ON GAIT AS A BIOMETRIC: PROGRESS AND PROSPECTS

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ABSTRACT

There is increasing interest in automatic recognition by gait given its unique capability to recognize people at a distance when other biometrics are obscured. Application domains are those of any noninvasive biometric, but with particular advantage in surveillance scenarios. Its recognition capability is supported by studies in other domains such as medicine (biomechanics), mathematics and psychology which also 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. Many of the 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 DARPA's 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. Equally, gait-recognition approaches concern extraction and description of moving articulated shapes and this has wider implications than just in biometrics.

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.: "*For that John Mortimer….in face, in gait in speech he doth resemble*" (Henry IV/II). 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*" [2]

Early medical studies [3] 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 [4], to recognising friends. Early approaches used marker-based technology, but a later one used video imagery [5], also showing discrimination ability in poor illumination conditions. As such there is much support 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 gait part of DARPA's Human ID at a Distance program before considerations for future research and conclusions.

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

Figure 1: Gait Recognition by Silhouette Analysis

2. APPROACHES TO GAIT BIOMETRICS

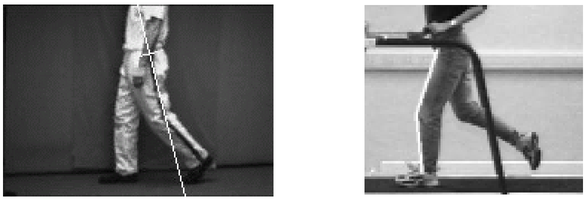
2.1 Early Approaches

The earliest approaches concerned recognition within small populations, with the volume of data limited largely by the computational performance available then. As illustrated by Fig. 1, 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[6]. 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.

Later, optical flow was used to derive a gait signature[7, 8]. 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 measured 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[9], using gait as an exemplar of their approach. The approach was similar in function to spatio-temporal image correlation, but used the parametric eigen-space approach to reduce computational requirement 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 then 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[10].

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[11,12]. This was demonstrated to achieve a recognition rate of 90% on a database of 10 subjects, illustrated in Fig. 2(a).

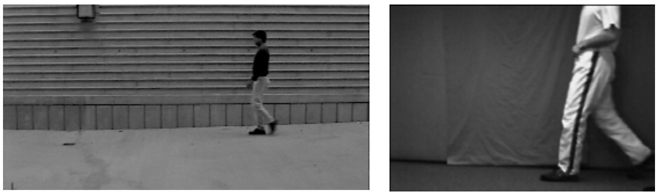


(a) Early (b) Recent

Figure 2: 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 [13] and eigenanalysis [14]; the National Institute for Standards in Technology / University of South Florida's (NIST/USF's) baseline approach matching silhouettes [15]; Georgia Institute of Technology's (GT's) data derivation of stride pattern [16]; Carnegie Mellon University's (CMU's) use of key frame analysis for sequence matching [17]; Southampton's newer approaches that range from a baseline-type approach by measuring area [18], to extension of technique for object description including symmetry [19] and statistical moments [20]; Massachusetts Institute of Technology's (MIT's) ellipsoidal fits [21]; Curtin's use of Point Distribution Models [22]; the Chinese Academy of Science's eigenspace transformation of an unwrapped human silhouette [23]; and Riverside's use of kinematic and stationary features [24]. 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. Further, the early model-based technique has been extended to include full limb movement [25] and show how a model-based approach can facilitate greater application capabilities, including analysis of running, as in Fig. 2(b).



(a) UCSD (b) Southampton

Figure 3: Early Gait Data

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 [13]; NIST/ USF's outdoor data, imaging subjects at a distance [26]; GT's data combines marker based motion analysis with video imagery [16]; CMU's multi-view indoor data [27]; and University of Southampton's data [28] 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).

(a) Maryland (b) CMU silhouette

Figure 4: Recent Gait Data

As gait is a partially 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 Figure 2. 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. Examples of Maryland's outdoor surveillance view data and a silhouette derived from CMU's treadmill data are given in Fig. **4**(a) and (b), respectively.

3. HUMAN ID AT A DISTANCE

The Defense Advanced Research Projects Agency's (DARPA's) Human ID at a Distance research programme 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.

Figure 5: 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.

	Viewpoint	Shoe
Maryland [36]	79	86
Carnegie Mellon [33]	98	90
MIT [34]	96	88
Southampton	93	88
USF [15]	87	76

Table 1: Example Gait Challenge Results

The gait challenge analysis [26] concerned evaluation on a set of baseline data, Fig. 5, which evaluated the effects of different covariates in (challenging) real world data. Recognition rates similar to those on other data have been reported, some of the example rates here are early [15, 32, 33, 36] with better results later. Some of the peak classification rates of the evaluations 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 with a view to refining technique development. The practical performance factors concern the intrinsic effects, such as the consequences of speed and load, and extrinsic effects which especially include variation in viewpoint. There is natural means to handle difficulty in image acquisition by using infrared [42], 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 [43,44]. Given that the biometric approaches essentially concern extraction and description of gait by markerless means, there is wider deployment capability. Though it would doubtless require an alternative focus, there is interest in markerless gait analysis for medical purposes [45,46] as whilst being much more convenient it 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 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, healthcare and socialcare arenas.

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