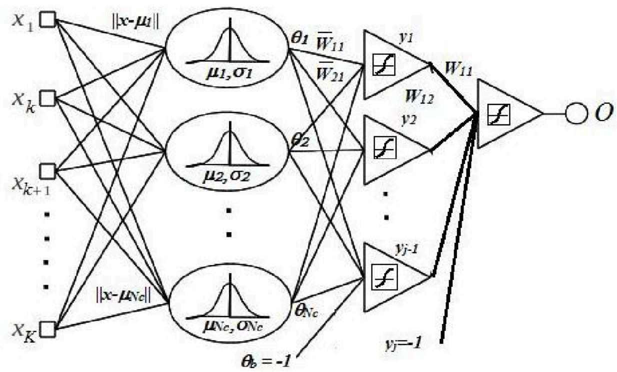

Figure 7. The Augmented Radial Basis Neural Network (ARBF)

IV. EXPERIMENTAL SETTINGS AND DATA COLLECTION

The algorithm was tested using data recorded from 11 participants. Three of the participants are elderly people aged over 55. The data was collected in an office environment. The data collection scheme was devised to resemble movements associated with ordinary daily living activities. Each data collection period consisted of ten to fifteen minutes of data collection per participant. During each data collection period, the subjects typically alternated between walking and not walking for a few minutes at a time.

The participants were encouraged to relax and move however they wanted to. The activities of the participants during non-walk periods included talking, browsing the internet, standing up/sitting down, lying down, making coffee, writing, drawing, playing a musical instrument, singing, playing computer games, stretching, and reading books. The participants were also encouraged to walk at a comfortable pace for a period of around two minutes to five minutes. Casual activity such as talking, eating and drinking was encouraged throughout the whole data collection period.

The experimental data composition can be seen in Table I. 3617.6 seconds (72352 samples) of walking signal and 5511.2 seconds (110223 samples) of not-walking signal were recorded.

TABLE I. EXPERIMENTAL DATA COMPOSITION

Data Type	Walk (samples)	Not-Walk (samples)	Ratio to total data	Included Subjects
Training	12661	19289	17.5%	1,2,3
Validation	2713	4133	3.75%	1,2,3
Test	56987	86801	78.75%	4-11

The spectrogram features used in this experiment are torso angle signals calculated using III.A, raw acceleration magnitude from accelerometer readings, and Anteroposterior acceleration (a_y). For each 400 samples, features are calculated using III.B to III.C. Swarm RCE is then used to cluster the features as described in III.D. The clustering result is used as the ARBF basis centroids. MLP segment of ARBF is then trained using resilient back-propagation.

V. RESULTS AND DISCUSSIONS

Table II shows the performance of the classifier using different features. From Table II, it can be seen that torso angle provides best performance. Features from torso angle signals reach up to 85.71% sensitivity and 91.34% specificity. The area under the curve (AUC) of torso angle is higher than the other algorithms (0.9454 compared to 0.9250 and 0.9024). These results suggest an improvement compared with prior research [4, 7]. The ROC curve can be seen in Figure 8.

We have observed that torso orientation obtained using ECF is insensitive to impacts. The resulting autocorrelation of the torso angle of a walking signal is very similar to a sinusoid which makes the spectrogram of walking and non-walking very distinct (III.B). This is true even when the subject is talking or coughing while walking.

TABLE II. CLASSIFIER PERFORMANCE

Feature	Performance		
	Sensitivity	*Specificity*	*AUC*
Torso Angle (θ)	85.71%	91.34%	0.9454
Acc. Magnitude ($\sqrt{a_x^2 + a_y^2 + a_z^2}$)	81.31%	90.69%	0.9250
Anteroposterior Acceleration (a_y)	78.93%	91.47%	0.9024

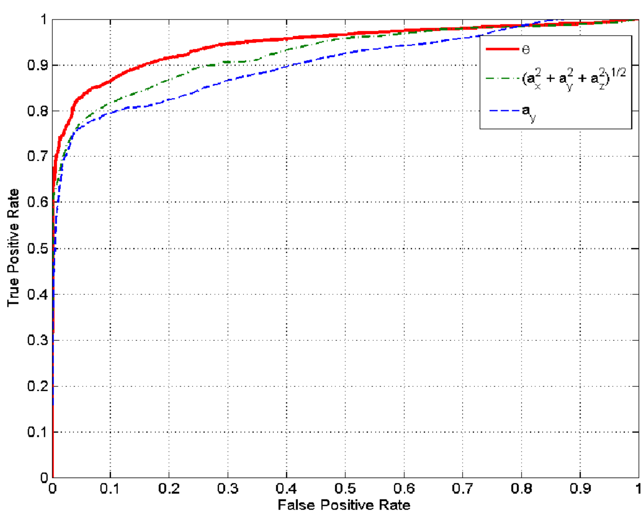

Figure 7. ROC curve of the classifier trained using different features

VI. CONCLUSIONS AND FUTURE DIRECTIONS

Using an accelerometer and a gyroscope, the results of the pilot study suggest that spectrum analysis may be useful to distinguish walking activity from other activity. We have shown that greater performance can be achieved by using spectrogram analysis, DWT, RCE and ARBF. Our plans for the future include further work to increase robustness and implementation in real time.

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