Advances in Automatic Gait Recognition

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Abstract

Automatic recognition by gait is subject to increasing interest and has the unique capability to recognize people at a distance when other biometrics are obscured. Its interest is reinforced by the longstanding computer vision interest in automated non-invasive analysis of human motion. Its recognition capability is supported by studies in other domains such as medicine (biomechanics), mathematics and psychology which continue to suggest that gait is unique. Further, examples of recognition by gait can be found in literature, with early reference by Shakespeare concerning recognition by the way people walk. Current approaches confirm the early results that suggested gait could be used for identification, and now on much larger databases. This has been especially influenced by the Human ID at a Distance research program with its wide scenario of data and approaches. Gait has benefited from the developments in other biometrics and has led to new insight particularly in view of covariates. As such, gait is an interesting research area, with contributions not only to the field of biometrics but also to the stock of new techniques for the extraction and description of objects moving within image sequences.

1. Biometrics and Gait

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]. 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. in *The Tempest* [Act 4 Scene 1], Ceres observes "*High'st Queen of state, Great Juno comes; I know her by her gait*" even more, in *Twelfth Night* Maria observes of Malviolo "*By the colour of his beard, the shape of his leg, the manner of his gait, …, he shall find himself most pleasingly personated*". The biomechanics literature makes similar observations: "*A .. person will perform his .. walking pattern in a fairly repeatable .. way, sufficiently unique that it is possible to recognize a person at a distance by their gait*" [2]

The aim of medical research has been to classify the components of gait for the treatment of pathologically abnormal patients. Murray *et al*. [3] produced standard movement patterns for pathologically normal people which were used to compare the gait patterns for pathologically abnormal patients [4]. These studies again suggested that gait appeared unique to each subject. The data collection system used required markers to be attached to the subject. This is typical of most of the data collection systems used in the medical field, and although practical in that domain, they are not suitable for identification purposes. Fig. 1 illustrates the terms involved in a gait cycle. A gait cycle is the time interval between successive instances of initial foot-to-floor contact 'heel strike' for the same foot. Each leg has two distinct periods: a stance phase, when the foot is in contact with the floor, and a swing phase, when the foot is off the floor moving forward to the next step.

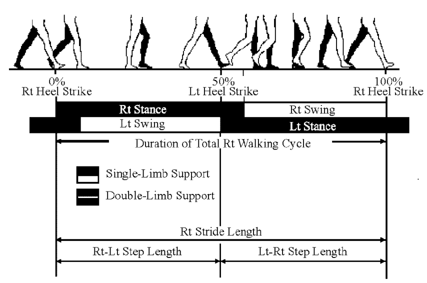


Figure 1: The Walking Cycle

In the earliest psychology studies of gait perception [5] participants were presented with images produced from points of light attached to body joints. When the points were viewed in static images they were not perceived to be in human form, rather that they formed a picture - of a

Christmas tree even. When the points were animated, they were immediately perceived as representing a human in motion. Later work showed how by point light displays a human could be rapidly extracted and that different types of motion could be discriminated, including jumping and dancing [6]. Later, Binham [7] showed that point light displays are sufficient for the discrimination of different types of object motion and that discrete movements of parts of the body can be perceived.

Naturally, studies in perception have also addressed gender as well as pure motion, again using point light displays. One early study [8] showed how gender could be perceived, and how accuracy was improved by inclusion of height information [9]. The ability to perceive gender has been attributed to anatomical differences which result in greater shoulder swing for men, and more hip swing for women [10]. Indeed, a torso index (the hip shoulder ratio) has been shown to discriminate gender [11] where the identification of gender by motion of the centre of movement was also suggested. It has been shown how subjects could recognise themselves and their friends [12], later explaining this by considering gait as a synchronous, symmetric pattern of movement from which identity can be perceived [13].

Essentially, research into the psychology of gait has not received much attention, especially using video, in contrast with the enormous attention paid to face recognition. One more recent study has shown that exaggerating temporal differences can improve recognition[14] and another [15], using video rather than point light displays, has shown that humans can recognise learn gait for purposes of recognition. The study confirmed that, even under adverse conditions, gait could still be perceived. As such there is much support in other fields or research for the notion of gait as a biometric.

We shall describe next some of the approaches to automatic recognition by gait, and then describe the current state-of-art in analysis before considerations for future research and conclusions.

2. Approaches to Gait Biometrics

2.1 Early Approaches

The earliest approaches concerned recognition within small populations, with the volume of data limited largely by the computational resources available then. As illustrated by Fig. 2, many sought to derive a human silhouette from an image and, as common in pattern recognition, then seek to derive a description which can be associated with the identity of the subject. In what was perhaps the earliest approach to automatic recognition by gait, the gait signature was derived from the spatio-temporal pattern of a walking person [16]. Here, in the XT dimensions (translation and time), the motions of the head and of the legs have different patterns. These patterns were processed to determine the body motion's bounding contours and then a five stick model was fitted. The gait signature was derived by normalising the fitted model for velocity and then by using linear interpolation to derive normalised gait vectors. This was then applied to a database of 26 sequences of five different subjects, taken at different times during the day. Depending on the values used for the weighting factors in a Euclidean distance metric, the correct classification rate varied from nearly 60% to just over 80%, a promising start indeed.

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

Figure 2: Gait Recognition by Silhouette Analysis

Later, optical flow was used to derive a gait signature [17, 18]. This did not aim to use a model of a human walking, but more to describe features of an optical flow distribution. The optical flow was filtered to produce a set of moving points together with their flow values. The geometry of the set of points was then derived by using a set of basic measures and further information was derived from the flow information. Then, the periodic structure of the sequence was analysed to show several irregularities in the phase differences; measures including the difference in phase between the centroid's vertical component and the phase of the weighted points were used to derive a gait signature. Experimentation on a limited database showed how people could be discriminated with these measures, appearing to classify all subjects correctly.

Another approach was aimed more at generic object-motion characterisation [19], using gait as an exemplar of their approach. The approach was similar in function to spatio-temporal image correlation, but used the parametric eigenspace approach to reduce computational requirements and to increase robustness. The approach first derived body silhouettes by subtracting adjacent images. Then, the images were projected into eigenspace, and eigenvalue decomposition was performed where the order of the eigenvectors corresponds to frequency content. Recognition from a database of 10 sequences of seven subjects showed classification rates of 100% for 16 eigenvectors and 88% for eight, compared with 100% for the (more computationally demanding) spatio-temporal correlation approach. Further, the approach appears robust to noise in the input images. This was later extended to include Canonical Analysis (CA) with better discriminatory capability [20], and extended to analyse flow rather than just silhouettes – to better effect [21].

In the only early model-based approach, the gait signature was derived from the spectra of measurements of the variation in the thigh's orientation [22,23]. This was demonstrated to achieve a recognition rate of 90% on a database of 10 subjects, illustrated in Fig. 3(a) – where the white line shows the inclination of the thigh.

(a) Early (b) Recent

Figure 3: Model Based Recognition

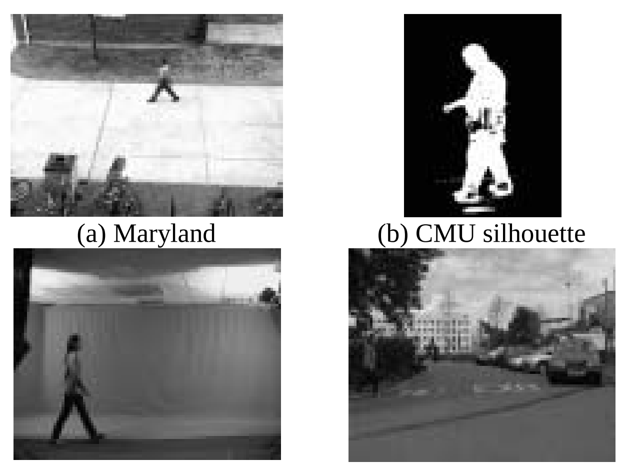
2.2 Recent Approaches

Of the current approaches, most are based on analysis of silhouettes, including: the University of Maryland's (UM's) deployment of hidden Markov models [24] and eigenanalysis [25]; the National Institute for Standards in Technology / University of South Florida's (NIST/USF's) baseline approach matching silhouettes [26]; Georgia Institute of Technology's (GaTech's) data derivation of stride pattern [27]; Carnegie Mellon University's (CMU's) use of key frame analysis for sequence matching [28]; Southampton's newer approaches that range from a baseline-type approach by measuring area [29], to extension of technique for object description including symmetry [30] (with some justification from psychology studies [13]) and statistical moments [31]; Massachusetts Institute of Technology's (MIT's) ellipsoidal fits [32]; Curtin's use of Point Distribution Models [33]; USF use the change in the relational statistics among the detected image features (which can handle running too) [34], the Chinese Academy of Science's eigenspace transformation of an unwrapped human silhouette [35] and eigenspace transformation of distance signals derived from sequences of silhouettes [36]; and Riverside's use of kinematic and stationary features [37]. 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. The early model-based technique [23] has been extended to include full limb movement [38] and to model running as well as walking (with the same model) and showed similar performance on a much larger database of subjects who were imaged both running and walking, as in Fig. 3(a) – where the red line depicts extraction of the front of the thigh and leg. Interestingly, there appeared to be more variation in running, presumably since running is a more forced motion. Using a model can also be used as a basis for statistical analysis [39].

2.3 Available Data

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 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 collected. These include: UM's surveillance data [24]; NIST/ USF's outdoor data, imaging subjects at a distance [40]; GaTech's data combining marker based motion analysis with video imagery [27]; CMU's multi-view indoor data [41]; and Southampton's data [42] 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). Examples of Maryland's outdoor surveillance view data, a silhouette derived from CMU's treadmill data, and of Southampton's indoor and outdoor data are given in Figs. 4(a)-(d), respectively.

As gait is partially a behavioural biometric there is much potential for within-subject variation. This includes footwear 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), as shown in Fig. 3(b). The new databases seek 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) Maryland (b) CMU silhouette

(c) Southampton indoor (d) Southampton outdoor

Figure 4: Recent Gait Data

3. Current Analyses

The main single contributor to gait has been the Defense Advanced Research Projects Agency's (DARPA's) Human ID at a Distance research programme which embraced three main areas: face; gait and new technologies. Gait is a natural contender for this aim, given its unique capabilities. The DARPA gait programme concentrated on three main areas: new technique; new data; and evaluation, essentially taking gait from laboratory-based studies on small populations to large scale populations of real world data. Of the current approaches, those from MIT, Maryland, Southampton, GaTech, CMU, USF and NIST were originally associated with Human ID at a Distance.

(a) successive clips of example subject

(b) general view

Figure 5: Subject from Gait Challenge Data

The data was described earlier and was developed especially for purposes of evaluation. The data is freely available for evaluation and it is very encouraging to see how research in gait has benefited from research in other biometrics: there is a range of scenarios, covariate and ground truth data already available. A confusion matrix derived from symmetry descriptions of the > 100 subject Southampton indoor database, subject as shown in Fig. 4(c), is shown in Fig. 6. Here, white indicates similarity and black represents difference and as most subjects can indeed be recognised, the result is consistent with a recognition rate of over 90%. The database is symmetric and the subjects repeat once, giving four similar quadrants. By the dark lines, it is evident that one block of subjects differs much from the others. These are in fact young children and are often removed from analyses since their gait even though it is mature (and analysis was height normalised) still differs considerably from the gait of adults.

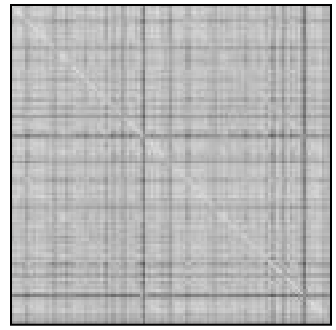


Figure 6: Analysis of Southampton Data

The databases have already been used to estimate the potency of various parts of the silhouette [43], aiming to determine where discriminatory capability can be derived. This shows that for averaged silhouettes the potent data is around the head and shoulders, which is to be expected given the motion of the other body parts. Further the role of motion and shape have been investigated as recognition cues via a model-based approach [44], confirming other results and showing the promise for motion based measures.

	CCR (%)	
	Viewpoint	Shoe
Maryland [46]	99	89
Carnegie Mellon [49]	98	90
MIT [50]	96	88
Southampton	93	88
USF [26]	87	76

Table 1: Example Gait Challenge Results

The gait challenge analysis [40] concerned evaluation on a set of baseline data which evaluated the effects of different covariates in (challenging) real world data. An example subject clipped from the overall view is shown in Fig. 5 together with the overall view and clearly all other biometric information is missing and only the subject's gait can be perceived. Recognition rates similar to those on other data have been reported, some of the example rates here are early [26, 45, 48, 49, 52]. Some of the peak correct classification rates (CCRs) for subjects imaged from a different viewpoint and from the same viewpoint but wearing other shoes are given in Table 1.

4. Future Work

Currently, the studies on gait as a biometric are considering innate performance factors, practical performance factors and wider deployment. The innate performance factors concern the effect of covariates on recognition performance, but with deeper analysis to determine data pertinent to recognition [53] with a view to refining technique development. The practical performance factors concern the intrinsic effects, such as the consequences of speed [54] and load, and extrinsic effects which especially include variation in viewpoint [55,52] and 3D analysis [57] with synchronization driving the need for novel (temporal) view synthesis [58]. There is natural means to handle difficulty in image acquisition by using infrared [59], and some of the recent developments in radar might also be used to good effect. There is also much current interest in multiple biometrics and gait can be deployed for purposes of enrolment and for fusion [60,61]. Given that the biometric approaches essentially concern extraction and description of gait by markerless means, there is wider deployment capability. There is interest in markerless gait analysis for medical purposes [62,63] as its convenience will also benefit analysis of children and the elderly. Further, there is opportunity for greater realism in animation, though this will doubtless require more sophisticated modelling strategies. In general, gait concerns the extraction and description of moving articulated objects, making it an excellent vehicle for technique development in the rapidly expanding research in spatio-temporal pattern analysis.

5. Conclusions

Gait recognition has come a long way in a short time: from early approaches on limited datasets, recognition has progressed to large real-world databases with analysis of covariate factors. In this it has benefited from the increasing number of studies in biometrics, addressing factors of practical significance in eventual deployment. The success is very encouraging: most techniques report similar performance on laboratory and on real-world data. There are natural public concerns over identity and surveillance technology, but there is now demonstrated capability to recognise identity when conventional biometrics cannot be deployed. This is a unique capability which will prove an asset to biometric systems. Further, the technology has generic interest in the analysis and description of moving articulated bodies, as well as wider application in markerless gait analysis which could prove beneficial for future developments in film, health-care and social-care arenas.

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