ON MEASURING TRAJECTORY-INVARIANT GAIT SIGNATURES

John N. Carter and Mark S. Nixon
Department of Electronics and Computer Science,
The University, Southampton, UK.
jnc@ecs.soton.ac.uk, msn@ecs.soton.ac.uk

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ABSTRACT

Biometrics are increasingly important as a means of personal identification, and as such automatic gait analysis is emerging as one of the most promising new techniques for non-contact subject recognition. There are many problems associated with obtaining a gait signature automatically, in particular the effects of footwear, clothing and walking speed. Furthermore, laboratory studies have constrained subjects to walk in a plane normal to the camera's view and have ignored the effects of pose. Methodologies based on modelling human walking offer the opportunity to develop analytic pose compensation techniques; here we develop a new geometric correction to the measurement of the hip rotation angle, based on the known orientation to the camera, using the invariance properties of angles under geometric projections. We present experimental results showing the application of our corrections to geometric targets and a real human walker. We also indicate that it is possible to derive the corrections from the gait data itself. As such we demonstrate that it is indeed possible, by geometric analysis, to provide invariant signatures for automatic gait recognition.

1 INTRODUCTION

Personal identification is becoming an ever-important issue in everyday life. The need for personal security, access control and identification is increasingly significant in individual and national political agendas. Further, the incidence of fraud and impersonation is rife. For example, US and UK welfare fraud costs billions of pounds per year, whilst one credit card company, MasterCard, estimates that it alone loses $450 million per year[1]. These issues can be addressed by an effective person identification system. There are many strategies for personal identification, based on knowledge (e.g. passwords), on possession (e.g. identity cards) or on some unique property of the individual, a personalised measurement or biometric.

Any human physiological characteristic is potentially a biometric, provided it is universal, unique, permanent and collectible[1]. That is, everybody has this property, it is unique to the individual, does not change over time and is measurable. Biometrics range from established methods such as fingerprints, through voice and face recognition, to new and emerging techniques such as iris identification.

No biometric is perfect, many suffering from social and practical problems, for example the need to make physical contact when using fingerprint systems, or the potential social embarrassment when interrogating a public voice recognition system. Unlike fingerprints and signatures, biometrics that need no subject contact (such as face recognition) are more acceptable to users but can be limited by practical issues (such as face visibility). Gait recognition is one of the newest of the emergent biometrics, and has the potential to overcome many problems. It is a non-contact biometric, requiring no subject interaction. Also, in general the whole body presents a larger and more accessible target than just the human face and in many applications scenarios, especially those involving serious crime, it is likely that the face will be wholly or partially obscured whereas the gait will not. For these reasons gait now attracts research interest. However, as yet there has been no study of the appropriate basis for measuring gait for purposes of automated recognition: that is the subject of this paper.

We first discuss the bases for gait measurement. The two main approaches are 'statistical' and 'model-based' and we discuss how the model-based approaches have better generalisation capability (to practical application), in the following section. In Section 3 we then investigate the principal basis of the model on which gait measurement is formed, showing how the variation in trajectory effects perceived gait signature. These observations are confirmed by experimental studies, prior to observations on appropriate invariance properties, in Section 4, then further work and the conclusions drawn from this study.

2 GAIT AS A BIOMETRIC

There is a rich literature, including medical and psychological studies, indicating the potential for gait for person identification[2]. Since people need to walk their gait is generally apparent. Additionally gait is hard to disguise. For example in a robbery, or other criminal activity, the need is to walk normally and unobtrusively rather than to attract attention.

Early medical studies suggest that if all gait movements are considered, gait is unique[3]. In all it appears that there are 24 different components to human gait, some are more variable than others and some are more difficult to measure than others, particularly out of the laboratory. Murray's work[3] indicates that gait has the richness necessary for a successful biometric which, with its no contact nature and the high visibility of body parts, makes it a fruitful candidate for a general-purpose remotely-sensed biometric. Some potential applications for a gait based recognition system include forensics, to identify individuals involved in serious crimes, and security to analyse gait patterns to monitor unusual subject behaviour.

The two main themes in current approaches to automatic gait recognition are statistical and model based. The statistical approaches derive a unique signature by computing a spatiotemporal pattern based on a sequence of segmented images of a moving person. Typically the shape of the body is reduced to a binary silhouette and some statistical measures are taken from the sequence of silhouettes. Techniques such a Principle Components Analysis and Linear Discriminant Analysis have been used to provide a statistical description of the sequence[4,5]. These techniques have been very successful, achieving 100% recognition rates, though on small subject populations. Most extant approaches to automatic gait recognition are statistical in nature, describing movement by optical flow or spatiotemporally[2]. However, as with all statistical measures, it is not clear exactly which features of gait contribute to the recognition and discrimination processes.

The alternative approach is to base recognition on a physical model of human motion. Following Murray, the hip rotation angle has been modelled as a simple pendulum, whose motion is approximately described by simple harmonic motion[6,7]. This assumes that the motion is basically sinusoidal in nature, repeating periodically with every step, with frequency, phase and amplitude closely related to the mechanics of the walking process. In fact, simple harmonic motion is insufficient to describe human motion, rather the motion is expressed as a Fourier series[7]. Gait recognition using this model-based approach relies on accurate feature identification, automatically or via human intervention and labelling. A straight line parallel to the upper leg is derived from each picture in a video sequence, and used to compute the hip rotation angle. These angles are then combined to produce a gait signature. Medical studies indicated that the significant information is contained in the low orders of the Fourier Sequence, and this has been borne out by achievement of 100% recognition rates with only the first two harmonics[7]. Again this was with a small number of subjects.

Figure 1 Subject walking, left to right, at an angle of 20° to the camera.

Current laboratory based experiments indicate that gait is highly promising as a biometric. However, before it can be of practical use the many different effects that may perturb and influence recognition rates must be quantified. In particular, the view angle and camera positions are all well controlled in laboratory experiments, usually by forcing the subject to walk normal to the line of sight of the camera. This will not be true in almost all-real world applications, where the angle of a subject's path with respect to the camera will be totally uncontrolled. This mandates that some form of invariance or correction is required to normalise the signatures of walking subjects to be independent of pose.

Consider a fixed video system, monitoring a person walking at a fixed angle to the view direction of the camera. If the camera optics have been fully calibrated, and the scene geometry is known, then it is entirely possible to reconstruct the motion of the walker. In principle this can be expedited by assuming that the person is walking perpendicular to the flat ground plane, and rotating the co-ordinate system such that labelled features appear as if they were viewed in laboratory conditions. This is not difficult to achieve but does impose severe constraints on generalisation capability, and the numerical processing required may introduce systematic errors to the derived gait signature. Clearly, this can affect statistically based approaches more than model-based ones, especially if it is possible to develop a system or algorithm that allows simple corrections to be made to the model (the hip rotation angle).

Measures of angle behave well under perspective transformation, retaining many of their properties regardless of the orientation from which they are observed. In the following section we will outline the basis of a simple geometric correction and show its efficacy experimentally. Subsequent to that, we will show how simple notions are inadequate when applied to a real walker and will develop a more sophisticated model. In the final section of the paper this leads to the notion of a pose invariant gait signature.

3 GAIT SIGNATURES AND THE TRAJECTORY ANGLE

As outlined above, the fundamental basis of model based gait analysis is the measured angle, in particular the hip rotation angle. As in any computer vision application, angles are determined using the inverse arc tangent applied to measured horizontal and vertical components. Thus in a calibrated camera system, under an orthographic projection, an angle can be computed correctly from simple distances measured in pixels. This is should also be valid under the perspective projection, if the object under scrutiny is sufficiently far from the camera. These are the conditions that hold for most laboratory investigations of gait analysis, where the subjects parade at right angles to the camera. However, in the real world, subjects under investigation will typically be viewed from an oblique angle, i.e. the camera may be looking down onto the subjects and the subject may be walking diagonal to the camera view, Figure 1. Let us consider these two cases separately and independently.

3.1 Elevation Angle

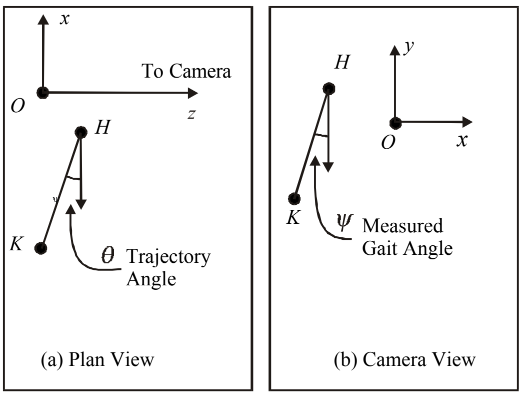

Figure 2 Looking down on the plan view (a) the positions of the Hip, H, and the Knee, K, are seen relative to the origin O. The vector HK defines the walking direction, and thus the trajectory angle θ. The view from the camera (b), shows the gait angle ϕ in relation to the coordinate svstem.

Consider a typical surveillance system where the camera system is mounted some height above the ground and is inclined towards the ground. The angle made by the optical axis of the camera and the ground plane is hereafter known as the elevation angle. Now consider a set of hip rotation measurements made as a subject walks across the field of interest and at right angles to the projection of the optical axis onto the ground plane. In an ideal system (neglecting calibration, distortion and perspective) the single effect of the elevated position on the component measurements of the rotation angle, will be a foreshortening of the vertical component by the cosine of the elevation angle.

Interpreting these measurements, in terms of a human walker, suggest that in any realistic measurement system the vertical component will be nearly constant and the angular information will be carried almost entirely in the horizontal component. This suggests that, within reason, the elevation angle will have no significant bearing upon the determination of the true hip rotation angle. More specifically, if ϕ is the true hip rotation angle, ψ is the measured hip rotation angle and ε is the elevation angle, and if small angle approximations hold we can write

$$\tan(\psi) = \frac{\sin(\phi)}{\cos(\phi)\cos(\varepsilon)} \quad \text{or} \quad \psi = \frac{\sin(\phi)}{\cos(\phi)\cos(\varepsilon)}, \qquad (1)$$

The interpretation of this equation is simply that at most the elevation angle will contribute a constant scaling factor to the measured gait angle and as such we will ignore its effect hereafter. Of course, in the limit, as ε tends to 90 degrees this will break down.

3.2 Trajectory Angle

Consider now the second case, where the camera is viewing the walking subject with the optical axis parallel to the ground plane. Furthermore, consider the effect of determining ψ if the subject is walking at an angle to the axis of the camera, we call this angle the trajectory angle, θ, see Figure 2, where H is the hip and K is the knee. In a similar manner to the elevation angle, the trajectory angle will manifest itself by foreshortening the horizontal component of the gait angle, suggesting that the equation

$$\tan(\psi) = \frac{\sin(\phi)\cos(\theta)}{\cos(\phi)} \quad \text{or} \quad \tan(\phi) = \frac{\tan(\psi)}{\cos(\theta)}, (2)$$

links the measured and the real gait angle. As in Eqn. 1, a simple scaling is suggested, but since the horizontal component of gait angle carries the majority of the angular information this cannot be accepted without proof.

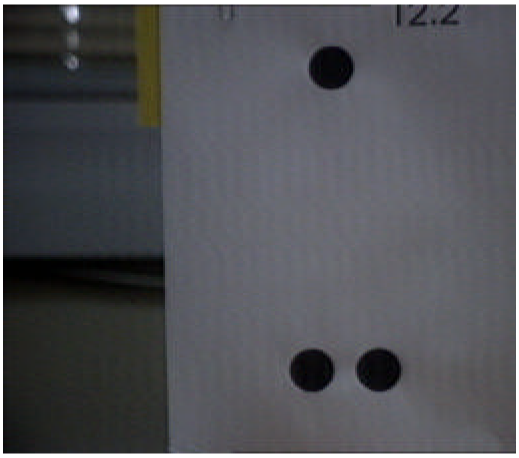

Figure 3 Simulated legs, hip rotation angle 12.2 , trajectory angle 14 and ~2m from the camera.

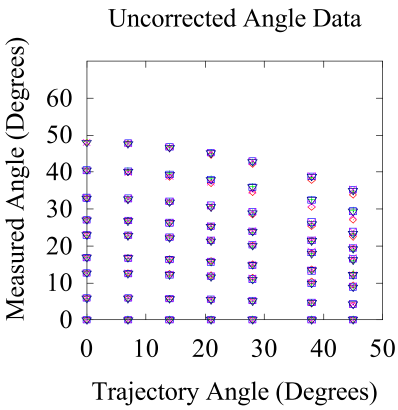

Figure 4 Measure angle, as a function of trajectory angle for camera/target distances between 1 and 4 meters. Diamonds are closest to the camera.

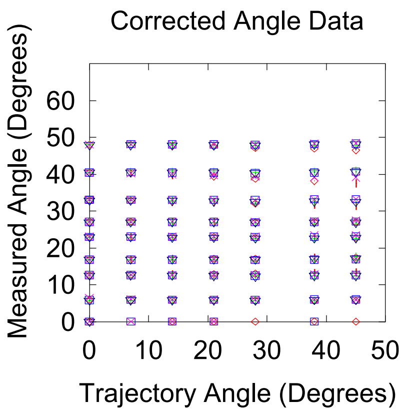

Figure 6 Measured angle, after application of trajectory correction to each half angle.

3.3 Laboratory Experiments

First, the hip rotation angle was simulated, by printing a target pattern as shown in figure 3. A walking subject was simulated by a printed set of black circles, representing the hip and two knee positions. A set of seven targets representing different angles from zero to 45 degrees was used. Each target was mounted, in turn, on a rotating table and viewed with an uncalibrated camera from a fixed distance. A Sony Video camera model XC-711P with a Sony Zoom lens Model TV-ZOOM (12.5mm to 75mm) was used for this and all other experiments. The zoom lens was adjusted such that the target filled as much of the field of view as possible. The output from the camera was digitised and a global threshold was applied to produce a binary image. After the circle positions had been marked manually, a minimum sized bounding box was generated automatically, and the centre of gravity of the circle was calculated. For each group of circles the apparent hip angle (γ) calculated and recorded as a function of simulated trajectory angle. Figure 4 shows the raw measured angle, for trajectory angles between 0° and 45°, for viewing distances of between 1 and 4 metres. Clearly, increasing the trajectory angle results in a decrease in the perceived angle.

Figure 5 shows the corrected hip rotation angles after the correction in Equation (2) has been applied directly. As can be seen, this naive approach is not effective, as the perceived angle

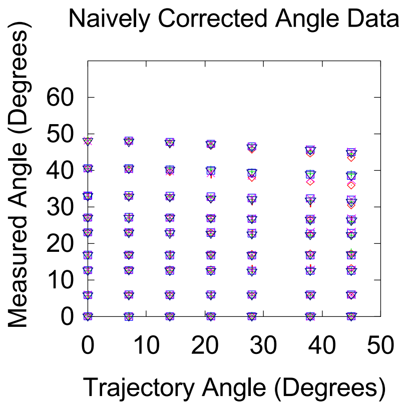

Figure 5 Application of Eqn. 2, to the data shown in Figure 4. Note the remaining dependence on trajectory angle.

is not independent of the trajectory angle, unlike figure 6. In figure 6, each half angle is considered separately and the horizontal components are corrected before the angles are calculated. The measured angles are now correct for all trajectory angles less than 45 and at distances greater than 1 meter. Detailed examination of the data reveals that there is some inaccuracy at large angles and when the camera is close to the target, again this is to be expected.

3.4 Human Walking

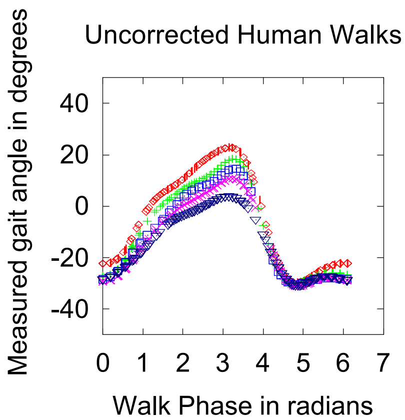

Figure 7 Hip rotation angle, plotted against walking phase. The trajectory angle is varied from 0 to 40 , in descending order on the graph.

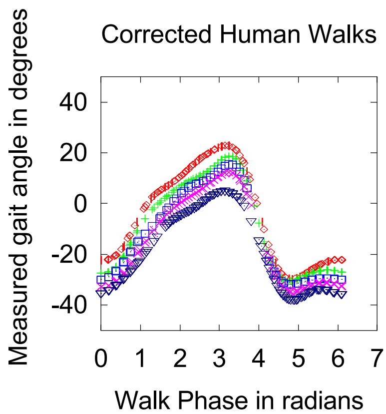

Figure 8 Hip rotation angles, corrected using Eqn. 2.

In the second experiment a female subject was videoed walking at different angles to the camera. The average distance between the subject and the camera was 4 metres, and the gait trajectory varied from 0° to 40° in 10-degree steps. The subject was constrained to walk along an 80cm track, laid out at a specified angle to the camera direction. The camera system described above was used, and the walking sequences were recorded on a Panasonic AG-73330-B SVHS video recorder. The sequences were digitised with a high-resolution direct-to-disk colour frame grabbing system. These experiments took place out-of-doors under bright but diffuse sunlight, against a natural backdrop. Placing two marks on each of the subject's legs, one just below the hip and the other just above the knee, facilitated image processing and angle determination. The contrasting colour used was easily recognisable in the digitised video data and was manually marked in each frame. Again the hip rotation angle was derived and recorded as a function of video frame. In each sequence the reference frame was chosen where the subject's leading foot was flat on the ground, and a complete cycle was measured. Other work has used the heel strike as reference[6,7]. Heel strike occurs just before our chosen reference point and was not used here, as it was difficult to determine in the range of poses used in this study. Figure 1, shows an example frame for a 20° walk. Repeated experiments were performed and, following Cunado[7], a 4th order Fourier series was fitted to the ensemble data to generate a gait curve. Figure 6 shows gait curves for the different trajectory angles studied. Equation (2) was used to correct the gait curve, with result in figure 7. It is clear that in this case the simple rotated pendulum model does not correct the gait angle. Close inspection of the uncorrected gait curves, and the raw data, indicates that not only must the gait signature be scaled but there is also an offset apparently proportional to the trajectory angle. The simple model developed in this section actually assumes that the leg swings in a plane perpendicular to the ground. Measurements made on the subject's legs indicate that the lower (knee) and upper (hip) marks lie on a plane approximately 18° from the vertical. This has the effect that even when the gait angle is zero, a non-zero trajectory angle will cause the apparent gait angle to be non-zero. This is the cause of the D.C. offsets apparent in Figure 7. Clearly, if the gait curves are to be invariant then a better correction model must be developed.

4 A MODEL FOR GAIT ANGLE CORRECTION

Consider a swinging pendulum, see Figure 2, representing the leg, which is characterised by an angle f, the angle the leg makes to the vertical, and an angle q, which is the angle the plane defined by the swinging leg makes with the direction to the camera, here after known as the trajectory angle. The hip position is at a point $H = [x \quad y \quad z]^{\mathrm{T}}$ in a 3-dimensional co-ordinate system also defined in Figure 1. The position of the knee K is

$$K = [l\sin(\phi) + x \quad l\cos(\phi) + y \quad z]^{\mathrm{T}}, \qquad (3)$$

where l is the length of the thigh. The effect of the trajectory angle is analogous to rotation about the vertical. This has no effect on the hip position, as this can be assumed to lie on the rotation axis, while the effect on the knee position can be calculated by conversion to homogeneous co-ordinates and multiplying by a standard y-axis rotation matrix giving position K' as

$$K' = \begin{bmatrix} \cos(\theta) & 0 & \sin(\theta) & 0 \\ 0 & 1 & 0 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} . \begin{bmatrix} l\sin(\phi) \\ l\cos(\phi) \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} x \\ y \\ z \\ 0 \end{bmatrix}$$

$$= \left[\cos(\theta) l \sin(\phi) + x \quad l\cos(\phi) + y \quad -\sin(\theta) l \sin(\phi) x + z \quad 1\right]^{\mathrm{T}} \qquad , \qquad (4)$$

$$H' = H$$

Applying the perspective transformation, the positions of the hip and knee can be calculated by the screen co-ordinates of a simple pinhole camera that is D units away from the walker and has a focal length of P units. From the transformed co-ordinates above, the apparent angle to the vertical ψ can be calculated from

$$\tan(\psi) = \left. \left(\frac{H'_x.P}{D - H'_z} - \frac{K'_x P}{D - K'_z}\right) \middle/ \left(\frac{H'_y.P}{D - H'_z} - \frac{K'_y P}{D - K'_z}\right) \right. , \qquad (5)$$

where subscripts denote the x, y or z components of the vectors H' and K', giving

$$\tan(\psi) = \frac{\left[x\dfrac{P}{D - x} - \left(\cos(\theta) l \sin(\phi) + x\right)\dfrac{P}{D + \sin(\theta) h \sin(\phi) - z} \right]}{\left[y\dfrac{P}{D - x} - \left(l\cos(\phi) + y\right)\dfrac{P}{D + \sin(\theta) l \sin(\phi) - z} \right]} . \qquad (6)$$

If the camera is assumed to be far away from the walker, and D is always greater than components of position, then x, y and z can be neglected and P, D and l cancel, so the equation for the measured angle then simplifies to

$$\tan(\psi) = \frac{\cos(\theta)\sin(\phi)}{\cos(\phi)} . \qquad (7)$$

or more usefully

$$\tan(\phi) = \frac{\sin(\psi)}{\cos(\theta)\cos(\psi)} . \qquad (8)$$

Equation 9 implies that once the trajectory angle is known, then the true hip angle can be calculated directly from the measured angle. Furthermore, in the limit of small angles, the correction is simply a linear scaling by $\cos^{-1}(\theta)$. Thus if gait trajectories are normalised to correct for natural variations in amplitude i.e. walking speed, then this pose correction is unnecessary.

The theory behind Equation (8) is easily extended to account for an inclined leg swinging plane, and can be reformulated as

$$\tan(\phi) = \frac{\sin(\psi)}{\cos(\psi)}\frac{1}{\cos(\theta)} - \tan(\alpha)\tan(\theta)\frac{1}{\cos(\phi)} . \qquad (9)$$

Here α is the leg angle described at the end of Section 3. above. Note that while the right hand side of Equation (9) is not independent of the measured angle, a unique solution for $\tan(\phi)$ does exist. Detailed calculations indicate that over the range of gait angles for ordinary walking, approximating $\cos(\phi)$ as unity is acceptable. This approximation has been used to generate the data plotted in Figure 9. The different gait curves overlap significantly and any residual differences are interpreted as experimental errors and limitations in the 4th order Fourier Series as a description of human gait. As such, a pose independent metric has been achieved by incorporating scene geometry.

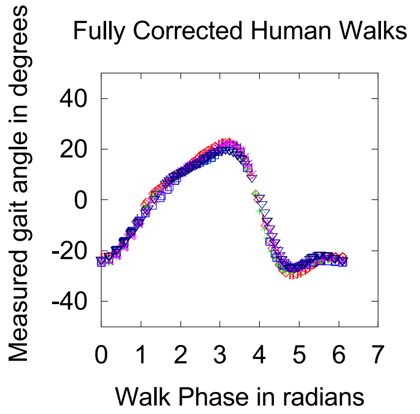

Figure 9 Hip rotation curves corrected for trajectory angle and leg angle using Eqn. 9.

5 A POSE INVARIANT MEASURE

Further consideration of Equation (9) suggests that if tan(ϕ), rather than the angle ϕ itself is used as a measure (and D.C. and scaling terms are ignored) then a personal biometric signature can be directly calculated from a measured signature without knowledge of the trajectory (θ) or leg (α) angles. The coefficients of the gait curves for the five different trajectory angles are tabulated in Table 1. The coefficients A_0 and A_1 vary as expected from Equation (9), but the remaining coefficients are constant within a few percent of each other.

Angle	A_0	A_1	θ_1	A_2	θ_2	A_3	θ_3
0	-0.083	0.411	-0.985	0.232	1.64	0.197	-2.56
10	-0.144	0.383	-1.017	0.204	1.67	0.228	-2.48
20	-0.184	0.356	-1.065	0.230	1.68	0.192	-2.47
30	-0.211	0.331	-1.106	0.215	1.68	0.199	-2.62
40	-0.247	0.272	-1.069	0.205	1.73	0.178	-2.61
Fit Function: $\tan(\psi) = A_0 + A_1.\left[\sin(\omega+\theta_1) + \sum_{n=2}^{N} A_n.\sin(n.\omega+\theta_n)\right]$ where $N = 3$ and $\omega \in [0..2\pi]$							

Table 1: Coefficients resulting from fitting a modified Fourier series to the average human walks at various angles.

This is consistent with the model presented in this paper, and indicates that phase and high order amplitude measurements of gait signatures are independent of pose. However this result must be conditional on the assumption that the variation seen is due primarily to measurement error and not to natural fluctuations in the subject's gait. A detailed study of the variation is beyond the scope of this paper.

6 FURTHER WORK

There is still considerable work required to bring the gait biometric to maturity. The effects of clothing, mood, footwear, speed of walking must all be studied and their effect quantified. In addition the geometrical corrections presented here must be developed to include cases where the subject does not walk in a straight line or where the camera tracks the subject, possibly using a zoom lens to achieve maximum resolution. Furthermore, following the surprising discovery of the effects of leg angle, the conclusions of Section 3.1 must be revisited experimentally.

Furthermore, detailed studies of the effects of experimental error, repeatability and subject variability must be carried out before the efficacy of gait as a biometric for large populations is known.

7 CONCLUSIONS

We have shown that the effects of gait trajectory can be discounted when deriving experimental gait signatures. Analytic measures have been developed to correct an angular measurement currently used as a basis for automatic gait recognition. Experimentation has shown that a cosine correction rule and its extended form can normalise hip rotation angle signatures with respect to the gait trajectory. Although the analysis presented here assumes that the camera and gait trajectories are coplanar it is easily extensible to other arrangements.

This work also suggests that it is more appropriate to use the tangent of the hip rotation angle as a gait signature rather than the hip rotation angle. This eliminates all requirements for the gait angle to be small and simplifies the correction to just shifting and scaling, which can be derived from the data and need not be known *a-priori.*

8 ACKNOWLEDGEMENTS

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