Gait Pattern Classification Using Compact Features Extracted From Intrinsic Mode Functions

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Abstract—Recent research work indicates that gait patterns are both non-linear and non-stationary signals and they can be analyzed using empirical mode decomposition. This paper describes gait pattern classification using features that are obtained by performing discrete cosine transforms (DCT) on intrinsic mode functions of five different human gait patterns. The DCT provides a compact 8-dimensional feature vector for gait pattern classification. Fifty two subjects participated in the experiment. The classification was performed using a Gaussian mixture model and an overall accuracy of 90.2% was achieved.

I. INTRODUCTION

Recent advances in information communications and sensor technologies have meant that telemedicine systems for automated monitoring of elderly subjects either living at home or in institutionalized care have become a near reality. The ability to monitor the ambulatory patterns of the elderly living alone would enable home telecare systems to detect risks of falling as well as better assess activities of daily living [1].

Walking is one of the most common and most important of these activities and therefore gait studies are critical to the monitoring of ambulatory patterns. Assessing different walking patterns can provide valuable information regarding an individual’s mobility, energy expenditure and stability during locomotion. Having the ability to automatically classify different walking patterns and the surrounding terrain over which the person is walking, provides useful information leading to further understanding of both gait and the person’s metabolic energy expenditure.

Previous research [2, 3, 4] on human movement classification from accelerometric data has focused on a small subset of possible motions and postures in controlled laboratory situations. This issue has been addressed to a certain extent in [4], investigating multiple walking patterns (level, stairs, and slopes).

A wide range of techniques have been investigated for the purpose of gait analysis including wavelet analysis [2] and the use of linear predictive biomechanical gait models [5] to identify key harmonic components of the human gait. Identification of gait disorders using ground reaction force measurement with self-organising maps has been investigated in [6]. Statistical methods [7], fuzzy and fractal methods [7] and methods using multiple sensors (accelerometer, altimeter) [3] have also been used to detect walking patterns, as have neural networks for gait pattern classification [8, 9].

Numerous previous studies have also used multiple accelerometers in evaluating daily physical activities by placing multiple accelerometers at a subset of the thighs, wrists, arms, sternum, hips and lower legs [10-12]. Apart from wearability and compliance issues, employment of multiple wearable sensors brings a number of restrictions 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.

Recently, Empirical Mode Decomposition (EMD) has been proposed by [13, 14] as an effective tool for gait pattern classification. However, the number of features used in their experiments was in the order of 20. The aim of this paper is to use the Discrete Cosine Transform (DCT) to reduce the feature dimension whilst maintaining high classification accuracy.

II. METHODOLOGY

A. Instrumentation

The sensor used in this study was a single waist mounted tri-axial accelerometer (triax) with a dynamic range of ±6g and is capable of measuring both static and dynamic acceleration along three orthogonal axes (X, Y and Z), resulting in three signal streams at a sampling rate of 50 Hz. The acquired signals are the net result of the body acceleration due to movement of the subject, acceleration due to gravity and other external forces. In most cases the external forces are negligible and thus the main components are body acceleration and acceleration due to gravity. The gravity component is usually found below 0.5 Hz while the body acceleration component can go up to 20 Hz in the frequency domain. Hence the sampling was chosen to be 50 Hz.

B. Data Collection

Gait data were collected from 52 subjects (13 females and 37 males) aged between 21 and 65 (mean age of 30 years) over a period of 3 months. Each subject was asked to walk over a set course of flat ground for a distance of 43 m, up and down a flight of 16 stairs. A triax was placed on the right side of the waist, with the X-axis being...
approximately aligned with an anteroposterior movement, the Y-axis with sideways movement, and the Z-axis with vertical movement.

C. Feature Extraction

Figure 1 shows a block diagram of a Gaussian Mixture Model (GMM) based walking pattern classification system. Such a classifier consists of a front-end (feature extractor) and a back-end (classifier) containing one GMM per class (walking pattern).

![Block Diagram of a GMM-based classifier](image)

The block diagram of the proposed front-end is shown in Figure 2. The three streams of accelerometric data are first low pass filtered (0-17 Hz). The signal is then decomposed into nine intrinsic mode functions (IMF) using a sifting process. The first three IMFs and the residue are chosen and used for features. The energy ($E_m$) of each IMF is then calculated as follows:

$$E_m = \frac{1}{S} \sum_{k=1}^{N} [\text{IMF}_m(k)]^2$$  \hspace{1cm} (1)

where $m$ is the mode number, $N$ is the total number of samples in the frame, $S$ is the number of walking steps in that frame. After computing equation 1 for X, Y, Z signals, we obtain a 12-Dimensional Energy vector as shown in Figure 2.

![A schematic representation of the front-end feature extraction](image)

It can be seen the IMF output in Figure 3 that the number of walking steps can be easily calculated by thresholding. In our experiment the threshold value is chosen as one third of the maximum peak within that frame.

![The vertical acceleration signal is shown by the line, the IMF 3 is shown by the dotted line and the threshold is shown by the bold line](image)

The energy per step is then represented by using the cosine basis function. This will reduce the number of dimensions used to represent the data. The cosine transform is an approximation of the optimal Karhunen Loeve Transform. The DCT is given by:

$$c_{ik} = w_k \sum_{n=1}^{N} x(n) \cos \left(\frac{n(2k-1)\pi}{2N}\right)$$  \hspace{1cm} (2)

where

$$w_k = \begin{cases} \frac{1}{\sqrt{N}} & k = 1 \\ \frac{2}{\sqrt{N}} & k \neq 1 \end{cases}$$

D. Feature Analysis

The SAMMON algorithm [15] was used as a visualization tool to observe the discrimination between the walking classes. It is a nonlinear mapping which maps from N dimensional data to M dimensions (M=2 or 3) by preserving the distance between the classes in the N dimension features space.

E. GMM-based Classifier

GMMs are a parametric representation of a probability density function, based on a weighted sum of multi-variate Gaussian distributions. When used as a classifier, a separate GMM is trained for every class of movement using the expectation maximization (EM) algorithm. The likelihoods of a test vector given each GMM are then computed and the maximum likelihood estimation is used to classify the vector. GMMs have been employed commonly in the pattern classification literature and are used in a range of applications including speaker and language...
identification. Previous work in our laboratory [16] has shown that this is a robust classifier of posture.

In order to accommodate for the individual’s gait pattern characteristic, Bayesian adaptation which was proposed by [16] was used. After the GMM models have been trained on a large set from multiple subjects using the EM (expectation-maximization) algorithm, the models are then re-trained with the individual’s gait pattern.

III. RESULTS AND DISCUSSION

The signal decomposition of the vertical acceleration signal (Z axis) is shown in figure 4. It can be seen that it is difficult to discriminate the walking patterns using higher IMFs. Therefore only the first 3 IMFs were chosen.

Figure 5 shows the non-linear mapping result from 8 dimensional feature space to a 2 dimensional feature space for a five-class problem. It can be seen that the five classes are well separated for the particular subject.

The correct classification accuracy is used as a performance measure. The classification accuracy is calculated from the number of frames being classified correctly.

Based on the selected 8 dimensional features extracted from the IMFs as obtained by means of the EMD, the overall classification accuracy of 90.2% was achieved for the five gait patterns using the 4-mixture GMM classifier. Table I presents the classification accuracies of different types of walking activities in the format of a confusion matrix. There were 10 subjects for validation and 42 subjects for training the GMM.

Fig. 4: The decomposition of the acceleration signal into nine IMF with the residue (flat – slope down – slope up – stairs down – stairs up).

Fig. 5: SAMMON Mapping of the 8-D feature vectors to 2-D vectors for subject no. 26.
It can be noted from Table I that walking stairs-down was classified with the highest accuracy of 93.9%.

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. Apart from that, the anterior-posterior component has a smaller acceleration due to a tendency of walking down one stair step at a time. On the other hand, walking slope-up was classified with the lowest accuracy of 85.8% because the system had confused it with stairs up which has similar gait characteristics.

The second experiment involved investigating the effectiveness of the cosine transform. There were three sets of features which were compared. The first set consisted of 8 DCT coefficients extracted from the energy features. The second set consisted of energies of the first 3 IMF from each of the axis except for the medio-lateral acceleration where only the two IMF energies were taken as features. The third set consisted of the 12 energy features from the IMFs and residue for each of the axes. It can be seen that the DCT provides better discrimination capability with a lower number of features. The results are shown in Table II.

### Table II. Comparison between Energy based EMD features.

<table>
<thead>
<tr>
<th>Energy (with DCT) – 8 features</th>
<th>Energy (without DCT) – 8 features</th>
<th>Energy (without DCT) – 12 features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy (%)</td>
<td>90.0</td>
<td>81.9</td>
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</table>

As a comparison, Wang et al. [13] presented classification accuracies of five walking pattern with 96%. However, they have used 20 features which is relatively large dimension-wise. Apart from that they have used 64 mixtures to represent the model while in this case only 4 mixtures are used. It can be seen from Table II that the DCT improved the overall for the same feature set. Kuchi et al. applied EMD to the kinematic signals in gait recognition [14]. However, their protocol was significantly more complex as they applied 15 marker sensors around the body compared to only one sensor used in our experiments.

### IV. Conclusions

A compact feature extraction technique based on Empirical Mode Decomposition has been shown to be effective in classifying five types of walking patterns. The experiments demonstrated that the discrete cosine transform has been able to provide feature compaction without degrading the overall classification accuracy of the system. We plan to investigate other features that may improve the system performance for various walking patterns. The proposed gait pattern classification system can be used for further investigation on incline walking energy expenditure calculations.

### REFERENCES


