Information Security Technical Report, Vol 7, No. 4 (2002) 23-35

New Advances in Automatic Gait Recognition

Mark S. Nixon, John N. Carter, Jamie D. Shutler and Michael G. Grant, Department of Electronics and Computer Science, University of Southampton UK

[msn | jnc | jds1 | mgg]@ecs.soton.ac.uk

Abstract

Recognising people by their gait is an emergent biometric. Until recently there was evaluation by few techniques on relatively small databases though with encouraging results. The potential of gait as a biometric has further been encouraged by the considerable amount of evidence available, especially in medicine and literature. This evident potential motivated development of new databases, new technique and more rigorous evaluation procedures. We describe the new techniques we have developed and their evaluation on our database to gain insight into the potential for gait as a biometric. We also describe some of our new approaches aimed to aid generalization capability for deployment of gait recognition. We show on these new and much larger databases, how our novel techniques continue to provide encouraging results for gait as a biometric, let alone as a human identifier, with especial regard for recognition at a distance.

1 Introduction and background

1.1 Gait as a biometric

A unique advantage of gait as a biometric is that it offers potential for recognition at a distance or at low resolution, when other biometrics might not be perceivable [1]. Recognition can be based on the (static) human shape as well as walking, suggesting a richer recognition cue. Further, gait can be used when other biometrics are obscured — criminal intent might motivate concealment of the face, but it is difficult to conceal and/or disguise motion as this generally impedes movement.

There is much evidence to support the notion of using gait to recognise people. This arises in literature, medicine, psychology, podiatry and mathematics. One of the earliest proponents was Shakespeare who makes several references to the individuality of gait:

*To seem like him: so that in speech, In **gait**, in diet, in affections of delight, In military rules, humours of blood, He was the mark and glass, copy and book. (Henry IV Part II);*

*'Tis Cinna; I do know him by his **gait** (Julius Caesar).*

Similar observations can be found in contemporary literature: "I noticed this figure coming, and I realised it was John Eubanks from the **way he walked**" [S. Ambrose: *Band of Brothers*].Early medical studies [2, 3] established many of the basic tenets of gait analysis. These studies suggested that gait appeared unique to subjects, but involved components that can only be derived from an overhead view (which is a less likely application scenario). Again though, the literature includes suggestions that individuals are indeed unique by their gait: "A given person will perform his or her walking pattern in a fairly repeatable and characteristic way, sufficiently unique that it is possible at a distance to recognise a person by their gait" [4]. Studies in psychology have progressed from establishing how humans can recognise subjects' motion [5] to recognising friends [6]. Early approaches used marker-based technology, but a later one used video imagery [7], also showing discrimination ability in poor illumination conditions. Research in podiatry focuses not only on forensic investigation of shoe type, but also of stride; mathematics offers no direct biometric support but does suggest advanced modelling strategies [8]. As such there is much support for the notion of gait as a biometric. This gives further possibility for using the moving human figure to prime application (and focus) of other biometric technologies.

1.2 Automatic recognition by gait

The earliest approaches to automated recognition by gait concentrated primarily on basic statistical techniques primarily processing silhouette images of subjects. These included analysis of a subject's trajectory [9], Principal Components Analysis (PCA) [10], moments (of flow) [11] and a combination of PCA with Canonical Analysis (CA) [12]. Only one approach favoured using a model to analyse the movement of the thigh [13].

This pattern is reflected in the current approaches, all but one are based on analysis of silhouettes, including: the University of Maryland's (UM's) deployment of hidden Markov models [14] and eigenanalysis [15]; the National Institute for Standards in Technology/University of South Florida's (NIST/USF's) baseline approach matching silhouettes [16]; Georgia Technical Research Institute's (GTRI's) data derivation of stride pattern [17]; Carnegie Mellon University's (CMU's) use of key frame analysis for sequence matching [18]; Massachusetts Institute of Technology's (MIT's) ellipsoidal fits [19]; Curtin's use of Point Distribution Models [20] and the Chinese Academy of Science's eigenspace transformation of an unwrapped human silhouette [21]. These show promise for baseline approaches that impose low computational and storage cost, together with deployment and development of new computer vision techniques for sequence-based analysis. These factors have also motivated our own approaches that range from a baseline-type approach by measuring area [22], to extension of technique for object description including symmetry [25] and statistical moments [23]. Further, we have extended our model-based technique to include full limb movement [28] and show how a model-based approach can facilitate greater application capabilities, especially that it can be used to recognise subjects not just by the way they walk, but also by how they run [29].

There are several factors of consequence if gait is to translate from a laboratory scenario to application capability. Naturally, the ability to handle surveillance video is paramount including not only the variation due to view angle, but also the poor quality (time lapse and interlaced) video produced by surveillance cameras.

1.3 Database development

Early approaches to automatic recognition by gait were analysed on relatively small databases consisting of, at maximum, 10 subjects. This was largely due to the large computational and storage requirements of gait. It has been very encouraging to note that similar levels of discrimination can be achieved on the much larger datasets now available. Naturally, the success and evolution of a new application relies largely on the dataset used for evaluation. Accordingly, it is encouraging to note the rich variety of data that has been developed. These approaches include: UM's surveillance camera data [14]; NIST/USF's outdoor data imaging subjects at a distance [30]; GTRI's data which combines marker-based motion analysis with video imagery [17]; CMU's multi-view indoor data [31]; MIT's indoor video data imaged over time [19]; and University of Southampton's data [32] which combines ground truth indoor data (processed by broadcast techniques) with video of the same subjects walking in an outdoor scenario (for computer vision analysis).

As gait is a behavioural biometric, there is much potential for within-subject variation. This includes footwear, clothing and apparel. None of these factors were accommodated in the early databases. Application factors concern deployment via computer vision though none of the early databases allowed facility for such consideration, save for striped trousers in an early Southampton database (aiming to allow for assessment of validity of a model-based approach). Our new database sought to include more subjects so as to allow for an estimate of inter-subject variation, together with a limited estimate of intra-subject variation thus allowing for better assessment of the potential for gait as a biometric. A further database is being constructed to allow in-depth assessment on intra-subject variation.

1.4 Overview

We shall first describe our advances in developing gait as a biometric, reviewing our approaches to moving articulated-object description for recognition, as well as enabling technology developed to derive generalised application capabilities. The description of our experimental evaluation starts with the database we have developed to investigate the basic potential of gait as a biometric. We then describe evaluation on our new database showing not only recognition capability but also generic application capability.

2 Advances in gait description and analysis

2.1 New recognition approaches

2.1.1 Holistic/silhouette approaches

Most approaches to automatic recognition by gait, develop measures to analyse the shape and movement of a human silhouette. This requires development of techniques that simultaneously describe planar shapes as well as factors of their movement. One of our earlier approaches extends statistical moments to include velocity. This is achieved [23] by reformulating the traditional (Zernike) moments equation:

$$A_{mn\mu\gamma} = \frac{m+1}{\pi} \sum_{i=2}^{images} \sum_{x,y} U(i,\mu,\gamma)\, S(m,n)\, P_{i_{x,y}} \quad (1)$$

where $S(m,n)$ is the usual spatial moment, in terms of order m and repetition rate n, and $U(i, \mu, \gamma)$ concerns the velocity component in terms of horizontal, μ, and, vertical, γ, movement between images based on image i. This is applied to a sequence of images P_i, such as those in Figure 1(a), resulting in a set of moments from which a reduced set is selected for recognition, as guided by ANOVA analysis. This superseded an earlier Cartesian velocity moments formulation [24].

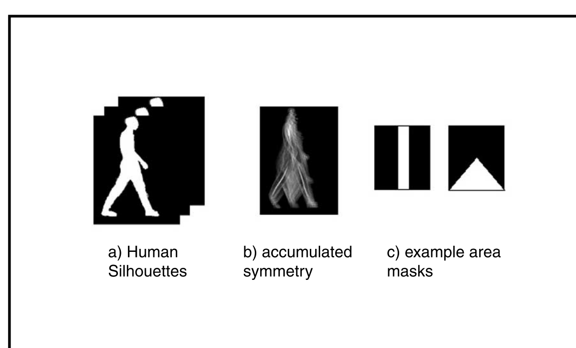
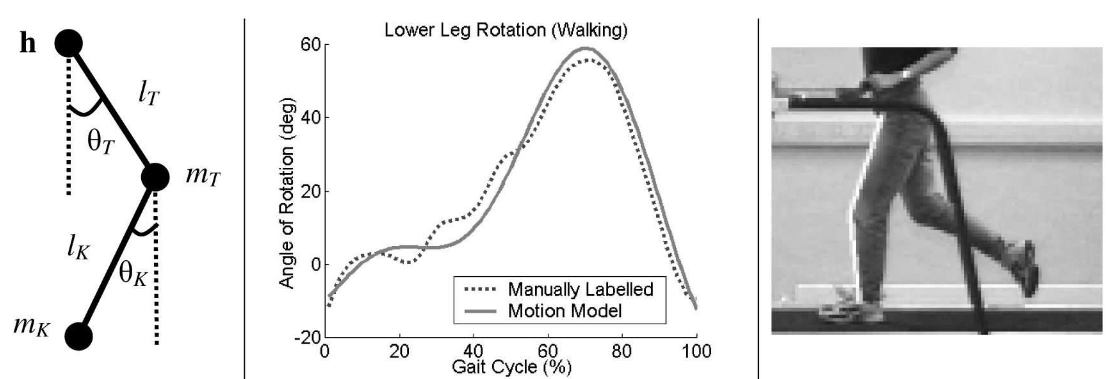


Figure 1: Gait recognition by silhouette analysis

$$FD_{T_{i,t}-T_{j,t-1}} = \frac{1}{\sqrt{2\pi\sigma_s}}\exp\left(-\frac{\left(\left\|T_{j,t}-T_{j,t-q}\right\|\right)-\mu_s}{2\sigma_s}\right)+\frac{1}{\sqrt{2\pi\sigma_T}}\exp\left(-\frac{\left(\left\|T_{j,t}-T_{j,t-q}\right\|\right)-\mu_T}{2\sigma_T}\right)W \qquad (2)$$

Similarly, inclusion of time within symmetry calculation can be achieved [25] by reformulating the distance functional to operate over time as well as space, as in equation (2) above where $T_{j,t}$ describes a point j in the silhouette at time t. The relative contribution of spatial and temporal symmetry is controlled by choice of the weighting W and their individual contributions moderated by choice of values for σ_s and μ_s and for σ_T and μ_T, respectively. Equation 2 is the modified distance functional in the discrete symmetry operator for which the other functionals (phase and intensity) remain unchanged. In application, the temporal symmetry is derived for a sequence of images first by edge detection. The accumulated symmetry, Figure 1(b), is then low-pass filtered from its Fourier representation to provide the recognition signature. This superseded (and gave better discriminatory capability than) an approach [26] that averaged symmetry calculations over the silhouette sequence whose generic capability was illustrated by discriminating animals by their movement [27].

In common with other baseline approaches, we also sought to develop a fast technique with specificity to gait. This is achieved [34] by using masking functions that are convolved with images to give a time variant signal describing gait. As it is a measure of area, not only is it fast in implementation, but it also allows for specificity to gait by choice of the masks used. In application, a selection of masks (of which two are shown in Figure 1(c)) is convolved to give the time variant signals that are resampled for matching purposes. Masks can be used alone, but greater discriminatory capability is



(a) basic model | (b) variation in knee angle | (c) image analysis

Figure 2: Model-based gait recognition [29].

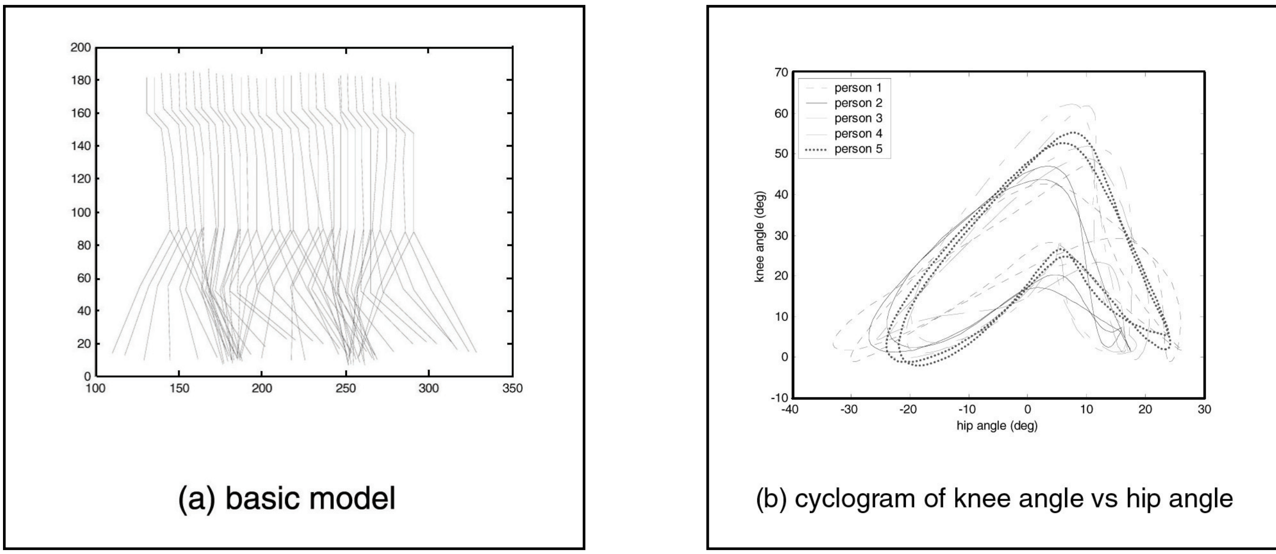


Figure 3: Anatomically-driven extraction and description [36].

derived by application of a combination of masks. Again, this was shown to be generic in nature by its capability to discriminate animals by their movement [22].

2.1.2 Model-based approaches

The earliest model-based approach relied on the use of frequency components of a thigh's motion. Naturally, this should also offer facility to model running as well as walking. Accordingly, we have extended the model to include both running and walking and to include the motion of the lower leg. This uses the concept of bilateral symmetry of the motion of the two legs, and phase coupling between the constituent sections. Our first approach was empirical, requiring specification of the value of a parameter to enforce modelling of the chosen gait mode. The model was then extended by considerations of mechanics to provide a unified model for walking and for running, without need for parameter selection [28]. The model is illustrated in Figure 2(a); the change in the knee angle θ_K with time is shown in Figure 2(b) superimposed on the analysis achieved by manual labelling. This can model successfully the motion of the thigh and the lower leg, for precise extraction of the thigh angle, and the lower leg angle, shown in Figure 2(c). This was achieved by considering the thigh as a free pendulum, forcing the motion of the lower leg, with solution for the thigh angle as

$$\theta_T = A\cos\left(\omega_T t + \phi_T\right) + B\sin\left(\omega_T t + \phi_T\right) \tag{3}$$

and for the lower leg (knee) angle as in equation (4) below where ωk and ωt represent the angular frequency of the knee and thigh angles, respectively. This is similar in principle to biomechanical models and offers potential for marker-less gait extraction [35]. This model

$$\theta_K\left(t\right) = A\cos\left(F\omega_K t\right) + B\sin\left(F\omega_K t\right) - \frac{m_T\omega_T^2}{\left(\omega_T{}^2 - \omega_K{}^2\right)}\left(C\cos\left(F\omega_T t + \phi_T\right) + D\sin\left(F\omega_T t + \phi_T\right)\right) \tag{4}$$

(a) one view	(b) reconstructed (moving) subject	(c) extracted thigh positions

Figure 4: 3D human extraction, reconstruction and analysis [37].

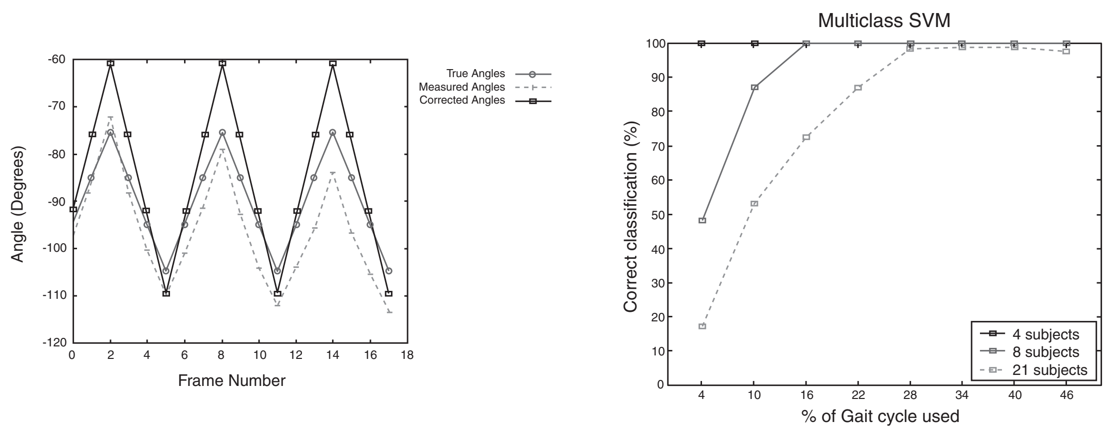
has been shown to good effect on a separately developed database of subjects who were filmed walking and running. This showed greater variation in the styles of running, consistent with the forced motion within a running gait. Further, the transformation between walking and running was shown [29] to have better discriminatory capability than the individual measures, which appears to be since the transformation subsumes both running and walking.

In order to investigate the basic nature of gait, and the link between silhouette-based descriptions and the human skeleton, we have been pioneering an anatomically driven approach that employs new cyclic descriptions for recognition. This model has been demonstrated to good effect on small laboratory databases [36], its target application is our laboratory data to acquire better understanding of the nature, and description, of gait. The motion of the skeleton derived from a silhouette sequence is shown in Figure 3(a) and the cyclogram derived from these new measures is shown in Figure 3(b).

2.2 Allied technology

It is not unlikely that subject extraction in complex scenarios will require full 3D extraction. In this respect we sought to use our model-based approach to aid 3D subject extraction from multi-view image sequences. In this, we have developed a new representation where reconstruction fidelity is dependent on view direction as well as on distance [37]. One of the viewed images is shown in Figure 4(a) where a subject walked outside our gait laboratory and under conventional 'domestic' illumination. The moving subject captured from within the image sequence and subtracted from the background, and reconstructed with our new representation is shown in Figure 4(b). The model of ambulatory human motion is then used to determine those points of the object with motion similar to that of the human thigh. The points so labelled are shown in Figure 4(c) superimposed in 3D in white on one of the original images.

As this approach requires synchronised imagery, we have also developed techniques



(a) viewpoint invariance [39]

(b) information content [40]

Figure 5: Generalisation capability analysis.

for moving binary-object interpolation as opposed to image interpolation [38]. This allows us to predict the position and shape of an object in between image frames, given knowledge of the motion history, as such allowing for potential synchronisation of independently timed cameras.

One of the main motivations for 3D analysis concerns the non-linearity associated with gait. With change in viewing angle, the motion of the leg will not be as shown in Figure 2(b). This motivates analysis for viewpoint correction or generation of analysis that makes gait signatures invariant to view direction. We have shown [39], in a laboratory scenario with images replicating human motion, that we can indeed correct for viewpoint using just the information present in the scene, rather than predefined geometrical analysis. This is illustrated in Figure 5(a) where the observed data is corrected to its true form from an error sometimes up to 20°. Further, not all of the gait cycle depicted in Figure 2(b) is actually required for recognition purposes [40].

By analysing motion captured joint data we have shown on smaller databases that high recognition capability can be achieved with using only a fraction of the gait cycle, as opposed to the complete one. This is illustrated in Figure 5(b), where a 100% correct recognition rate for a database of 21 subjects can be achieved using just 33% of the gait cycle.

There is generic interest in extracting moving objects from a sequence of images, as opposed to tracking them through the sequence. The earliest version of our extraction approach was derived by extracting an arbitrary shape moving with constant velocity. By using a Fourier shape description of the target shape and of its motion trajectory, a technique was developed [41] that can be used to extract an arbitrary shape with arbitrary motion. This requires an 8D accumulator space that was reduced to 4D (i.e. those parameters describing the shape's general appearance) with a constraint of smooth motion under analysis using a genetic algorithm [42].

3 Analysing recognition by gait

3.1 The Southampton database

3.1.1 Technological considerations

Our target was for over 100 subjects for each of whom we would like approximately 60 sequences of 1.5 steps (as gait is periodic, heel strike of one foot though heel-strike of the same foot to heel-strike of the other) together with background and other supporting data. Given that Digital Video (DV) is now an established technology at reasonable cost and since our evaluation of quality suggested that it could equal that of conventional CCIR with A/D, we chose DV [32]. Naturally, this is a compromise; an alternative is to stream uncompressed video to disk. As such, we chose to acquire imagery via good quality progressive scan and interlaced DV camcorders. The database construction software was Python (and XML for labelling); recognition implementations use standard languages, primarily for reasons of speed.

3.1.2 Database design

In order to provide an approximation to ground truth and to acquire imagery for application analysis, we chose to film subjects indoors and outdoors, respectively. Indoors, treadmills are most convenient for acquisition as long gait sequences can be acquired by their use though there is some debate as to how they can affect gait. Some studies hold that kinetics are affected rather than kinematics, but our experience with using untrained subjects and limitations on footwear and clothing motivated us to consider the track as the most suited for full analysis. The track was of the shape of a 'dog's bone', shown in Figure 6(a), so that subjects walked constantly and passed in front of the camera in both directions. The track was prepared with chromakey cloth (bright green, as this is an unusual clothes' colour) and the background was illuminated by photoflood lamps, viewed from either end in Figures 6(b) and (c), viewed normally and at an oblique angle. This enables chromakeyed subject separation from background, as in broadcast technology. The same camera view and

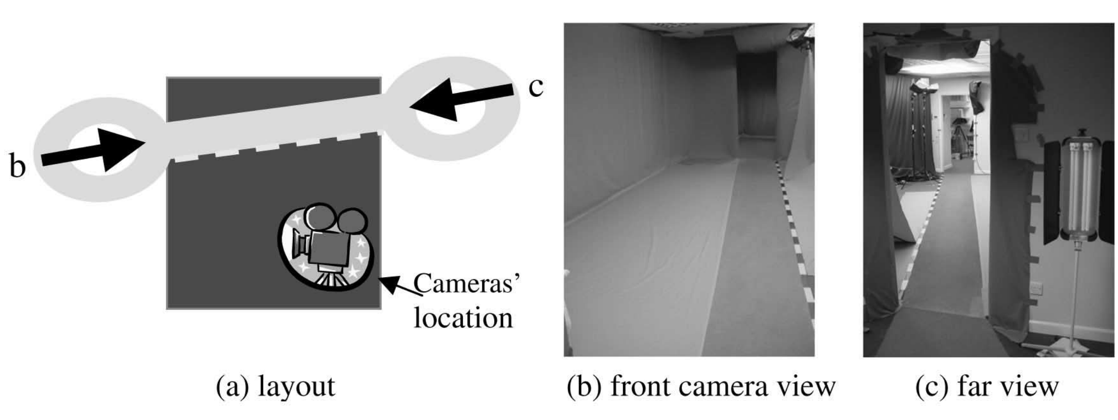


Figure 6: Indoor walking track.

(a) track | (b) treadmill | (c) outside

Figure 7: Example data from Southampton's large gait database.

chromakey arrangements were used for the treadmill, but here subjects were highlighted with diffuse spotlights.

The treadmill was set at constant speed and inclination, aimed to support a conventional walk pattern. Psychology suggested that all personnel should be outside the laboratory during recording, to avoid any embarrassment and any movement of the head during conversation. Further, a talk-only radio was used to ease familiarity with the laboratory. Placing a mirror in front of the treadmill aided balance and stopped the subject from looking at their feet and/or the treadmill control panel. Example images from the indoor data are shown in Figures 7(a) and (b). A similar track layout was used outdoors, Figure 7(c), where the background contained a selection of objects such as foliage, pedestrian and vehicular traffic, buildings (also for calibration) as well as occlusion by bicycles, cars and other subjects. As such, subjects' silhouettes can be extracted from outdoor Figure 7(b) and indoor Figure 7(a) imagery and their signatures compared, comparing a version of ground truth with application data.

The imagery for the large database was completed with a high resolution still image of each subject in frontal and profile views, allowing for comparison with face recognition and for good estimates of body shape and size. Further, 10 subjects were filmed on the track wearing a variety of footwear and clothing, carrying a variety of objects and at different times, to allow for estimation of intra-subject variability. The initial track data was segmented into background and walking sequences and further labels were introduced for each heel strike and direction of walking. This information is associated with the data as XML; these labels include subject ingress, egress, direction of walk and heel-strikes, together with laboratory and camera set-up information recorded for each recording session. This allowed for basic analysis including manually imposed gait cycle labels. The treadmill and outside data was segmented into background and walk (including direction) data only.

3.2 Recognition by gait

3.2.1 Overview

The approaches described in Section 2.1 process a sequence of images to provide a gait signature. Ideally, the sequence of images is taken from heel-strike to the next heel strike of

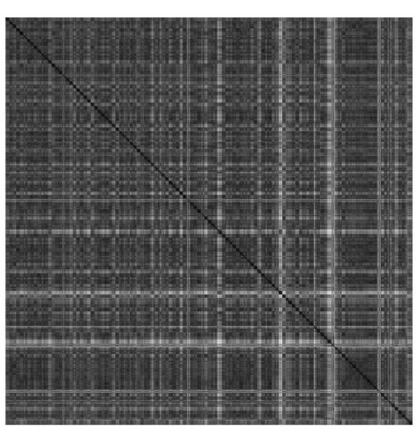
Algorithm	No. of Subjects	No. of Sequences	Classifier Result (%)	
			k = 1	k = 3
Symmetry [23]	28	4	97	96
Velocity Moments [43]	50	4	97	96
Area Moments [44]	114	8	87	-

Figure 8: Progression of results on the large gait database.

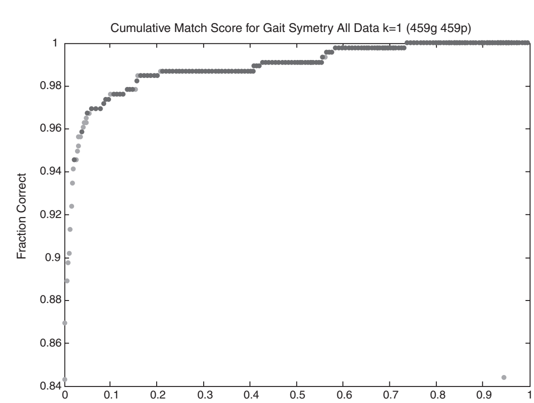
the same foot. The holistic approaches require a silhouette to be derived, or optical flow, resulting in a set of connected points in each analysed image. These are then classified. Here we use the *k*-nearest neighbour approach, whilst noting that more sophisticated classifiers can offer better performance, often in respect of generalization capability. The Euclidean distance metric is used to provide ranking lists describing the difference between signatures. In accordance with current practice, we used training, probe and gallery sets to develop sets of ranked lists and cumulative match scores.

3.2.2 Analysis of Southampton database — recognition capability

To date, different recognition approaches — all holistic — have been applied to our new data, all with encouraging results. This analysis of the database suggests that it has indeed met its design objectives. First, high gait recognition performances have been achieved on the largest yet number of subjects for gait, an overview of these results can be seen in Figure 8. The progression of these results reflects the gradual construction of the database and detailed explanations of these results can be found in [23, 43, 44]. It is of note

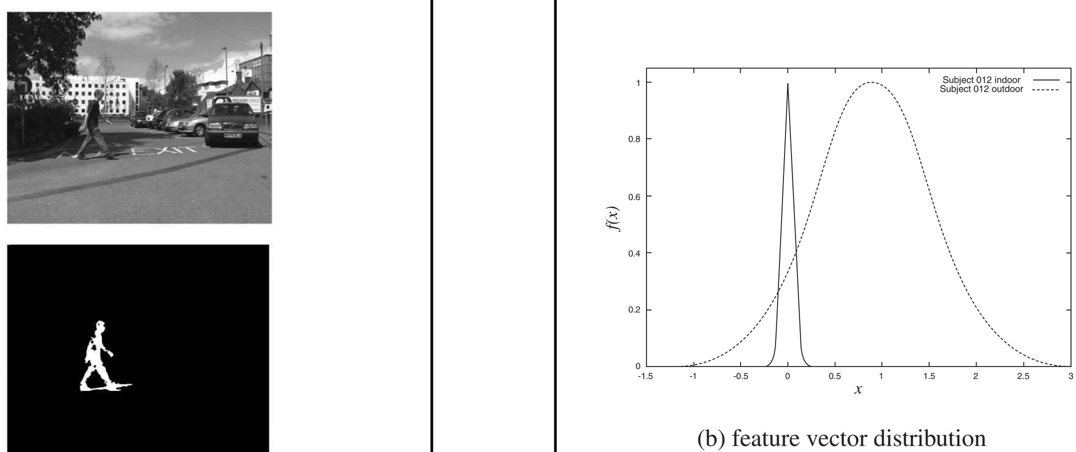


(a) distance measures



(b) CMS curve

Figure 9: Data analysis descriptions.



(a) outside view and extracted silhouette

(b) feature vector distribution

Figure 10: Generalising to outside data.

that symmetry has the most potent performance, moments have the greatest invariance properties whereas the area moments are formulated more for speed. In these respects we are encouraged by the lower performance of the area measures and anticipate much better discriminatory capability by the other approaches on the full database. The processing of the data used much of the available support material, enabling streamlined and in some cases automated analysis. These results used a selection of binary silhouettes and optical flow descriptions generated from the inside laboratory data.

The distance analysis and the cumulative match score (CMS) are shown in Figures 9(a) and (b), respectively. The distance measures show that most subjects are clearly distinguished by their gait and most classes are highly disparate (black represents similarity and white is difference), but there is some potential for class confusion. This is reflected by the CMS curve starting at over 80% but note that 98% correct of the probes are within nearly the first 10% of the gallery.

3.2.3 Analysis of Southampton database — deployment capability

A preliminary analysis of the outdoor data concerns the increased variance of features extracted from application scenario imagery as opposed to ground truth [32], shown here for two subjects in Figure 10. In Figure 10(b) the tight Gaussian represents the variance of the inside data, whereas the larger Gaussian (greater variance) is the outdoor data. The difference between the two means represents the feature point drift of the outside data with respect to the inside (ground truth) data.

4 Discussion and further work

These techniques and databases can be used beyond pure gait-as-a-biometric research. In terms of biometric analysis, the model-based approaches remove many of the deployment factors, but at computational cost. Techniques have already been analysed in respect of translation to surveillance video, but this can be extended in view of camera position, and perspective distortion. In terms of technique development, the database allows for the evaluation of background removal techniques, high level moving-feature analysis techniques (both rigid and non-rigid) and face recognition analysis. As such, our new database allows not just for evaluation of the potential of gait as a biometric but also the evaluation of many other sequence-based vision and image processing problems.

5 Conclusions

We firmly believe that by our new technique and by our results, gait continues to show encouraging potential as a biometric. We have constructed one of the largest gait databases, specifically designed to investigate the potential of gait as a biometric. The database allows for investigation of the inter- and intra-class subject variance. The techniques have specifically been designed to provide silhouette-based analysis with specificity to gait, by generic formulation tailored to the target application and/or analysis. These techniques include velocity moments, temporal symmetry, and area masks that all describe not only the shape, but also how it moves. We have also extended our model-based approach to include full limb movement and have demonstrated how it can be used to recognise people by the way they walk *and* by the way they run. A further approach uses anatomy to guide signature extraction, aimed to support further investigation of gait's basic potential. These have been supported by studies in allied technology such as viewpoint invariance, 3D reconstruction, object-based synchronisation and information content analysis. These studies continue to confirm that gait is a richer study than it originally appeared. There are many avenues by which the already encouraging potential for gait as a biometric can be improved, not only by result but also by generalization capability.

Acknowledgements

We gratefully acknowledge the inputs of Jeff Foster, James Hayfron-Acquah, Chew Yean Yam, Richard French, Layla Gordon, Vijay Laxmi, Peloppidas Lappas, Nick Foster, Stuart Prismall, Jang-Hee Yoo, Peter Myerscough, and Rob Boston together with the many discussions we have had with other members of the DARPA HumanID programme, and the use of their data.

We gratefully acknowledge support by the European Research Office of the US Army under Contract No. N68171-01-C-9002.

References

[1] M.S. Nixon, J.N. Carter, D. Cunado, P.S. Huang and S.V. Stevenage, 1999. Automatic Gait Recognition, In: A.K. Jain, R. Bolle and S. Pankanti Eds., *Biometrics: Personal Identification in Networked Society*, Kluwer Academic Publishing, 1999, pp. 231-250.

[2] M.P. Murray, A.B. Drought, R.C. Kory, 1964. Walking Patterns of Normal Men, *Journal of Bone and Joint Surgery*, Vol. 46-A(2), 1964, pp. 335-360.

[3] M.P. Murray, 19676. Gait as a Total Pattern of Movement, *American Journal of Physical Medicine*, Vol. 46(1), 1967, pp. 290-332.

[4] D. Winter, 1991. *The Biomechanics and Motor Control of Human Gait*, 2nd Edn., Waterloo, 1991.

[5] G. Johannson, 1973. Visual Perception of Biological Motion and a Model for its Analysis, *Perception and Psychophysics*, Vol. 14, 1973, pp. 201-211.

[6] L.T. Kozlowski and J.E. Cutting, 1977. Recognising the Sex of a Walker from a Dynamic Point Light Display, *Perception and Psychophysics*, Vol. 21, 1977, pp. 575-580.

[7] S.V. Stevenage, M.S. Nixon and K. Vince, 1999. Visual Analysis of Gait as a Cue to Identity, *Applied Cognitive Psychology*, Vol. 13, 1999, pp. 513-526.

[8] I. Stewart, 1999. Symmetry-breaking Cascades and the Dynamics of Morphogenesis and Behaviour, *Science Progress*, Vol. 82(1), 1999, pp. 9-48.

[9] S.A. Niyogi, E.H. Adelson, 1994. Analyzing and Recognizing Walking Figures in XYT, *Proc. Conf. Comp. Vis. and Pattern Recog. 1994*, pp. 469-474.

[10] H. Murase and R. Sakai, 1996. Moving Object Recognition in Eigenspace Representation: Gait Analysis and Lip Reading, *Pattern Recog. Letters*, Vol. 17, 1996, pp. 155-162.

[11] J. Little and J. Boyd, 1998. Recognising People by Their Gait: the Shape of Motion, *Videre, International Journal of Computer Vision*, Vol. 14(6), 1998, pp. 83-105.

[12] P.S. Huang, C.J. Harris and M.S. Nixon, Recognizing Humans by Gait via Parametric Canonical Space, *Artificial Intelligence in Engineering*, Vol. 13(4), 1999, pp. 359-366.

[13] D. Cunado, M.S. Nixon and J.N. Carter, 1997. Using gait as a biometric, via phase-weighted magnitude spectra, *Proc. 1st Int. Conf. on Audio- and Video-Based Biometric Person Authentication*, pp. 95-102.

[14] A. Kale, A.N. Rajagopalan, N. Cuntoor and V. Kruger, 2002. Gait-based

Recognition of Humans Using Continuous HMMs, *IEEE Conf. Face and Gesture Recognition*, pp. 336-341.

[15] C.B. Abdelkader, R. Cutler, H. Nanda and L. Davis, 2001. EigenGait: Motion-Based Recognition Using Image Self-Similarity, *Proc. 3rd Audio- and Video-Based Biometric Person Authentication*, pp. 289-294.

[16] P.J. Phillips, S. Sarkar, I. Robledo, P. Grother and K. Bowyer, 2002. Baseline Results for the Challenge Problem of Human ID Using Gait Analysis, *Proc. IEEE Conf. Face and Gesture Analysis '02*, pp. 137-143.

[17] A.Y. Johnson and A.F. Bobick, 2001. A Multi-View Method for Gait Recognition Using Static Body Parameters, *Proc. 3rd Audio- and Video-Based Biometric Person Authentication*, pp. 301-311.

[18] R. Collins, R. Gross and J. Shi, 2002. Silhouette-based Human Identification from Body Shape and Gait, *Proc. IEEE Conf. Face and Gesture Analysis '02*.

[19] L. Lee and W.E.L. Grimson, 2002. Gait Analysis for Recognition and Classification, *Proc. IEEE Conf. Face and Gesture Analysis '02*, pp. 155-162.

[20] E. Tassone, G. West and S. Venkatesh, 2002. Temporal PDMs for Gait Classification, *16th International Conference on Pattern Recognition*, pp. 1065-1069.

[21] L. Wang, W. Hu and T. Tan, 2002. A New Attempt to Gait-based Human Identification, 16th International Conf. on Pattern Recognition, pp. 115-119.

[22] J.P. Foster and M.S. Nixon, 2001. A. Prugel-Bennet, Recognising Movement and Gait by Masking Functions, *Proc. Audio Visual Biometric Person Authentication 2001*, Stockholm, pp. 278-283.

[23] J.D. Shutler and M.S. Nixon, Zernike Velocity Moments for Description and Recognition of Moving Shapes, *Proc. British Machine Vision Conference 2001*, pp 705-714, 2001

[24] J. D. Shutler, M. S. Nixon and C. J. Harris, 2000. Statistical Gait Description via Temporal Moments, *Proc. 4th IEEE SSIAI*, Texas, pp. 291-295.

[25] J.B. Hayfron-Acquah, M.S. Nixon and J.N. Carter, 2002. Human Identification by Spatio-Temporal Symmetry, *16th International Conf. on Pattern Recognition.*

[26] J.B. Hayfron-Acquah, M.S. Nixon and J.N. Carter, 2001. Automatic Gait Recognition by Symmetry Analysis, *Proc. Audio Visual Biometric Person Authentication 2001*, Stockholm, pp. 312-317.

[27] J.B. Hayfron-Acquah, M.S. Nixon and J.N. Carter, 2001. Recognising Human and Animal Movement by Symmetry, *Proc. IEEE International Conf. on Image Processing*, Thessaloniki, Greece, pp. 290-293.

[28] C.-Y. Yam, M.S. Nixon and J.N. Carter, 2002. Gait Recognition by Walking and Running: a Model-Based Approach, *Proc. Asian Conf. on Computer Vision ACCV 2002*, pp. 1-6.

[29] C.-Y. Yam, M.S. Nixon and J.N. Carter, 2002. On the Relationship of Human Walking and Running: Automatic Person Identification by Gait, *16th International Conf. on Pattern Recognition.*

[30] P.J. Phillips, S. Sarkar, I. Robledo, P. Grother and K. Bowyer, 2002. The Gait Identification Challenge Problem: Data Sets and Baseline Algorithm, *16th International Conf. on Pattern Recognition*, pp. 385-389.

[31] R. Gross and J. Shi, 2001. The CMU Motion of Body (MoBo) Database, *CMU-RI-TR-01-18*, 2001.

[32] J.D. Shutler, M.G. Grant, M.S. Nixon and J.N. Carter, 2002. "On a Large Sequence-Based Human Gait Database", Accepted for Special Session on Biometrics, *4th International Conf. on Recent Advances in Soft Computing*, Nottingham (UK), 2002.

[33] J.P. Foster, 2002. A. Prugel-Bennet, Gait Recognition by Moment Based Descriptors, Accepted for Special Session on Biometrics, *4th International Conf. on Recent Advances in Soft Computing*, Nottingham (UK), 2002.

[34] J.P. Foster, M.S. Nixon and A. Prugel-Bennet, 2001. New Area Based Metrics for Automatic Gait Recognition, *Proc. British Machine Vision Conf. 2001*, pp. 233-242.

[35] C.-Y. Yam, M.S. Nixon and J.N. Carter, 2002. Automated Markerless Analysis of Human Walking and Running by Computer Vision, *Proc. World Congress on Biomechanics*, 2002.

[36] J.-H. Yoo, M.S. Nixon and C.J. Harris, 2002. Model-Driven Statistical Analysis of Human Gait Motion, *Proc. IEEE International Conf. on Image Processing*, 2002.

[37] K.J. Sharman, M.S. Nixon and J.N. Carter, 2002. Extraction and Description of 3D (Articulated) Moving Objects, *Proc. 3D Data Processing Visualisation Transmission*, 2002.

[38] S.P. Prismall, M.S. Nixon and J.N. Carter, 2002. On Moving Object Reconstruction by Moments, *Proc. British Machine Vision Conference 2002*, pp. 73-82.

[39] N. Spencer and J.N. Carter, 2002. Viewpoint Invariance in Automatic Gait Recognition, *Proc. AutoID 2002*, pp. 1-6.

[40] V.J. Laxmi, J.N. Carter and R.I. Damper, 2002. Support Vector Machines and Human Gait Classification, *Proc. AutoID 2002*, pp. 17-22.

[41] M.G. Grant, M.S. Nixon and P.H. Lewis, 2002. Extracting Moving Shapes by Evidence Gathering, *Pattern Recognition*, Vol. 35, 2002, pp. 1099-1114.

[42] P. Lappas, J.N. Carter and R.I . Damper, 2001. Robust Evidence-Based Object Tracking, *Pattern Recognition Letters*, Vol. 23(1-3), 2001, pp. 253-260.

[43] J.B. Hayfron-Acquah, M.S. Nixon, J.N. Carter, 2001. Automatic Gait Recognition by Symmetry Analysis, At press, *Pattern Recognition Letters*, Special Issue on AVBPA 2001.

[44] J.P. Foster, M.S. Nixon and A. Prugel-Bennet , 2002. Automatic Gait Recognition using Area Based Metrics, *Pattern Recognition Letters*, in press.