G

Gait Recognition

Darko S. Matovski, Mark S. Nixon and John N. Carter
School of Electronics and Computer Science, University of Southampton, Southampton, Hampshire, UK

Synonyms

Automatic gait recognition; Gait analysis; Gait biometrics

Related Concepts

►Face Recognition; ►Hough Transform; ►Iris Recognition; ►Optical Flow; ►Principal Component Analysis (PCA)

Definition

The way a person walks (or runs) combined with their posture is known as gait. Recognizing individuals by their particular gait using automated vision-based algorithms is known as gait recognition.

Background

Gait has few important advantages over other forms of biometric identification. It can be acquired at a distance when other biometrics are obscured or the resolution is insufficient. It does not require subject cooperation and can be acquired in a noninvasive manner. It is easy to observe and hard to disguise as walking is necessary for human mobility. Gait can be acquired from a single still image or from a temporal sequence of images (e.g., a video).

Shakespeare made several references to the individuality of gait, e.g., in *The Tempest* [Act 4 Scene 1], Cares observes "*High'st Queen of state, Great Juno comes; I know her by her gait*" and in Henry IV Part II [Act 2, Scene 3], "*To seem like him: so that, in speech, in gait, in diet, in affections of delight, in military rules, humors of blood, he was the mark and glass, copy and book.*"

The aim of medical research has been to classify the components of gait for the treatment of pathologically abnormal patients. Murray et al. [17] created standard movement patterns for pathologically normal people. Those patterns were then used to identify pathologically abnormal patients.

The biomechanics literature makes observations concerning identity: "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" [27].

Psychophysiological studies such as [5, 11] have shown that humans can recognize friends and the sex of a person solely by their gait with 70–80 % accuracy. These and similar studies have inspired the use of gait as a biometric trait.

Recently, there has been a rapid growth in the number of surveillance systems, aimed to improve safety and security. These systems are yet to include recognition capabilities, and gait recognition could be a most suitable choice. The primary aim of surveillance videos is to monitor people. However, the video data can be of a low quality (poor resolution, time lapse,

K. Ikeuchi (ed.), *Encyclopedia of Computer Vision*, DOI 10.1007/978-0-387-31439-6,

etc.), and the subject can try to conceal the more conventional biometrics. Nevertheless, such video can provide sufficient data for gait recognition technology, and there is already research in using gait biometrics as a forensic tool [4]. Gait recognition could be employed at a border crossing or any high-throughput environment. Gait contains very rich information and is considered to be unique. Studies have shown that gait can also be used to reveal a person's identity, gender, emotional state, etc.

Recognition by gait is one of the newest biometrics since its development only started when computer memory and processing speed became sufficient to process sequences of image data with reasonable performance. The potential for gait recognition is great, and hence there is a vast interest in computer vision research in extracting gait features.

Theory

A gait recognition system primarily consists of a computer vision system. A gait signature is created by extracting images of a walking subject which is then compared to the signatures of known subjects. Figure 1 shows an example of some of the basic steps in a gait recognition system.

Step 1: Data can be acquired using a single or multiple cameras. If data is acquired using a single camera, recognition can be performed using a 2D gait signature such as the Gait Energy Image (GEI – shown in step 4). However, if multiple but synchronized cameras are used, the number of possibilities is greater. Examples of the usage of multiple-synchronized cameras include:

- Producing a 3D gait model and using it for recognition.
- 3D information can be used to improve recognition for a 2D approach by producing a non-normalized version of a 2D signature.
- Achieving a view-invariant recognition. A gait signature from any view can be re-created using 3D data which can be mapped to a signature acquired in an outdoor environment where typically only a single and nonoptimal view is available.

Step 2: An example of preprocessing step is background subtraction or background segmentation. The subject can be acquired easily and reliably by using chroma-keying if there are clear color difference between the subject and the background. Background subtraction can measure the naturally occurring scene behind the walking subject using one of the plethora of computer vision techniques.

Step 3: As human gait is periodic, a gait sequence (sample) can consist of multiple gait cycles. Identifying the most suitable cycle can lead to better recognition rates. Signal processing techniques can be applied to the foreground signal (sum of foreground pixels) in the case of binary image.

Step 4: There are number of approaches to produce a gait signature, some of which are described later. A baseline gait signature was proposed in [22]. An example of a signature is shown in step 4.

Step 5: A gait signature can be used directly within a classifier. Alternatively, features can be extracted from a signature, and those features can be used for classification. Again, there is a selection of classification techniques; in the simplest case, a classifier such as k-nearest neighbor (using Euclidian distance) can be used.

Databases

A database can be collected for various purposes. Primary concerns include uniqueness and practicality. A database should contain enough subjects to allow for an estimate of inter- and intra-subject variation. The current databases contain smaller number of subjects compared to databases used to evaluate performance of other biometrics (e.g., face, fingerprint). However, there are databases that include covariate factors and application potential. Some of the most well-known databases together with some of their characteristics are shown in Table 1.

Approaches to Gait Recognition

The approaches to gait recognition can be divided in two main groups: *model-based* and *model-free* (see Table 2). Model-based approaches use the human body structure, and model-free methods use the whole motion pattern of the human body. Which approach is adopted depends on the acquisition conditions. Model-free (appearance-based) approaches use the input images directly to produce a gait signature without fitting a model. These approaches can perform recognition at lower resolutions which makes them suitable for outdoor applications, where a subject can be at a large distance from the camera. Model-based approaches typically require higher resolution images of a subject to be able to fit the model accurately.

The table is taken from [18, 19]. Example papers for all of the approaches can be found in the original sources.

Model-Free Approaches

The model-free approaches derive the human silhouette by separating the moving object from the background. The subject can then be recognized by measurements that reflect shape and/or movement. The simplest approach is to simply form an average of the silhouettes over a complete gait cycle [15]. The approach is called the Gait Energy Image (GEI), and it is shown in Fig. 2. Motion Silhouette Image (MSI) is a similar representation to the GEI. The value of each pixel is computed as a function of motion of that pixel in the temporal dimension over all silhouettes that are part of a single gait cycle. Both the GEI and MSI are easy to compute, but they are vulnerable to appearance changes of the human silhouette. Frieze pattern represents the information contained in a gait sequence by horizontal and vertical projections of the silhouettes. Its extension, SVB Frieze patterns, use key frame subtraction in order to mitigate the effects of appearance changes on the silhouette (see Fig. 2). The Gait Entropy Image (GEnI) is another example of a compact gait representation (signature). GEnI is computed by calculating the Shannon entropy for each pixel. Shannon entropy measures the uncertainty associated with a random variable.

The gait signatures for the approaches shown in Fig. 2 are usually used directly for classification. There are additional ways of extracting gait signatures without using a model. Some examples are described below:

- Little and Boyd [14] derive a dense optical flow for each image sequence. Scale-independent scalar features of each flow, based on moments of the moving point, characterize the spatial distribution of the flow. The periodic structure of these sequences of scalars is analyzed. The scalar sequences for an image sequence have the same fundamental period but differ in phase, which is used as a feature for recognition of individuals by the shape of their motion.
- BenAbdelkader et al. [2] use background modeling to track the subject for a number of frames and extract a sequence of segmented images of the person. A self-similarity plot is computed via correlation of each pair of images in this sequence. For recognition, PCA (principal component analysis) is used to reduce the dimensionality of the plots. A k-nearest neighbor rule is used on the reduced space for classification. Another silhouette-based gait recognition technique using PCA has been proposed by Liang et al. [13]. Eigenspace transformation based on principal component analysis (PCA) is applied to time-varying distance signals derived from a sequence of silhouette images to reduce the dimensionality of the input feature space. Supervised pattern classification techniques are performed in the lower-dimensional eigenspace for recognition.
- Hayfron-Acquah et al. [8] proposes a method for automatic gait recognition based on analyzing the symmetry of human motion. The Generalised Symmetry Operator is used to locate features according to their symmetrical properties rather than relying on the boarders of a shape. The symmetry operator is used on the optical flow image to produce a gait signature. For purposes of classification, the similarity differences between the Fourier descriptions of the gait signatures are calculated using Euclidean distance.
- Gait is a temporal sequence and can be modeled using hidden Markov models (HMM). The statistical nature makes the model relatively robust. The postures that an individual adopts are regarded as states of the HMM and are typical to that individual and provide means of discrimination [24].
- Kale et al. [10] use two different image features to directly train a HMM: the width of the outer contour of a binary silhouette and the entire binary silhouette itself.

Model-Based Approaches

The advantages of the previous approaches (silhouette or features derived from it) are speed and simplicity. However, model-based approaches are better at handling occlusion, noise, scale, and rotation. Model-based approaches require a high resolution therefore not very suitable for outdoor surveillance.

Model-based approaches incorporate knowledge of the shape and dynamics of the human body into the extraction process. These approaches extract features that fit a physical model of the human body. A gait model consists of shapes of various body parts and how those shapes move relative to each other (motion model). The shape model for a human subject can use ellipse to describe the head and the torso, quadrilaterals to describe the limbs, and rectangles to describe the feet. Alternatively, arbitrary shapes could be used to describe the edges of the body parts. The motion model describes the dynamics of the motion of the different body parts. Using a model ensures that only image data corresponding to allowable human shape and motion is extracted, reducing the effect of noise. The models can be 2- or 3-dimensional. Most of the current models are 2-dimensional, but deliver good results on databases of more than 100 subjects.

Some examples of model-based approaches are described below:

- Yam et al. [28] have used pendular motion and the understanding of biomechanics of human locomotion to develop two models: a bilateral symmetric and analytical model (employs the concept of forced couple oscillator). See Fig. 3. The gait signature is the phase-weighted magnitude of the Fourier description of both the thigh and knee rotation.
- Bouchrika and Nixon [3] have proposed a new approach to extract human joints. Spatial model templates for human motion are derived from the analysis of gait data collected from manual labeling. Motion templates describing the motion of the joints are parameterized using the elliptic Fourier descriptors

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) \\ \sin(\alpha) & \cos(\alpha) \end{bmatrix} \begin{bmatrix} X(t) * S_x \\ Y(t) * S_y \end{bmatrix}$$

  where α is the rotation angle, s_x and s_y are the scaling factors across the horizontal and vertical axes, respectively, and $X(t)$ and $Y(t)$ are the Fourier summation. Hough transform is used in the feature extraction process.
- Wang et al. [26] have proposed an algorithm based upon the fusion of static and dynamic body information. The static body information is in a form of a compact representation obtained by Procrustes shape analysis. The dynamic information is obtained by a model-based approach which tracks the subject and recovers joint-angle trajectories of lower limbs. A fusion at the decision level is used to improve recognition results. Figure 1 shows an example of the results obtained.

There have been moves towards developing 3D gait models. Examples of work in this fields are [7, 25]. Guoying et al. [7] use video sequences from multiple cameras to construct 3D human models. The motion is tracked by applying a local optimization algorithm. The length of key segments is extracted as static parameters, and the motion trajectories of lower limbs are used as dynamic features. Linear time normalization is used for matching and recognition. Three-dimensional approaches are robust to changes in viewpoint and have a great potential. However at present, experiments only on small databases are possible mainly due to high computational requirements.

Gait is dependent on large number of parameters (joint angles and body segment size) which leads to complex models with many free parameters. Finding the best fit model for a subject leads to searching a high-dimensional parameter space. Therefore, there is a trade off between the accuracy of the model (complexity) and computational cost. The models are often simplified based on certain acceptable assumptions, e.g., a system could assume constant walking speed. However, as computing power increases, the problems arising of high complexity can be mitigated.

Experimental Results

The current state of the art achieves very high recognition rates (close to 100 %) on relatively large databases (>300 subjects) when the training and test data are recorded under similar conditions. An example of progression in performance over time is shown in Table 2. However, recognition rate can drop with change of clothing, shoes, walking surface, and pose. Many current studies focus on solving these problems. Recent major achievements in gait recognition are described in [16, 20]. Matovski et al. [16] have shown that elapsed time does not affect gait recognition and that gait can be used as a reliable biometric over time and at a distance. The world's largest gait database of more than 1,000 people has been constructed to enable statistically reliable performance evaluation of gait recognition performance [20] (Table 3).

The HumanID gait challenge problem [22] was set up to outline a baseline algorithm for gait recognition and propose a number of difficult experiments for the existing gait matchers. The gallery set consists of 122 subjects walking on a grass surface recorded by a single camera.

Table 4 shows the differences of the probe set compared to the gallery set for each of the challenge experiments.

The results in Fig. 5 show the progress in gait recognition over a period of 2 years for the experiments shown in Table 4.

Application

Gait research is currently at an evaluation stage rather than an application stage. However, the potential for gait recognition is great. The complete unobtrusiveness without any subject cooperation or contact for data acquisition makes gait particularly attractive for identification purposes. It could be used in applications including forensics, security, immigration, and surveillance.

Many surveillance systems capture only a low-resolution video at varying lighting conditions, and gait recognition might be the only plausible choice for automatic recognition. A bank robber may wear a mask so you cannot see his face, wear gloves so you cannot get fingerprints, and wear a hat so you cannot get DNA evidence – but they have to walk or run into the bank, and they could be identified from their gait.

Gait recognition has been used as evidence for conviction in some criminal cases. A man in Bolton (UK) was convicted based on his distinctive gait. A CCTV footage of the burglar captured near the crime scene was compared to a video captured at the police station by a podiatrist specializing in gait analysis. In 2004, a perpetrator robbed a bank in Denmark. The Institute of Forensic Medicine in Copenhagen was contacted by the police to perform gait analysis, as they thought the perpetrator had a unique gait. The institute instructed the police to establish a covert recording of the suspect from the same angles as the surveillance recordings for comparison. The gait analysis revealed several characteristic matches between the perpetrator and the suspect. For example, both the perpetrator (to the left) and the suspect showed inverted left ankle (white arrow) during left leg's stance phase and markedly outward rotated feet (see Fig. 6). The suspect was convicted of robbery, and the court found that gait analysis is a very valuable tool [12].

One system named the Biometric Tunnel [23] has led to the first live demonstration of gait as a biometric and could indicate a possible route for future deployment of the technology. The left side of Fig. 7 depicts the system. It consists of a simple corridor with 12 synchronized and fixed cameras. The subjects are asked to walk through the middle, and the lighting and background are controlled to facilitate analysis. The right side of Fig. 7 shows the details of the arrangement. The system is designed with a high-throughput environment in mind.

Open Problems

Although a large number of gait recognition algorithms have been reported, it is important to note that gait biometrics is still in its infancy. The majority of studies achieve good recognition rates on gallery and probe acquired in similar conditions. However, it is very challenging to extract gait features that are invariant to change in appearance as well as to conditions that affect a person's gait. Examples of things that can change and negatively affect the effectiveness of current gait algorithms are change of clothing, shoe type, carrying a load, and injuries/medical conditions. Clothing for instance can change the observed pattern of motion and make it difficult to accurately locate joint position. Furthermore, there are certain factors that are related to the environment and not the subjects themselves that can cause difficulties for current gait matchers. Examples of environmental confounding factors are camera viewing angle, background, and illumination.

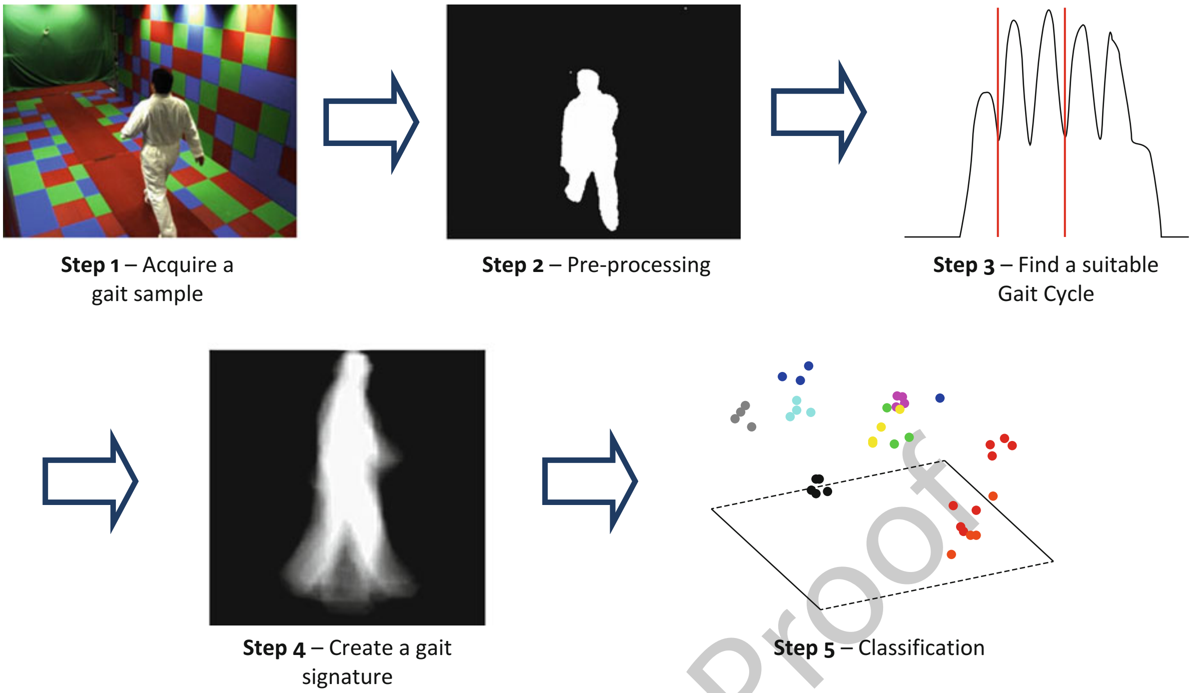
Recently, studies have reported progress in solving some of the issues outlined above. A study by

Goffredo et al. [6] describes a self-calibrating view-invariant gait recognition algorithm. Hossain et al. [9] have developed a clothing invariant gait matcher. Aqmar et al. [1] are the most recent approach focussed on speed variation.

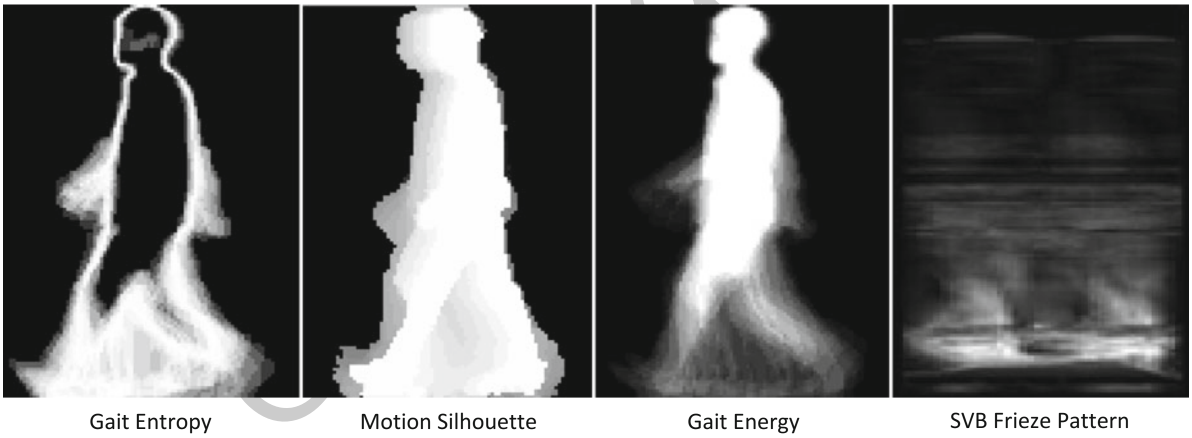
Currently, gait recognition can deliver very high recognition rates in a constrained environment and if certain factors are controlled. A move towards developing algorithms invariant to change over time is needed. Furthermore, additional work is required to translate the research to outside environment and to explore how scalable it is. Attempts so far suggest that developing highly reliable gait-based human identification system in a real-world application is, and will continue to be, very challenging. In the short term, some of the challenges associated with gait recognition can be addressed by fusing gait with other biometrics [29].

References

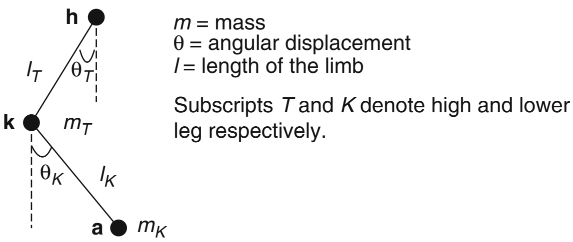
1. Aqmar MR, Shinoda K, Furui S (2010) Robust gait recognition against speed variation. In: Proceedings of 20th IEEE international conference on pattern recognition (ICPR), Istanbul, Turkey
2. Benabdelkader C, Cutler R, Davis L (2002) Motion-based recognition of people in eigengait space. In: Proceedings of IEEE international conference automatic face and gesture recognition (AFGR). IEEE, Piscataway, pp 267–272
3. Bouchrika I, Nixon M (2008) Exploratory factor analysis of gait recognition. In: 8th IEEE international conference on automatic face and gesture recognition (AFGR), Amsterdam, The Netherlands
4. Bouchrika I, Goffredo M, Carter JN, Nixon MS (2010) On using gait in forensic biometrics. Journal of Forensic Sciences 56(4):882–889 July 2011
5. Cutting JE, Kozlowski LT (1977) Recognizing friends by their walk: gait perception without familiarity cues. Bull Psychon Soc 9(5):353–356
6. Goffredo M, Bouchrika I, Carter JN, Nixon MS (2010) Self-calibrating view-invariant gait biometrics. IEEE Trans Syst Man Cybern Part B Cybern 40(4):997–1008
7. Guoying Z, Guoyi L, Hua L, Pietikainen M (2006) 3D gait recognition using multiple cameras. In: Proceedings of 7th IEEE international conference automatic face and gesture recognition (AFGR), Southampton, pp 529–534
8. Hayfron-Acquah J, Nixon M, Carter J (2003) Automatic gait recognition by symmetry analysis. Pattern Recognit Lett 24(13):2175–2183
9. Hossain MA, Makihara Y, Junqui W, Yagi Y (2010) Clothing-invariant gait identification using part-based clothing categorization and adaptive weight control. Pattern Recognit 43(6):2281–2291
10. Kale A, Sundaresan A, Rajagopalan A, Cuntoor N, Roy-Chowdhury A, Kruger V, Chellappa R (2004) Identification of humans using gait. IEEE Trans Image Process 13(9):1163–1173
11. Kozlowski LT, Cutting JE (1977) Recognizing the sex of a walker from a dynamic point-light display. Percept Psychophys 21(6):575–580
12. Larsen PK, Simonsen EB, Lynnerup N (2008) Gait analysis in forensic medicine. J Forensic Sci 53(5):1149–1153
13. Liang W, Tieniu T, Huazhong N, Weiming H (2003) Silhouette analysis-based gait recognition for human identification. IEEE Trans Pattern Anal Mach Intell 25(12):1505–1518
14. Little J, Boyd J (1998) Recognizing people by their gait: the shape of motion. Videre: J Comput Vis Res 1(2):1–32
15. Liu Z, Sarkar S (2004) Simplest representation yet for gait recognition: averaged silhouette. In: Proceedings of 17th IEEE international conference pattern recognition (ICPR), Cambridge, UK, pp 211–214
16. Matovski DS, Nixon MS, Mahmoodi S, Carter JN (2010) The effect of time on the performance of gait biometrics. In: 4th IEEE international conference biometrics: theory, applications and systems (BTAS), Washington, DC, USA
17. Murray M, Drought A, Kory R (1964) Walking patterns of normal men. J Bone Jt Surg 46(2):335
18. Nixon MS, Carter JN (2006) Automatic recognition by gait. Proc IEEE 94(11):2013–2024
19. Nixon MS, Tan TN, Chellappa R (2005) Human identification based on gait. Springer, New York
20. Okumura M, Iwama H, Makihara Y, Yagi Y (2010) Performance evaluation of vision-based gait recognition using a very large-scale gait database. In: 4th IEEE international conference biometrics: theory, applications and systems (BTAS), Washington, DC
21. Samangooei S, Bustard J, Nixon MS, Carter JNN (2010) On acquisition and analysis of a dataset comprising of gait, ear and semantic data. In: Bhanu B, Govindaraju V (eds) Multibiometrics for human identification. Cambridge University Press, Cambridge. (in press)
22. Sarkar S, Phillips PJ, Zongyi L, Isidro Robledo V, Grother P, Bowyer KW (2005) The HumanID gait challenge problem: data sets, performance, and analysis. IEEE Trans Pattern Anal Mach Intell 27(2):162–177
23. Seely R, Samangooei S, Lee M, Carter J, Nixon M (2008) University of Southampton multi-biometric tunnel and introducing a novel 3d gait dataset. In: Proceedings of 2nd IEEE international conference biometrics: theory, applications and systems (BTAS), Washington, DC
24. Sundaresan A, Roychowdhury A, Chellappa R (2003) A hidden markov model based framework for recognition of humans from gait sequences. In: Proceedings of IEEE international conference image processing (ICIP), Barcelona, pp 93–96
25. Urtasun R, Fua P (2004) 3D tracking for gait characterization and recognition. In: Proceedings of 6th IEEE international conference automatic face and gesture recognition (AFGR), Seoul, pp 17–22
26. Wang L, Ning H, Tan T, Hu W (2004) Fusion of static and dynamic body biometrics for gait recognition. IEEE Trans Circuits Syst Video Technol 14(2):149–158
27. Winter DA (2009) Biomechanics and motor control of human movement. Wiley, Ottawa
28. Yam C, Nixon M, Carter J (2004) Automated person recognition by walking and running via model-based approaches. Pattern Recognit 37(5):1057–1072
29. Zhou X, Bhanu B (2008) Feature fusion of side face and gait for video-based human identification. Pattern Recognit 41(3):778–795



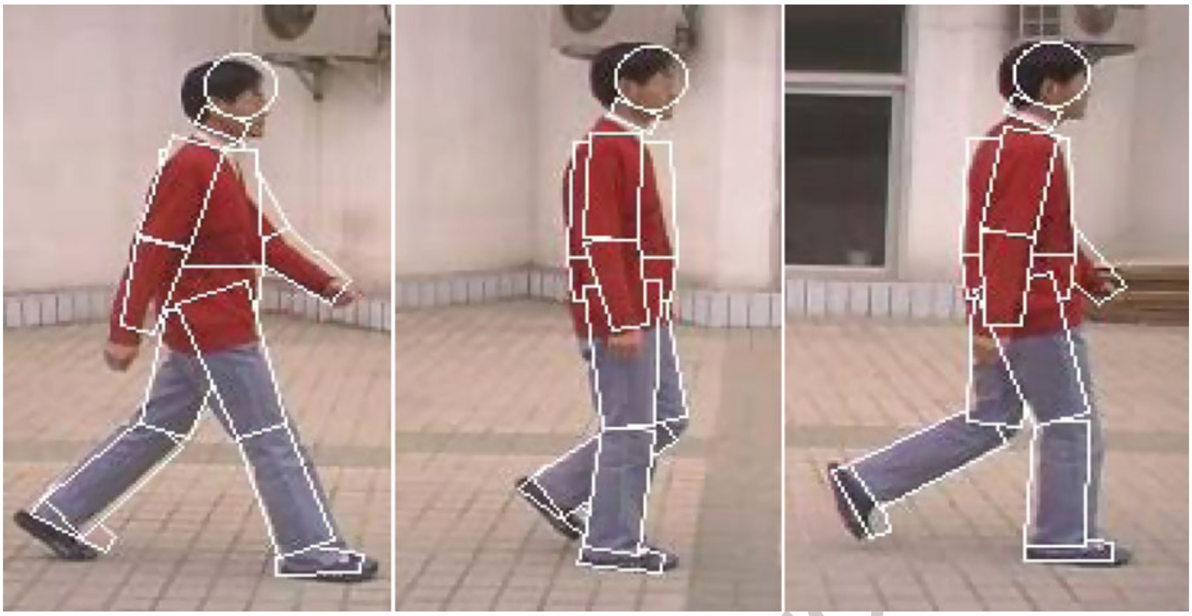
Gait Recognition, Fig. 1 General steps of a gait recognition system



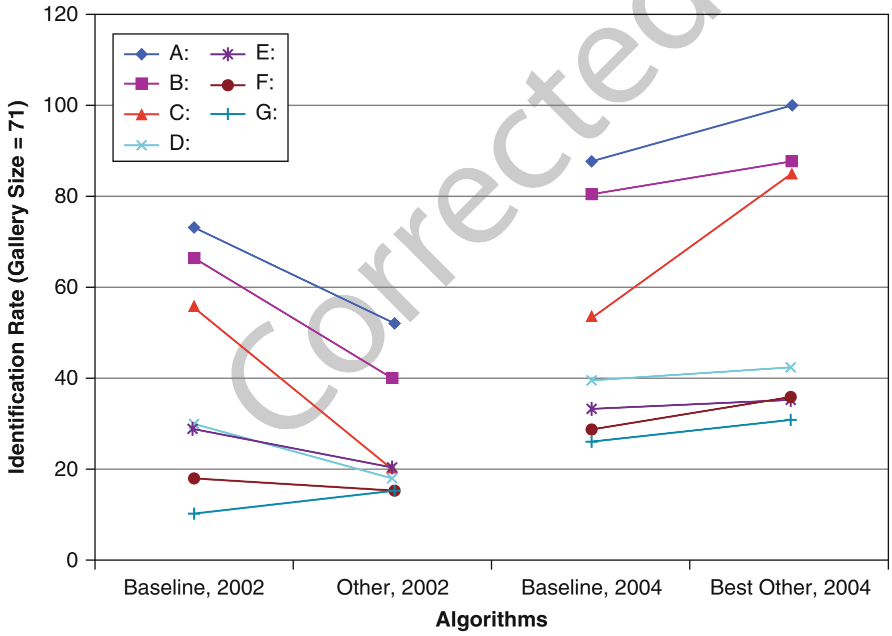
Gait Recognition, Fig. 2 Examples of model-free gait signatures



Gait Recognition, Fig. 3 Example of a gait model – the dynamically coupled pendulum model [28]

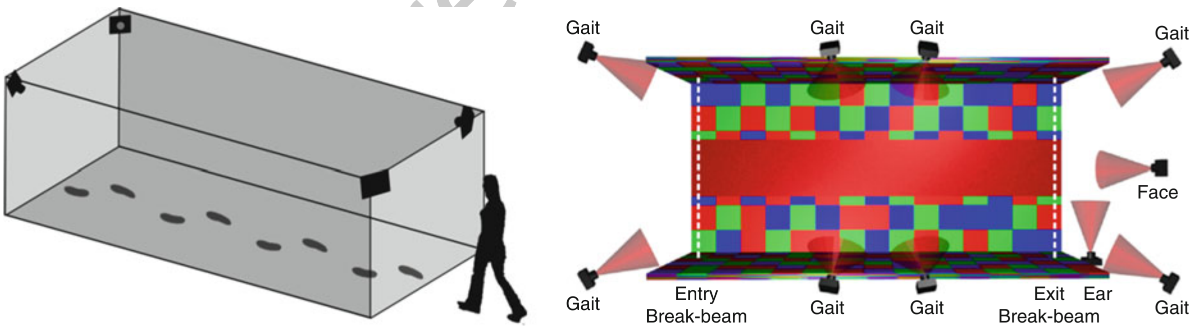


Gait Recognition, Fig. 4 Example of results [26]



Gait Recognition, Fig. 5 The progress from the baseline over 2 years for the various experiments shown in Table 4 [22]

Gait Recognition, Fig. 6 Bank robbery



Gait Recognition, Fig. 7 The biometric tunnel t1.1 **Gait Recognition, Table 1** Details of some of the well-known gait databases

	Name	Subjects	Sequences	Covariates	Viewpoints	Indoor(I)/outdoor(O)
t1.2	Name	Subjects	Sequences	Covariates	Viewpoints	Indoor(I)/outdoor(O)
t1.3	HumanID (USF)	122	1, 870	Y	2	O
t1.4	SOTON 2002	114	>2, 500	Y	2	I/O
t1.5	CMU MoBo	100	600	Y	6	I (treadmill)
t1.6	MIT 2002	24	194	Y	1	I
t1.7	UMD 2002	44	176	N	1	O
t1.8	CASIA 2006	124	1, 240	Y	11	I
t1.9	SOTON multimodal [21]∗1	>300	>5, 000	Y	12	I
t1.10	Osaka University	1, 035	2, 070	N	2	I

t2.1 **Gait Recognition, Table 2** Approaches to gait recognition

	Model-free analysis		Model-based analysis	
t2.2	Model-free analysis		Model-based analysis	
t2.3	Moving shape	Shape + motion	Structural	Modeled
t2.4	Unwrapped silhouette; silhouette similarity; relational statistics; self-similarity; key frame analysis; frieze patterns; area; symmetry; point distribution models; key poses	Eigenspace sequences; hidden Markov model; average silhouette; moments; ellipsoidal fits; kinematic features; gait style and content	Stride parameters; human parameters; joint trajectories	Articulated model; dual oscillator; linked feature trajectories

t3.1 **Gait Recognition, Table 3** Progression of gait recognition systems

	Time period	No of subjects	Source	Recognition rate	Notes
t3.2	Time period	No of subjects	Source	Recognition rate	Notes
t3.3	1990s	∼10	USC	95.2	
t3.4	2000s	∼120	HiD, CASIA, Southampton	75–99 %	Recognition rate depends on covariates
t3.5	Recent (2010)	>300	Southampton multimodal	95–100 %	Includes time-dependent covariates
t3.6	Recent (2010)	>1000	Osaka University	90 %	No covariates

t4.1 **Gait Recognition, Table 4** Some experiments comprising the HumanID gait challenge problem

	Experiment	Probe	# of subjects	Difference
t4.2	Experiment	Probe	# of subjects	Difference
t4.3	A	Different camera view than gallery	122	View
t4.4	B	Subjects wore different shoes	54	Shoe
t4.5	C	Different camera view and different shoes	54	Shoe, view
t4.6	D	Subjects walked on a different surface	121	Surface
t4.7	E	Different shoes and different walking surface	60	Surface, shoes
t4.8	F	Different walking surface and different camera view	121	Surface, view
t4.9	G	Different walking surface, different shoes, and different camera view	60	Surface, shoe, view