Using Gait as a Biometric, via Phase-Weighted Magnitude Spectra

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Abstract. Gait is a biometric which is subject to increasing interest. Current approaches include modelling gait as a spatio-temporal sequence and as an articulated model. By considering legs only, gait can be considered to be the motion of interlinked pendula. We describe how the Hough transform is used to extract the lines which represent legs in sequences of video images. The change in inclination of these lines follows simple harmonic motion; this motion is used as the gait biometric. The method of least squares is used to smooth the data and to infill for missing points. Then, Fourier transform analysis is used to reveal the frequency components of the change in inclination of the legs. The transform data is then classified using the *k*-nearest neighbour rule. Experimental analysis shows how phase-weighted Fourier magnitude spectra afford an improved classification rate over use of just magnitude spectra. Accordingly, it appears that it is not just the frequency content which makes gait a practical biometric, but its phase as well.

1 Introduction

Although there has been little study of gait as a biometric, there has been much medical research into gait. This research has aimed to classify the components of gait for the treatment of pathologically abnormal patients. Murray [10,11] produced standard movement patterns for pathologically normal people. These were used to compare the gait patterns for pathologically abnormal patients [10]. No statistical or mathematical analysis was performed on the collected data. The data collection system used required a marker to be attached to the subject. This is typical of most of the gait-data collection systems used in the medical field, and although practical for that area, they are not suitable for identification purposes, since they require contact.

In computer vision, in techniques for automated people tracking, Rohr [14] developed a way of recognising pedestrians from real image sequences. This method used a model-based kinematic approach, and could recognise pedestrians but not individuals. Similarly, Hogg [7] developed a program that identifies a walking person. The program uses the *WALKER* model, representing the human body as a collection of cylinders connected in a hierarchical structure. The model also defines the possible spatial and temporal relationships between each cylinder within a sequence of postures that "*characterise the articulation of a walking person*". It captures the sequence of movements that are "*essential for an action to be recognisable as someone walking*" and appears to have potential for extension to a system to identify individuals. Recently, there have been systems developed to track a single non-occluded person in arbitrarily complex scenes, aiming to avoid accurate initialization and large computational demand [3]. Since the basis is modelling people by a set of connected blobs, it is perhaps unlikely to be translated to biometrics.

A computer vision technique to recognise human body motion by using curves in a space comprising axes of angles of joints, torso location and attitude [4]. The technique learns, and accurately recognises from them, the constraints which apply during a particular motion sequence. The technique has been demonstrated to learn nine classical ballet steps. The technique has yet to be focused on biometrics.

Recently, Niyogi and Adelson [13] have developed a heuristic method for gait recognition. Gait was extracted from a sequence of images as a spatio-temporal pattern. This involved finding "*translating blobs in image sequences*". This method had an 79% recognition rate - a promising start. However, the approach was not directly related to the mechanics of walking or body structure which might offer potential for improvement in classification accuracy.

The gait recognition method by Murase & Sakai [9] uses silhouettes of a walking person to form an input sequence image. Spatio-temporal correlation is used to measure the similarity between the input sequence and a reference sequence. Their work has achieved a recognition rate of 100% on images of 7 subjects. Like Niyogi and Adelson's work, this approach lacked an explicit, and attributable, metric although it evidently has achieved encouraging results.

By Murray's work [10,11] it can be concluded that if all gait movements were considered, gait is unique. In all there appear to be twenty distinct gait components, some of which can only be measured from an overhead view of the subject. Murray found "*pelvic and thorax rotation to be highly variable from one subject to another*". These patterns are difficult to measure, even from an overhead view, which would also not be suited to many applications. Murray also suggested that these rotation patterns were not found to be consistent for a given individual in repeated trials.

In Murray [10,11], ankle rotation, pelvic tipping and spatial displacements were shown to possess individual consistency in repeated trials. Unfortunately, these components would be difficult to extract from real images. For these reasons, the components for investigation have been limited to the rotation patterns of the hip and knee. These patterns are possible to extract from real images, and possess a high degree of individual consistency and inter-individual variability. Fig. 1 shows the rotation angles for the hip and knee, as measured by Murray.

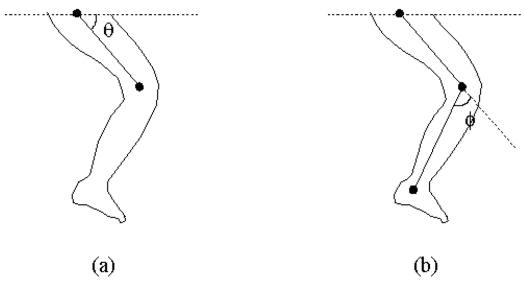


Fig. 1. (a) Hip and (b) Knee rotation angles.

The normal hip rotation pattern is characterised by one period of extension and one period of flexion in every gait cycle. Fig. 2 gives the average rotation pattern as given in Murray. The upper and lower lines indicate the standard deviation from the mean. In the first half of the gait cycle, the hip is in continuous extension as the truck moves forward over the supporting limb. In the second phase of the cycle, once the weight has been passed onto the other limb, the hip begins to flex in preparation for the swing phase. This flexing action accelerates the hip so as to direct the swinging limb forward for the next step. The angle of rotation is measured as the angle between the line joining the hip and knee, and the line passing through the hip point parallel to the ground. Leg motion includes the knee as well as the thigh. The pattern for normal knee rotation is more complex than that for the hip rotation. It shows two phases of flexion and two phases of extension.

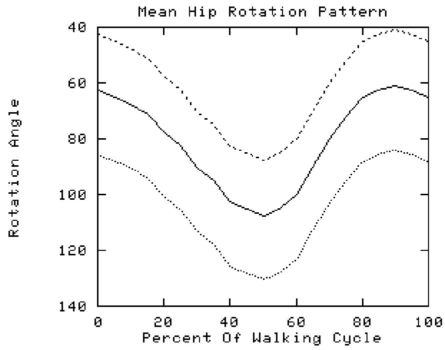


Fig. 2. Variation in Hip Rotation.

2 Modelling Gait

In preceding work, Kuan [8] modelled legs as two pendula joined in series, as in Fig. 1. The upper pendulum modelled the thigh and was suspended between the hip and the knee. The lower pendulum modelled the lower leg suspended from the knee to the ankle. This pendulum model is backed by Murray [10] - "*for normal gait, the duration of successive temporal components and the length of successive steps are rhythmic*".

This model is used as the leg motion is periodic and each part of the leg (upper and lower) appear to have pendulum-like motion. Fourier theory allows periodic signals to be represented as a fundamental and harmonics - the gait motion of the lower limbs can be described in such a way. The model of legs for gait motion allows these rotation patterns to be treated as periodic signals. Fourier Transform techniques can be used to obtain a frequency spectrum. The spectra of different subjects can be compared for distinctive, or unique, characteristics. The magnitude component of the FT is time shift invariant; it will retain its spectral envelope regardless of where in time the FT is performed. The phase component does not share this characteristic, and a time shift in the signal will change the shape of the phase envelope.

When comparing the phase components for different subjects, the time shift must be the same to ensure a valid comparison. For a given subject, the rotation patterns of the hip and knee can be assumed to be identical for both legs. Therefore, to ensure valid comparisons between phase components of different subjects, a starting point to the gait cycle must be chosen - *heel strike*, which is when the heel of the swinging leg strikes the floor. The DFT can be applied to the data to produce the frequency spectrum of the rotation patterns. Kuan [8] obtained the frequency spectra of the hip rotation pattern for three subjects, and phase and magnitude plots were made. The magnitude plots showed little variation between subjects and so seem unsuitable as a means of identification. The phase plots exhibited a great deal of variation between subjects. Consistency in the phase plots for a given individual in repeated trials needs to be investigated. This is the first known use of phase in gait recognition.

Trousers, or other clothing, can obscure the shape of the lower leg, thus making the knee rotation angle difficult to extract exactly. If the phase information is being considered, then a consistent error margin in the knee angle will not affect the phase content of the rotation pattern. The manner in which the angle changes is of more interest than the actual angle values themselves.

Although gait research has not used phase for recognition, it has found some use in other areas as a measure for classification. Achimowicz [1] has analysed the variability of electrical potentials in the brain to single trial visual stimulus. Pattern recognition of the stimulus is performed in the phase-domain. "*The phase of the signal contains almost all the information about the localisation of events on the time axis*". The use of phase for pattern recognition is supported by Chen et al. [5]. Their work presents a new method of matching a 2-dimensional image to a translated, scaled and rotated reference image. They use Fourier-Mellin descriptors for the images that are matched using Symmetric Phase-Only Match Filtering (SPOMF). Phase-only match filtering is used as "*the spectral phase preserves the location of objects, but is insensitive to image energy*".

Nandi et al. [12], and Soliman et al. [15,16] have studied the classification of modulation type signals. In [16] a number of key features (parameters) of the signal are derived on which a decision theory algorithm is based. The majority of these key-features are based upon the phase component of the signal. Yang and Soliman use the statistical properties of moments of the phase component of a signal. In one case the phase distribution is approximated by a Tikhonov function, and in the other the exact phase distribution is extracted from the Fourier Series expansion of the signal.

3 Extracting Gait by Computer Vision

To collect data, the camera was situated with a plane normal to the subject's path, and with a static background, an example is given in Fig. 3.

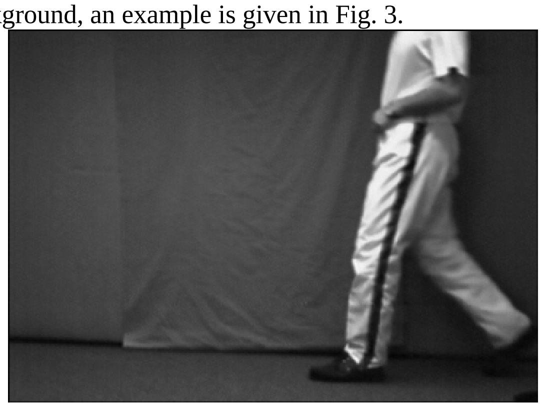


Fig. 3. Example Image of Walking Subject.

The environment was controlled to improve the data collection with a simple, plain background, with controlled lighting. To resolve difficulty in occlusion, subjects wore trousers which had a stripe painted on the outside. As such, some useable data could still be collected when the legs crossed. The video sequences were averaged to reduce high frequency noise and an edge image was produced by applying the Canny operator with hysteresis thresholding.

The Hough Transform (HT) is applied to the edge image. The result is an accumulator space that has several maxima, each corresponding to a line in the edge image. A peak detection algorithm is applied to extract the parameters of each of these lines (in x and y co-ordinates) using the foot-of-normal form

$$s = x\cos\phi + y\sin\phi$$

where s and f are the distance and angle to the foot of normal. This alleviates the large memory requirement associated with the Cartesian HT implementation.

There are several methods for peak detection. In back-mapping [6], the peak in the accumulator at (s_{pk},ϕ_{pk}) is found. For each edge point in the image which lies on the line represented by (s_{pk},ϕ_{pk}), the points in the accumulator associated with that edge point are decremented. This effectively removes the votes cast by the line (s_{pk},ϕ_{pk}), and so the peak is reduced. This process is repeated until the parameters for all the lines have been found. An example of the variation in thigh angle θ for the walking cycle of one subject is shown in Fig. 4. Gaps in the data occur when the legs cross where it is difficult to discriminate between the legs. There is also some high frequency noise on the data. To in fill for missing data, and to smooth noisy components, we used curve fitting.

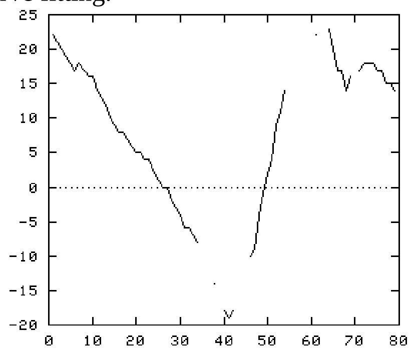


Fig. 4. Extracted Thigh Angle for Subject 2.

Murray [10,11] shows that the lower limbs move through a limited range of angles. Taking the angles of measurement as shown in Fig. 1, the range for the lower limbs is 30° to 150°. This takes into the account the swinging of the lower leg through the cycle. Converting this range to the co-ordinate systems used in the HT gives a range of -60° to 60°. By limiting the range of angles the search space is reduced, decreasing processing time and the number of spurious responses.

The thigh angles given by the lines' inclinations were then fitted to a high order polynomial by least squares. For variation in the thigh angle θ with time t, we have an eighth-order polynomial:

$$\theta(t) = a_0 + a_1 t + a_2 t^2 + \ldots + a_8 t^8$$

and for N points θ_i we obtain by least squares

$$\begin{bmatrix} N & \sum_{i=1}^{N} t_i & \cdots & \sum_{i=1}^{N} t_i^{8} \\ \sum_{i=1}^{N} t_i & \sum_{i=1}^{N} t_i^{2} & & \sum_{i=1}^{N} t_i^{7} \\ \vdots & & & \vdots \\ \sum_{i=1}^{N} t_i^{8} & \sum_{i=1}^{N} t_i^{9} & \cdots & \sum_{i=1}^{N} t_i^{16} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_9 \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{N} \theta_i \\ \sum_{i=1}^{N} \theta_i t_i \\ \vdots \\ \sum_{i=1}^{N} \theta_i t_i^{8} \end{bmatrix}$$

An example of the least squares fit for four sequences of single cycles of subject 2 are shown in Fig. 5.

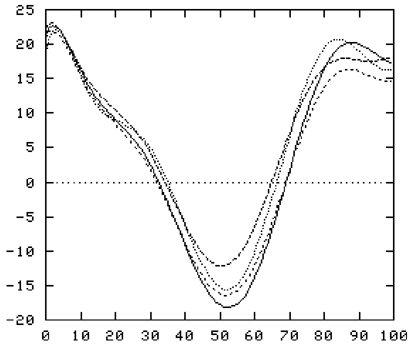
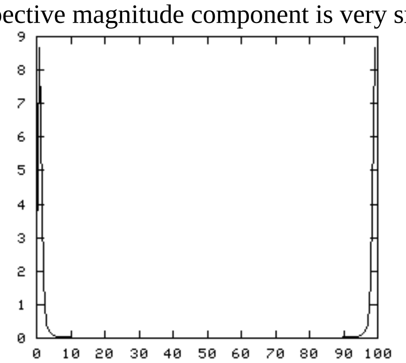
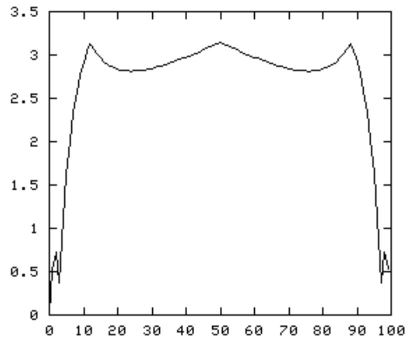


Fig. 5. Least Squares Fitting for Subject 2.

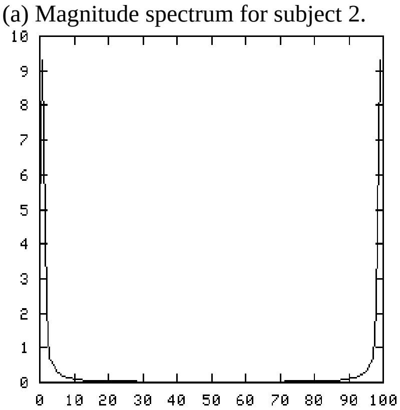
These data are then analysed using the DFT to provide phase and magnitude spectra. The magnitude and phase spectrum for one walking cycle of subjects 2 and 5 are shown in Fig. 6. The magnitude spectrum drops to near-zero above the fifth harmonic, as reflected in recent studies [2]. The magnitude spectra for the two subjects can be used to distinguish between them. However, the phase spectra are much more different but some components carry little information since their respective magnitude component is very small.



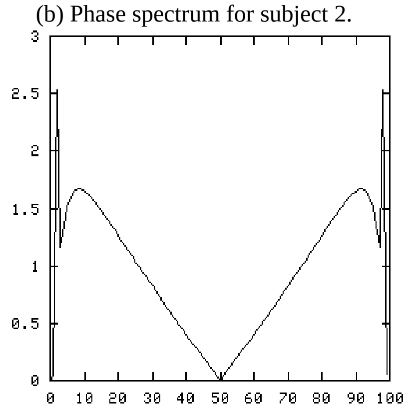
(a) Magnitude spectrum for subject 2.



(b) Phase spectrum for subject 2.



(c) Magnitude spectrum for subject 5.



(d) Phase spectrum for subject 5.

Fig. 6. Phase and Magnitude Gait Spectra.

4 Classification Results

The *k*-nearest neighbour rule is then used to classify the transform data using the 'leave one out' rule, for k = 3 and for k = 1. Four video sequences were acquired for each of ten subjects. An analysis of the differences of the measurements for one subject, from those derived for all other subjects is shown in Fig. 7.

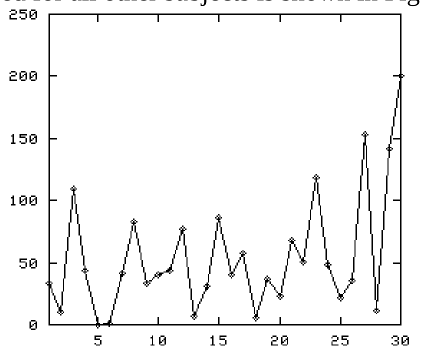


Fig. 7. Difference between subject 2 and all others.

Given a single test sequence, the difference is very low for two of the other three samples of subject 2 (tests 5 and 6) though it is higher for third sequence, test 4. The difference is higher for the three sequences of the other subjects, though two single subjects are close to subject 2 (tests 13 and 18). As such, a higher value for k in the k-nearest neighbour rule should increase classification capability.

The correct classification rates (CCR) are summarised in Table 1 which gives analysis for classification by magnitude spectra alone, and for multiplying the magnitude spectra by the phase, both for differing values of k. This multiplication appears reasonable, since gait is not characterised by extent of flexion alone, but is controlled by musculature which in turn controls the way the limbs move. Accordingly, there is physical constraint on the way we move our limbs. However, we cannot use phase alone, since some of the phase components occur at frequencies for which the magnitude component is too low to be of consequence. By multiplication of the spectra, we retain the phase for significant magnitude components. Clearly, in this analysis, using phase-weighted magnitude spectra gives a much better classification rate (90%) than use of just magnitude spectra (40%), for k = 3. Selecting the nearest neighbour, as opposed to the 3-nearest neighbour, reduced the classification capability, as expected.

No. of Nearest Neighbours	Magnitude CCR	Phase$\times$Magnitude CCR
k = 1	50 %	80 %
k = 3	40 %	90 %

Table 1. Overall classification performance.

5 Conclusions and Further Work

Gait has similar potential to faces as a biometric: its measurement is non-invasive and it is difficult to disguise. Modelling gait as articulated pendula parallels earlier medical work. First, limbs are extracted from image sequence by using the Hough transform for lines. The change of inclination with time is the then processed by least squares fitting to provide data suitable for Fourier transformation. Magnitude spectra of the frequency content of the change in angle can be used for recognition but the classification rate can be improved by inclusion of phase. In these studies, the overall classification rate via the phase-weighted magnitude spectra using the *k*-nearest neighbour rule had considerably better correct classification rate (90%) than using the magnitude data alone (40%). This approach provides a new avenue for gait modelling and recognition and further work will concentrate on using a wider database, translation of imaging to arbitrary viewpoint, and on computer vision algorithms to alleviate restrictions on data acquisition.

6 Acknowledgement

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7 References

[1] J.Z. Achimowicz, "Variability analysis of visual evoked potentials in humans by pattern recognition in phase domain", *Acta Neurobiologiae Experiments*, **55**(3), pp.177-191, 1995.

[2] C. Angeloni, P.O. Riley, D.E. Krebs, "Frequency content of whole body gait kinematic data", *IEEE Trans. Rehab. Eng.*, **2**(1), pp.40-46, 1994.

[3] A. Azarbayejani, C. Wren and A. Pentland, "Real-Time 3-D Tracking of the Human Body", Proc. IMAGE'COM, May 1996.

[4] L. Campbell and A. Bobick, "Recognition of Human Body Motion using Phase Space Constraints", MIT Media Lab Perceptal Computing Report 309, 1995.

[5] Q. Chen, M. Defrise and F. Decconinck, "Symmetric phase-only matched filtering of Fourier-Mellin Transforms for image registration and recognition", *IEEE Trans. PAMI*, **16**(12), pp.1156-1168, 1994.

[6] G. Gerig and F. Klein, "Fast contour identification through efficient Hough Transform and simplified interpretation strategy", *Proc. 8th ICPR*, pp.498-500, 1986.

[7] D. Hogg, "Model-based vision - a program to see a walking person", *Image and Vision Computing*, **1**(1), pp.5-20, 1983.

[8] E.L. Kuan, "Investigating gait as a biometric", *Report, Department of Electronics and Computer Science, University of Southampton,* 1995.

[9] H. Murase and R. Sakai, "Moving object recognition in eigenspace representation: gait analysis and lip reading", *Pattern Recognition Letters*, **17**, pp155-162, 1996.

[10] M.P. Murray, "Gait as a total pattern of movement", *American Journal of Physical Medicine*, **46**(1), pp.290-332, 1967.

[11] M.P. Murray, A.B. Drought, R.C. Kory, "Walking patterns of normal men", *Journal of Bone and Joint Surgery*, **46**-A(2), pp.335-360, 1964.

[12] A.K. Nandi and E.E. Azzouz, "Automatic analogue modulation recognition", *Signal Processing*, **46**, pp.211-222, 1995.

[13] S.A. Niyogi, E.H. Adelson, "Analyzing and recognizing walking figures in XYT", *Proc. Conf. Comp. Vis. and Pattern Recog. 1994*, pp.469-474, 1994.

[14] K. Rohr, "Towards model-based recognition of human movements in image sequences", *CVGIP*, **59**(1), pp.94-115, 1994.

[15] S.S. Soliman and S. Hsue, "Signal classification using statistical moments", *IEEE Trans. Comms.*, **40**(5), pp.908-916, 1992.

[16] Y. Yang and S.S. Soliman, "An improved moment-based algorithm for signal classification", *Signal Processing*, **43**, pp.231-244, 1995.