Research article

Automatic recognition by gait: progress and prospects

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Abstract

Recognising people by their gait is a biometric of increasing interest. Recently, analysis has progressed from evaluation by few techniques on small databases with encouraging results to large databases and still with encouraging results. The potential of gait as a biometric was encouraged by the considerable amount of evidence available, especially in biomechanics and literature. This potential motivated the development of new databases, new technique and more rigorous evaluation procedures. We adumbrate some of the new techniques we have developed and their evaluation to gain insight into the potential for gait as a biometric. In particular, we consider implications for the future. Our work, as with others, continues to provide encouraging results for gait as a biometric, let alone as a human identifier, with a special regard for recognition at a distance.

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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 (Nixon *et al.*, 1999). Further, it is difficult to disguise gait without hampering progress, which is of particular interest in scene of crime analysis. Recognition can be based on the (static) human shape as well as on movement, 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. Shakespeare made several references to the individuality of gait, e.g.:

> For that John Mortimer. . .in face, in gait in speech he doth resemble (Henry IV/II).

Further, the biomechanics literature makes similar observations:

> A given person will perform his or her walking pattern in a fairly repeatable and characteristic way, sufficiently unique that it is possible to recognize a person at a distance by their gait (Winter, 1991).

Similar observations can be found elsewhere, even in contemporary literature. Early medical studies (Murray *et al.*, 1964) established many of the basic tenets of gait analysis. These studies again suggested that gait appeared unique to subjects. Studies in psychology have progressed from establishing how humans can recognise subjects' motion (Johannson, 1973), to recognising friends. Early approaches used marker-based technology, but a later one used video imagery (Stevenage *et al.*, 1999), also showing discrimination ability in poor illumination

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conditions. As such there is much support for the notion of gait as a biometric.

1.2 Recognising people by their gait

Early approaches were limited to using more standard techniques processing silhouettes. These included analysing subjects' trajectories (Niyogi and Adelson, 1994), principal components analysis (PCA) (Murase and Sakai, 1996), moments (of flow) (Little and Boyd, 1998) and a combination of PCA with canonical analysis (CA) (Huang *et al.*, 1999). Only one approach used a model to analyse leg movement (Cunado *et al.*, 2003). 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 (Kale *et al.*, 2002) and eigenanalysis (Abdelkader *et al.*, 2001); the National Institute for Standards in Technology/University of South Florida's (NIST/USF's) baseline approach matching silhouettes (Phillips *et al.*, 2002a); Georgia Institute of Technology's (GT's) data derivation of stride pattern (Johnson and Bobick, 2001); Carnegie Mellon University's (CMU's) use of key frame analysis for sequence matching (Collins *et al.*, 2002); Massachusetts Institute of Technology's (MIT's) ellipsoidal fits (Lee and Grimson, 2002); Curtin's use of Point Distribution Models (Tassone *et al.*, 2002) and the Chinese Academy of Science's eigenspace transformation of an unwrapped human silhouette (Wang *et al.*, 2002). These show promise for 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 newer approaches that range from a baseline-type approach by measuring area (Foster *et al.*, 2003) to extension of technique for object description including symmetry (Hayfron-Acquah *et al.*, 2003) and statistical moments (Shutler and Nixon, 2001). Further, we have extended our model-based technique to include full limb movement (Yam *et al.*, 2002a) and show how a model-based approach can facilitate greater application capabilities.

1.3 Database development

Early approaches used relatively small databases. This was largely enforced by limited computational and storage requirements at that time. It has been very encouraging to note that similar levels of discrimination can be achieved on the much larger datasets 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 have been developed. These approaches include: UM's surveillance data (Kale *et al.*, 2002); NIST/USF's outdoor data, imaging subjects at a distance (Phillips *et al.*, 2002b); GT's data combines marker-based motion analysis with video imagery (Johnson and Bobick, 2001); CMU's multi-view indoor data (Gross and Shi, 2001); and University of Southampton's data (Shutler *et al.*, 2002) 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. 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 databases 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.

2. Advances in gait description and analysis

2.1 New recognition approaches

2.1.1 Holistic/silhouette approaches

Essentially, we seek to process video images (Figure 1(a)) to derive silhouettes of the moving subject (Figure 1(b)) from which we derive numbers that reflect the identity of the subject (Figure 1(c)). This then describes a subject, not just by shape but also by motion. As with earlier holistic approach (Huang *et al.*, 1999), this is achieved (Shutler and Nixon, 2001) by reformulating a traditional description (by moments) to include motion (time) and applying it to a sequence of images. In Figure 1(c), there are four such sequences from each of ten subjects in each cluster for

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Figure 1 Gait recognition by silhouette analysis

(a) Video Data (b) Silhouette (c) Feature space

three such measures. The clustering reflects that recognition can indeed be achieved.

Similarly, inclusion of time within a symmetry calculation can include (Hayfron-Acquah *et al.*, 2003) contributions of spatial and temporal symmetry. A modified distance functional changes and the other functionals (phase and intensity) remain unchanged. In application, the temporal symmetry is derived for a sequence of images first by edge detection. In common with other baseline approaches, we also sought to develop a fast technique with specificity to gait (Foster *et al.*, 2003). This is achieved by using masking functions that are convolved to give a time variant signal describing gait. As it is a measure of area, not only it is fast in implementation, but it also allows for specificity to gait by choice of the masks used.

2.1.2 Model-based approaches

The earliest model-based approach relied on the use of frequency components of a thigh's motion (Cunado *et al.*, 2003). Naturally, this should also offer facility to model running as well as walking. Accordingly, we 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. The new model provides a unified model for walking and running, without the need for parameter selection (Yam *et al.*, 2002a). The model is shown 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, This model has been shown to have 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 measures describing the transformation between walking and running were shown (Yam *et al.*, 2002b) to have better discriminatory capability than the individual measures (for walking and running alone), 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 developing an anatomically driven approach that employs new cyclic descriptions for recognition. This model has been demonstrated to have a good effect on small laboratory databases (Yoo *et al.*, 2002), 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).

3. Analysing recognition by gait

3.1 The Southampton database

3.1.1 Technological considerations

We sought to acquire two main databases: one of over 100 subjects to examine inter-subject distance (the difference between individuals), the other is of ten subjects and assesses intra-subject variance (the change within an individual subject). Given that digital video (DV) is now an established technology at reasonable cost and since our evaluation of quality suggested that it could be equal to that of conventional CCIR with A/D, and to reduce data volume, we chose DV (Shutler *et al.*, 2002). We chose to acquire imagery via good quality progressive scan and interlaced

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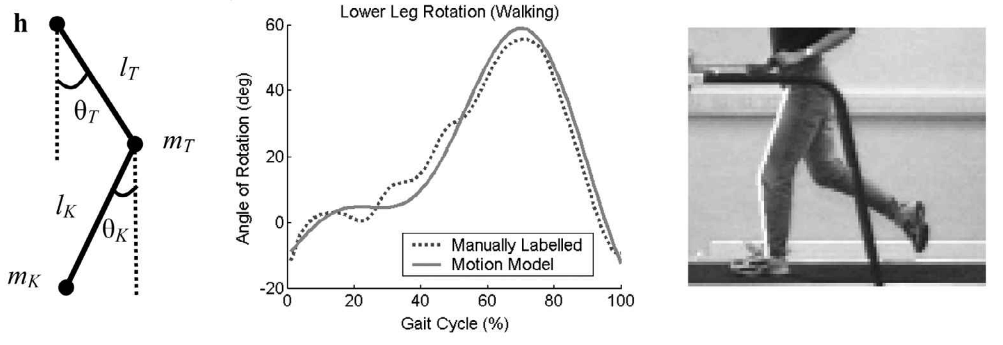
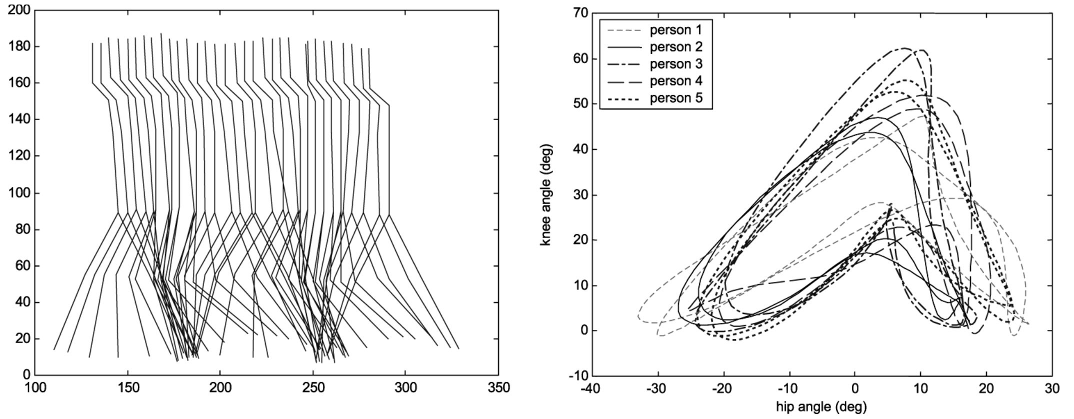
Figure 2 Model-based gait recognition (Yam *et al.*, 2002b)



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

Figure 3 Anatomically-driven extraction and description (Yoo *et al.*, 2002)



(a) basic model (b) cyclogram of knee angle vs. hip angle

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 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 4(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, seen from either end in Figure 4(b) and (c), viewed by cameras frontally, normally and at an oblique angle (an additional surveillance view is not shown). The arrangement enables chromakeyed subject separation from background, as in broadcast technology. On the treadmill, subjects were highlighted with diffuse spotlights and 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 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 Figure 5. A similar track layout was used outdoors (Figure 1(a)), where the

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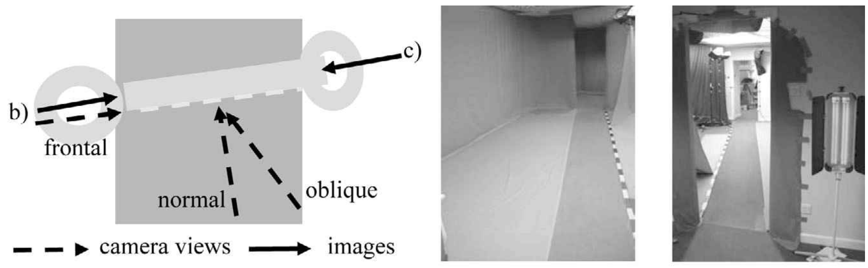
Figure 4 Indoor walking track (Shutler *et al.*, 2002)



(a) layout and views (b) front camera view (c) far view

Figure 5 Example data from Southampton's gait databases (Shutler *et al.*, 2002)

(a) normal (b) bag (c) shoe

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.

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, ten 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 were segmented into background and walk (including direction) data only.

3.2 Recognition by gait

3.2.1 Overview

Our approaches 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 the same foot.

The holistic approaches require a silhouette to be derived, or optical flow (which describes motion), resulting in a set of connected points in each analysed image. These are then classified. Here we use the *k*-nearest neighbour approach to allow comparison with other approaches, 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. Again, more sophisticated measures are available. 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 via analysis by symmetry can be seen in Figure 6. The progression of these results reflects the gradual construction of the databases. It is of note that symmetry has the most potent

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Figure 6 Progression of recognition results by symmetry

No. of Subjects	No. of Sequences	Classifier Result (%)	
		$k = 1$	$k = 3$
28	4 with 1 cycle	97	96
50	4 with 1 cycle	95	93
114	8 with 1 cycle	94	90

performance, moments have the greatest invariance properties whereas the area moments are formulated more for speed. These results show a recognition rate that is perhaps higher than originally anticipated. Other techniques equal this discriminatory capability (Johnson and Bobick, 2001; Kale *et al.*, 2002, 2003; Phillips *et al.*, 2002a). Further outdoor investigation has been reported elsewhere (Nixon *et al.*, 2002).

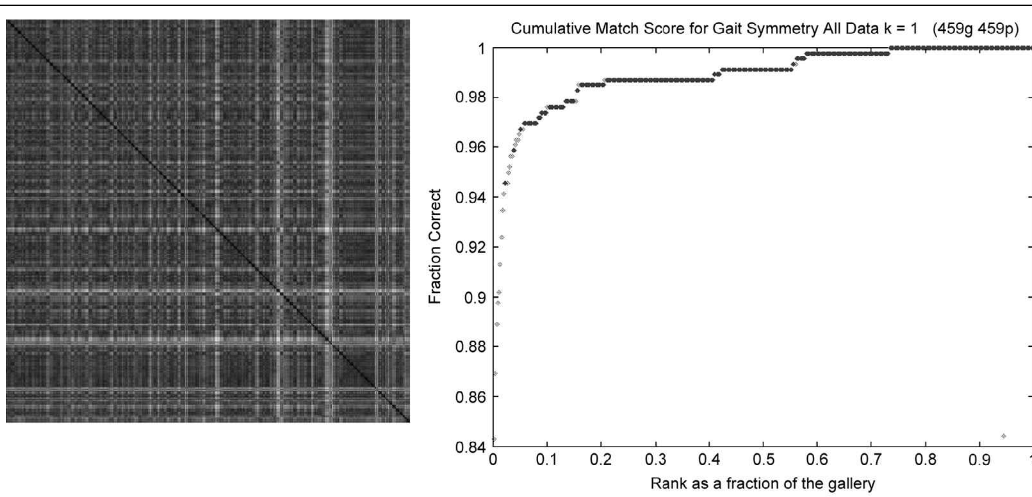
The distance analysis and the cumulative match score (CMS) are shown in Figure 7(a) and (b), respectively. The distance measures show that most subjects are clearly distinguished by their gait and most classes are highly disparate (black represents similarity and white represents difference), but there is some potential for class confusion. This is reflected by the CMS curve starting at over 80 per cent but note that 98 per cent correct of the probes are within nearly the first 10 per cent of the gallery.

4. A future for gait?

The future for gait is unlikely to be just for biometric purposes. There are medical implications (for markerless gait), forensic implications (scene of crime analysis), and potential links to animation and the film industry. In terms of biometric deployment, 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 (Sharman *et al.*, 2002). One of the viewed images is shown in Figure 8(a), where a subject walked outside our gait laboratory and under conventional "domestic" illumination. The moving subject was extracted from the background, and reconstructed with our new representation, as shown in Figure 8(b). A 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 8(c) superimposed in 3D in white on one of the original images.

One of the main motivations for 3D analysis concerns the non-linearity associated with gait. With change in viewing angle, the perceived motion of the leg will not be as shown in Figure 2(b). This motivates analysis

Figure 7 Data analysis descriptions



(a) distance measures (b) CMS curve (by moments)

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Figure 8 3D human extraction, reconstruction and analysis (Sharman *et al.*, 2002)

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

for viewpoint correction or generation of analysis that makes gait signatures invariant to view direction. We have shown (Spencer and Carter, 2002), 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. Further, not all of the gait cycle depicted in Figure 2(b) is actually required for recognition purposes (Laxmi *et al.*, 2002). By analysing motion captured joint data, we have shown on smaller databases that high recognition capability can be achieved by using only a fraction of the gait cycle, as opposed to the complete one.

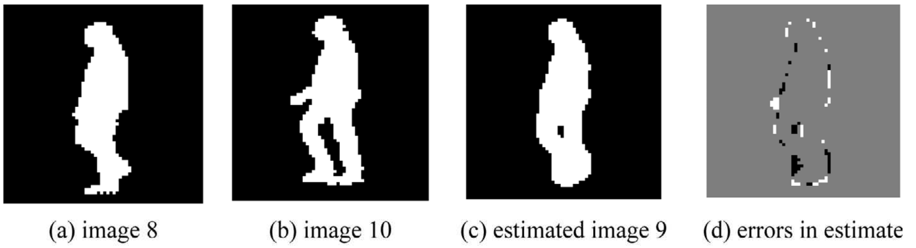
There are many covariate factors in gait. In this respect, it is encouraging that gait's progress has been helped, not only in database construction but also by early concentration on covariate factors. Though speed would appear to be a covariate, it has been studied as integral to the basic nature of gait (Tanawongsuwan and Bobick, 2003). Further factors including carrying load and wearing different clothing have to be studied in one of the Southampton databases. Interestingly, increase in resolution can be performed in time as well as in space (Prismall *et al.*, 2003). Figure 9 shows the ability to predict new frames from within a sequence of images, a new form of in-betweening specific to gait. Here, a missing frame (no. 10) is estimated from the one's either side and the motion of the leg is predicted well. This will allow for synchronising of multiple views.

The future also concerns other applications. Essentially, we have ability to detect and describe gait without subject contact (Yam *et al.*, 2002c). This lends itself to deeper analysis (for its use is now more convenient) as well as a richer application domain. We hope to deploy our analysis for medical use: we already have better ability to process larger databases automatically and look forward to new insight that this might bring. It could also lead to better animation, for our procedures, describe motion with accuracy and allow for analysis of "average" motion as well as individual motion. Since these differ from biometric use, we anticipate that there might be accompanying refinement to our gait description techniques.

5. Conclusions

We firmly believe that by our new technique and 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

Figure 9 In-betweening a silhouette's motion (Prismall *et al.*, 2003)



(a) image 8 (b) image 10 (c) estimated image 9 (d) errors in estimate the target application and/or analysis. These techniques describe not only the shape, but also how it moves. We have also extended and demonstrated how a model-based approach can be used to recognise people by the way they walk and run. 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, and deployed.

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