LINEAR PREDICTIVE MODELLING OF GAIT PATTERNS

Ronny K. Ibrahim[1], Eliathamby Ambikairajah[1], Branko G. Celler[1], and Nigel H. Lovell[2,3]

[1]School of Electrical Engineering, University of New South Wales, Sydney, NSW, 2052, Australia
[2]Graduate School of Biomedical Engineering, University of New South Wales, Sydney, NSW, 2052
[3] National Information Communications Technology Australia (NICTA), Eveleigh, NSW, 1430
z3153320@student.unsw.edu.au, ambi@ee.unsw.edu.au, b.celler@unsw.edu.au, N.Lovell@unsw.edu.au

ABSTRACT

The use of a wearable triaxial accelerometer for unsupervised monitoring of human movement has become a major research focus in recent years. In this paper, the relationship between accelerometry signals and human gait is analysed using a linear prediction (LP) model. We explore the use of the LP model for analysing five gait patterns and show that the LP cepstrum can be used for gait pattern classification with high accuracy. This is then compared to a filterbank based approach to estimate the cepstral coefficients. Fifty subjects participated in collection of gait pattern data involving walking on level surfaces, and walking up and down stairs and ramps. The results show that an overall accuracy of 93% can be achieved using features derived from the cepstral coefficients for the five different walking patterns.

Index Terms- *Gait Modelling, Gait Classification*

1. INTRODUCTION

Gait analysis when applied to the study of walking provides detailed information on body movements. The ultimate goal of such an analysis is to provide reliable objective data for making clinical judgements and assessments. Thousands of gait features/parameters have been used over the years for such analyses. The selection of optimal gait features forms an important part of any gait analysis research process. In this application biomechanical gait models are used to relate visual features extracted from video with rotations and translations of parts of the body, such as thighs, hips, ankles and knees, over time[1].

In the past few years, accelerometric sensors have been used in studying daily physical activities and considerable work has been done in applying accelerometric technology to gait studies. Three-dimensional models for gait analysis of human motion have been constructed as described in [2], and [3] links gait characteristics to acceleration data recorded at the waist. Changes in gait patterns due to ageing by using support vector machines and neural networks have been investigated in [4]. Normal gait-pattern acceleration signals, measured at the thigh, have been documented by [5]. In [6], the use of a Kalman filter to estimate inclination from a trunk-mounted accelerometer is explored, and [7] used a gyroscope placed at the shank to detect stair climbing.

The human gait is a very complex process, involving the movement of many body segments. Modelling gait patterns has been a challenging task and can be accomplished in a number of different ways, including using biometric sensors where the displacement of different parts of the body is measured. The main objective of the work reported in this paper is to model the acceleration signals corresponding to five gait pattern (flat-slope down-slope up-stairs down-stairs up), captured by an accelerometer positioned on the person's waist. We also aim to classify the different gait patterns using features extracted from the model.

2. GAIT MODEL

Acceleration is the second derivative of displacement and consequently the measured acceleration signal captured through the accelerometer comprises translational acceleration, rotational acceleration, gravitational acceleration, vibrations of muscles, the coupling impact resulting from the movement of the different parts of the body, and the impact of the foot-strike event. Even though muscles can be modelled as a mass, a spring and a dampener [8] (Figure 1), its complexity makes it difficult to analyze the gait pattern in detail. Therefore, assumptions are made during gait patterns modelling. The common assumption is that hip acceleration comprised of impulse excitations (from the foot strikes) propagate through the biomechanical model (spring-mass-dampener system) to the hip.

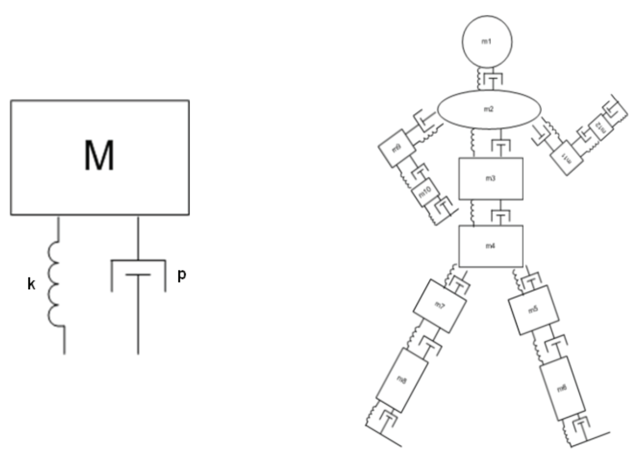

Figure1. Biomechanical model of muscles of a human, where M is the mass, k is the spring constant and p is the damping coefficient.

In this paper, hip acceleration is modelled by placing poles at the frequencies which produces a good model. This process can be estimated using a linear predictor model where the present value is formulated as a linear combination of the past values.

3. THE ACCELEROMETER MODEL

The accelerometer signal measured can be modelled as the sum of the hip acceleration, the gravitational acceleration and artefacts caused by the muscles and the foot-strike events.

$$x_a = x_{hip} + x_{gravity} + x_{artefacts} \qquad (1)$$

Omitting the gravitational component, the acceleration signal can be modelled as shown in Figure 2. It has been shown that the hip movement acceleration can be modelled as a 2nd order all pole system since it is known to be a quasi-periodic signal [1]. The artefacts from the muscles and foot-strike events can be modelled as an auto-regression-moving-average (ARMA) model. The model transfer functions are found using the MATLAB System Identification Toolbox.

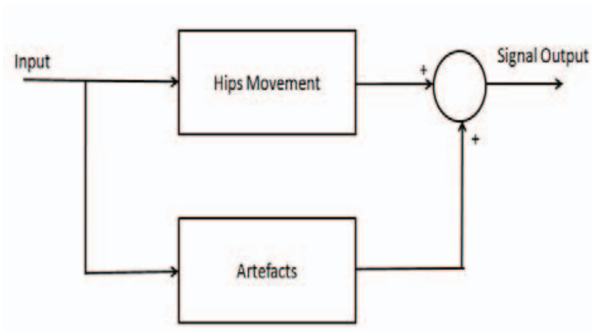

Figure2. Accelerometer signal modelling

The model in Figure 2 combining a 15th order ARMA model of the artefacts and a 2nd order LP model of the hip movement is then approximated by a 30th order linear predictor model. The linear predictor model is given by:

$$\hat{x}(n) = K + \sum_{k=1}^{p} c_k x(n-k) \qquad (2)$$

where c_k is the kth predictor coefficient, p is the number of previous samples used in the prediction, and K is an arbitrary gain factor.

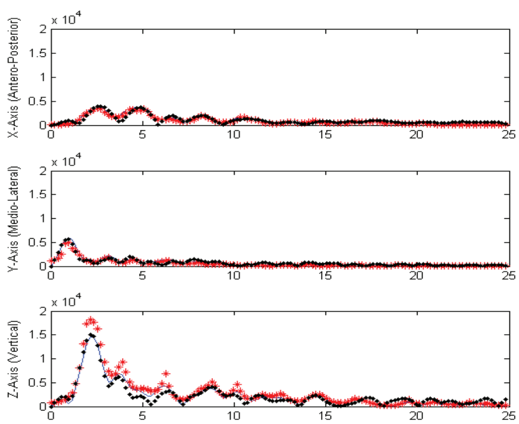

Figure3. The model comparison of the original signal spectrum(blue lines), the gait model(black dots), and the LP model shown by the red star for stairs down walking.

The magnitude spectra of the original 15th order ARMA model (black dots) and the 30th order linear predictor model (red crosses) are compared to the magnitude spectrum of the measured acceleration signal (blue line) for a gait pattern corresponding walking downstairs is shown in Figure 3. It can be seen that the 30th order LP model is reasonably accurate in modelling walking pattern (down stairs). We have used similar models for other gait patterns as well.

4. CLASSIFICATION

We tried to visualize the LP coefficients of the five gait patterns using non linear mapping [9]. The LP coefficients are mapped to a lower dimension space, while maintaining the relative distances between them in the original feature space.

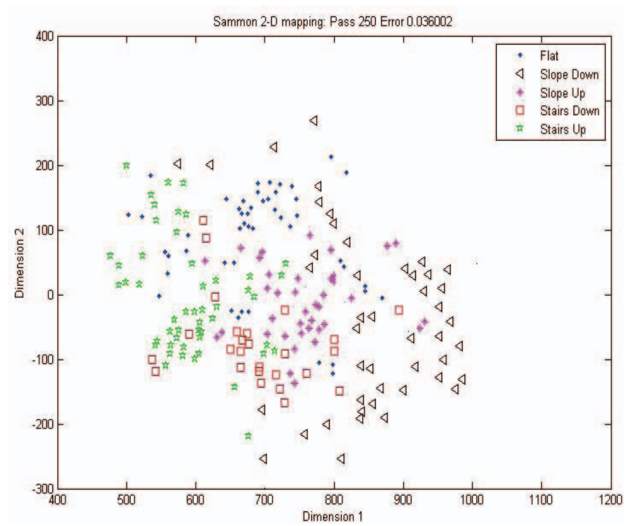

Figure4. Nonlinear mapping of the linear prediction coefficients of five gait patterns

The large amount of overlap among the LP coefficients of different gait patterns as can be seen in Figure 4 suggests that they are not suitable to be used as features for gait pattern classification directly. For classification purposes, we transformed the LP coefficients into the cepstral domain. This is done using the following equations:

$$c_0 = ln(\sigma^2) \qquad (3)$$

$$c_m = a_m + \sum_{k=1}^{m-1} \left(\frac{k}{m}\right) c_k a_{m-k} \quad \text{for } 1 \le m \le p \qquad (4)$$

where a_m is the mth LP coefficient, c_0 is the LP gain, p is the LP order and c_m is the mth cepstral coefficient.

The separation between the five gait patterns is much better when using the LP based cepstral coefficients as seen in Figure 5 than when using the LP coefficients directly.

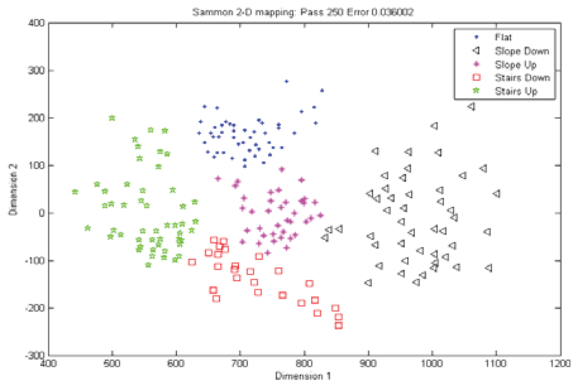

Figure 5. Nonlinear mapping of the LP based cepstral coefficients of five gait pattern

Alternately, speech processing literature suggests that cepstral features can be obtained using a set of bandpass filters. This approach is more robust than obtaining the cepstral coefficients from the LP coefficients and is used in the work reported in this paper. Here the cepstral features are extracted by first taking the DFT (256 point DFT) of the signal.

$$X_i(k) = \sum_{n=0}^{N-1} x_i(n).e^{-j.\frac{2\pi nk}{N}} \quad (5)$$

where X is the frequency domain signal, x is the time domain signal, i represents the different axis(1 – antero-posterior, 2-medio-lateral, 3 - vertical).

The spectral magnitude coefficients are then grouped into bands. In each of the axes, three bands are used. The bandwidths are fixed where the first band is used to capture the gravitational acceleration, the second band is used to capture the energy of the foot strike cycle and the third band is used to capture the other acceleration components such as muscle vibrations and the rotational acceleration components. The gravitational band was selected at 0-0.5Hz where previous researchers have selected a number of different values from 0 to 0.25-0.5Hz [10-12]. The main foot strike band was selected from 0.5 Hz-3.5 Hz. The main basis for bandwidth selection was a separate experiment where the subjects were asked to walk at various speeds from 3km/h to 7km/h on a treadmill and it was found that the foot strike frequency lies between 1 Hz to 3 Hz (Figure 6). The artefacts bandwidth was selected to be from 3.5 Hz to 13.5 Hz because from observations (see Figure 6), there are little energy that lies beyond 13.5 Hz.

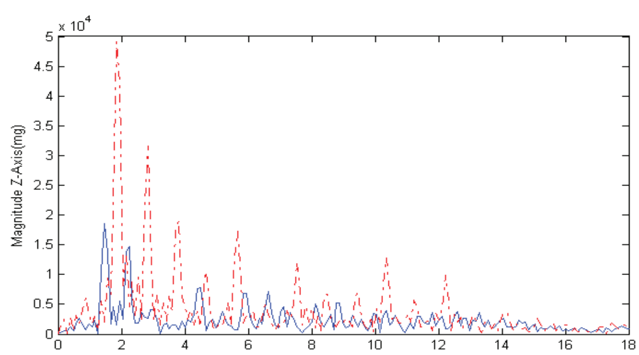

Figure 6. FFT of flat gait pattern with different speed (solid – 3km/h; dotted – 7km/h).

Figure 7 shows an example of this band grouping. The bandwidth specification is listed in Table 1.

Table1. The bandwidth specifications of the bandpass filters

Feature Number	Axis	Bandwidth no.	Bandwidth (Hz)
1		1(gravitational)	0.5
2	X	2(peak)	3
3		3(artefacts)	10
4		1(gravitational)	0.5
5	Y	2(peak)	3
6		3(artefacts)	10
7		1(gravitational)	0.5
8	Z	2(peak)	3
9		3(artefacts)	10

We hypothesized that the artefacts in the signal for the different walking patterns are different. Hence, we propose the use of zero crossing counts in the artefacts band (3rd band). The zero crossing counts can be estimated as:

$$n_{ZCC_i} = \frac{1}{2}\sum_{m=1}^{N}\left|sign\left(s_i(m)\right) - sign\left(s_i(m-1)\right)\right| \quad (6)$$

where i=*1,2,3* is the axis label, N is the window size, and s is the time domain signal.

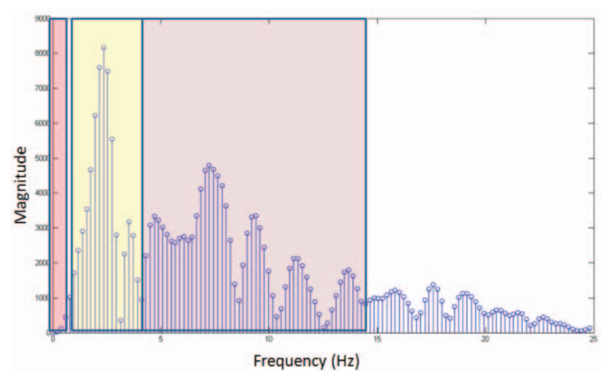

Figure7. Bands allocation for the Antero-Posterior acceleration

The cepstral coefficients obtained from the filterbank are able to separate the five classes very well as can be seen from Figure 8.

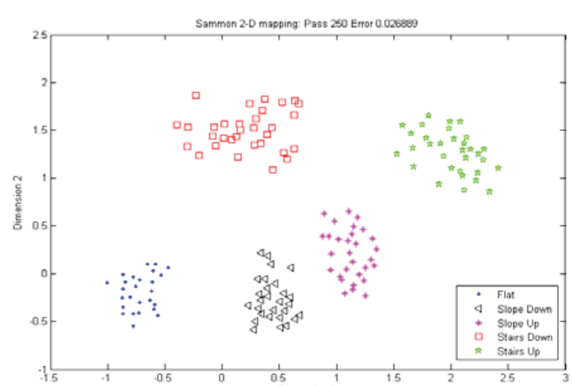

Figure8. Nonlinear mapping of the filterbank based cepstral coefficients of five gait pattern

5. DATABASE

The accelerometric data used in this work was collected from 50 participants (13 females and 37 males) aged between 21 and 65 (with a mean age of 30 years). Each participant was asked to walk 10 times over a set course of flat ground for a distance of 43 m, up and down an incline of approximately 10^o for a distance of 22 m and up and down a flight of 16 stairs. A triaxial accelerometer (triax) was placed on the right side of the waist, with the X-axis being approximately aligned with an anterio-posterior movement, the Y-axis with sideways movement, and the Z-axis with vertical movement.

6. EXPERIMENTS AND DISCUSSIONS

A classification experiment was performed using the cepstral features extracted from the LP model (equation 2-3) and an 8^{th} mixture Gaussian Mixture Model (GMM) as a backend. This system was then compared to another one using cepstral features extracted from the bandpass filters (Table 2). The subjects were divided into two groups, with 40 subjects for training and 12 subjects for testing.

Table2. Classification accuracy of different features using GMM

Movement	Classification Accuracy (%)	
	LP Cepstral	Filterbank Cepstral
Flat	80.4	90.5
Slope Down	85.5	87.6
Slope Up	78.9	94.5
Stairs Down	90.5	98.7
Stairs Up	83.9	96.1

Table 2 gives the classification accuracy for each of the five gait patterns for both LP based cepstral features and filterbank based cepstral features. It can be seen that the filterbank based cepstral features performed better than the LP based ones. This is also supported by the nonlinear mapping plots shown in figures 5 and 8.

A second experiment involving addition of zero crossing counts (ZCC) to the cepstral features obtained using the filterbank for the classification was also performed. When both features were combined it can be seen from Table 3 that the classification accuracy is higher than when either one is used on its own.

Table3. Correct classification rate of adding ZCC features

Features	Classification Accuracy (%)
ZCC	48
Filterbank Cep	93.5
Filterbank Cep + ZCC	95

As for comparison, [13] has implemented a spectral based features where the whole FFT points are transformed into spectral coefficients using the DCT to be used for gait classification. It has been reported that an accuracy of 86% was achieved with 60 features. The method described in this paper has fewer features and better classification accuracy.

7. CONCLUSION

This paper shows that the accelerometer signal derived from a waist worn triax can be modelled using an LP model. Cepstral features derived from the LP model can be used to classify the five pre-specified gait patterns. The experimental results also show that cepstral features obtained from bandpass filters result in a high gait pattern classification rate. When combined with zero crossing count features from the artefact filter bands the classification rate is improved further. Further investigations are underway to study the robustness of these features on a larger database.

REFERENCES

[1] W. Ziljstra et al, “Displacement of the pelvis during human walking : experimental data and model predictions”, *Gait & Posture* 6, pp 249-262, 1997.

[2] S. L. Dockstader et al, “Feature Extraction for the Analysis of Gait and Human Motion”, 2002

[3] T. Wark, et al, “A framework for linking gait characteristics of patients with accelerations of the waist,” IEEE – EMBS. 27th Annual Conference EMBS, pp. 7695-7698, 2005.

[4] R. K. Begg et al, “Computational Intelligence for Movement Sciences : Neural Networks, Support Vector Machines and Other Emerging Technologies” *Idea Group Pub* 2006

[5] B. J. Bussmann et al, “Measuring daily behaviour using ambulatory accelerometry: The Activity Monitor *Behaviour Research Method” Instruments & Computers* vol. 33 pp. 349-356, 2001.

[6] P. H. Veltink “Inclination Measurement of Human Movement Using a 3-D Accelerometer with Autocalibration” *IEEE Transactions on Neural Systems and Rehabilitation Engineering vol.12,* 2004.

[7] Coley et al “Stair climbing detection during daily physical activity using a miniature gyroscope” *Gait & Posture* vol. 22 pp. 287-294, 2004.

[8] B. M. Nigg, W. Herzog, “Biomechanics of the Musculo-skeletal system” Wiley 3rd ed.

[9] J. W. Sammon, “A Nonlinear Mapping for Data Structure Analysis,” IEEE Trans. On Computers, vol. c-18, 1969.

[10] F. R. Allen, et al, “Classification of a known sequence of motions and postures from accelerometry data using adapted Gaussian mixture models”, Physiological Measurement vol. 27 pp. 935-951, 2006.

[11] J. Fahrenberg, et al, “Assessment of posture and motion by multichannel piezoresistive accelerometer recordings,” Psychophysiology, vol. 34, pp. 607-612, 1997.

[12] F. Foerster, et al, “Motion pattern and posture : correctly assessed by calibrated accelerometers,” Behavior Research Methods, Instruments and Computers, vol. 32, pp/ 450-457, 2000.

[13] R. K. Ibrahim, et al, “Gait Pattern Classification Using Spectral Features,” IET Irish Signals and Systems Conference, Galway, Ireland, July 2008.