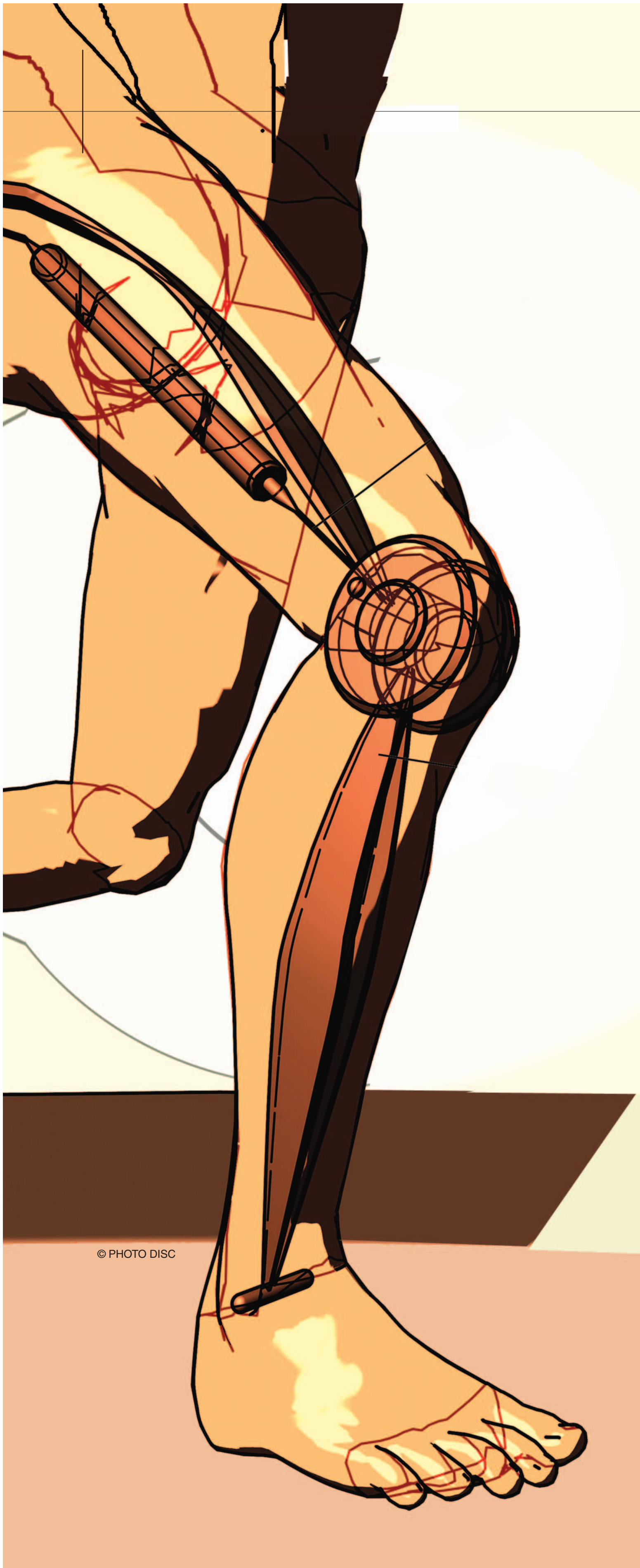

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Gait Recognition:

A challenging signal processing technology for biometric identification

Dr. Walker arrives at the high-security research facility where he works, eager to see the results of his latest experiments. To access his office, he has to undergo an authentication process. The main entrance is at the end of a well-lit corridor, 20 m in length, equipped with several cameras. Dr. Walker walks steadily towards the entrance. As he gets close, his gait is recognized, the door opens automatically, and the intelligent system that manages the building welcomes him with a friendly, albeit synthesized, voice.

Although today there is no practical system that can support the above authentication scenario, the latest research on gait-based identification—identification by observation of a person's walking style—provides evidence that such a system is realistic and is likely to be developed and used in the years to come. The study of human gait, as well as its deployment as a biometric for identification purposes, is currently an active research area. This article outlines the application of gait technologies for security and other purposes.

IDENTIFICATION METHODS

Despite the imperative need for efficient security architectures in airports, border crossings, and other public access areas, most currently deployed identification methods were developed and established several years ago. It is now clear that these methods cannot cover contemporary security needs. Moreover, in some cases, such as in metropolitan public transport stations, authentication or

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verification using conventional technologies is practically infeasible. For the above reasons, the development and deployment of biometric authentication methods (fingerprint, hand geometry, iris, face, and gait identification) has recently attracted the attention of government agencies and other institutions. Gait analysis and recognition can form the basis of unobtrusive technologies for the detection of individuals who represent a security threat or behave suspiciously. The concerns that arise from the capturing and analysis of gait in surveillance applications are outlined in the "Privacy and Other Concerns" sidebar.

GAIT VERSUS OTHER BIOMETRIC TRAITS

Compared to other biometrics, gait has some unique characteristics. The most attractive feature of gait as a biometric trait is its unobtrusiveness, i.e., the fact that, unlike other biometrics, it can be captured at a distance and without requiring the prior consent of the observed subject. Most other biometrics such as fingerprints [1], face [2], hand geometry [3], iris [4], voice [5], and signature [6] can be captured only by physical contact or at a close distance from the recording probe. Gait also has the advantage of being difficult to hide, steal, or fake.

Although the study of kinesiological parameters that define human gait can form a basis for identification, there are apparent limitations in gait capturing that make it extremely difficult to identify and record all parameters that affect gait. Instead, gait recognition has to rely on a video sequence taken in controlled or uncontrolled environments. Even if the accuracy with which we are able to measure certain gait parameters improves, we still do not know if the knowledge of these parameters provides adequate discrimination power to enable large-scale deployment of gait recognition technologies. Moreover, studies report both that gait changes over time and that it is affected by clothes, footwear, walking surface, walking speed, and emotional condition [7]. The above facts impose limitations on the inherent accuracy of gait and question its deployment as a discriminative biometric.

The ambiguity regarding the efficiency of gait-assisted identification differentiates gait from other biometrics whose uniqueness and invariability, and therefore appropriateness for use in identification applications, can be more conclusively determined by the study of the similarities and differences between biometrics captured from several subjects under varying conditions. This is why, at present, gait is not generally expected to be used as a sole means of identification of individuals in large databases; instead, it is seen as a potentially valuable component in a multimodal biometric system.

GAIT AS MULTIBIOMETRIC COMPONENT

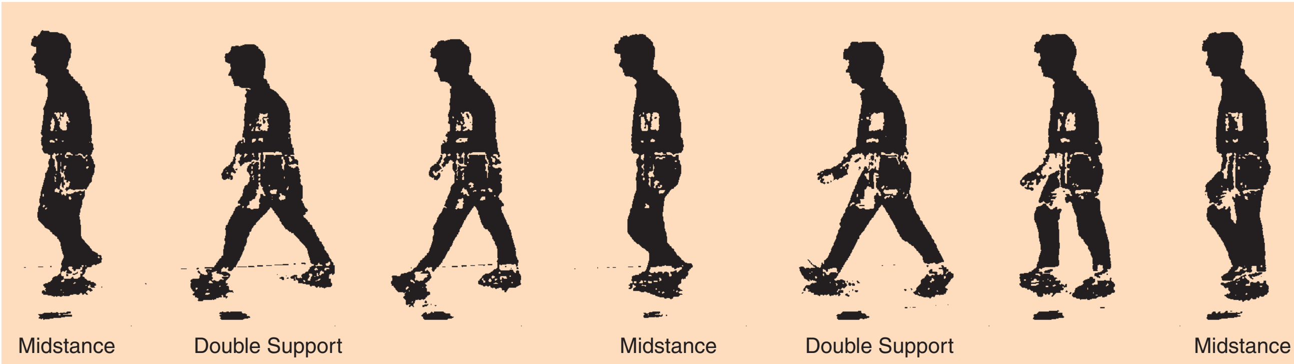
Research conducted thus far in the area of gait recognition has shown that gait can be reliable in combination with other biometrics. If we assume that palm, fingerprint, and iris methods belong to a different (obtrusive) class of biometrics, additional biometrics that could be used in conjunction with gait in a multibiometric system would be face and foot pressure [8] (the latter requiring some specialized equipment for measuring the ground reaction force).

PRIVACY AND OTHER CONCERNS

Although contemporary security needs, as outlined previously, largely necessitate the use of biometrics as a means of identification, several concerns have been raised regarding the wide deployment of biometric systems. The most important of these concern the fact that surveillance infrastructures might violate a citizen's right to anonymity and invade his/her privacy. In the particular case of gait recognition, these concerns are even more pronounced due to the unobtrusiveness of the gait capturing process, which could allow continuous monitoring and recording of all traffic in public places. Apart from this, there is a growing concern that biometrics might be used for purposes beyond the original scope or that unauthorized persons may gain access to biometric information and use it for unlawful purposes. Others are concerned about parameters that affect gait, such as fatigue, injuries, and psychological condition; this may make the gait of a lawful person resemble the gait of a suspicious person. In such cases, a lawful person may be held, questioned, and possibly banned from boarding a flight or accessing a public place. Other concerns will also be raised if radiation is used to get an accurate picture of the human body. Such technologies, which are currently tested in a few airports for the purpose of detecting dangerous objects hidden under passengers' clothes, are likely to be met with objections by passengers who fear that the process is not safe for their health or who feel uncomfortable with having pictures of their body seen by airport officers. Finally, since the study of gait patterns might possibly reveal medical conditions, the compilation of gait databases will be regarded as a threat to the medical privacy of individuals.

Some of the above concerns sound reasonable and should generally be expected. The major concern about continuous monitoring is largely unfounded. Gait-based technologies could be used in verification applications in controlled environments or in other monitoring applications, but at present it is technically infeasible to record all gait parameters of a person walking in a public place and identify him/her by searching in a database of thousands of subjects. A conceivable application could be the discrimination between classes of people (gender, age) for statistical purposes. But the implementation of a large-scale surveillance system that continuously identifies and monitors all individuals in public places is not possible, at least in the foreseeable future.

The other concerns are largely unfounded as well. It is unlikely that dangerous rays will ever be used for gait capturing since this would represent a greater threat to the population than the one the technology tries to deter. Moreover, regarding medical privacy, gait is not more revealing than other biometrics. Iris, palm, and fingerprints can also disclose medical conditions. In the case of gait, however, the large volume of information that exists in a gait sequence prohibits the storage of all the information. Instead, the most practical approach would be that only information that is useful for recognition will be retained, rendering the possibility of gait being used for diagnostic purposes even more remote.



[FIG1] Several stances during a gait cycle. The silhouettes are from CMU's MoBo database [15].

In a multibiometric system, gait and foot pressure could be used to narrow down the database of subjects. Subsequently, face recognition could be used for identification of a test subject among the reduced set of candidate subjects. Otherwise, the three biometrics could be combined altogether, e.g., using the techniques described in [9].

A system fusing gait and ground reaction force was presented in [10]. The combination of gait with face recognition was examined in [11] and [12]. In [12], it was shown that gait is more efficiently utilized in a multimodal framework when it is combined directly with the facial features rather than preceding the face recognition module as a filter. In both works, concrete recognition performance gains were reported compared to using face or gait alone. The above results indicate that there is much value in combining gait with other biometrics.

TERMINOLOGY

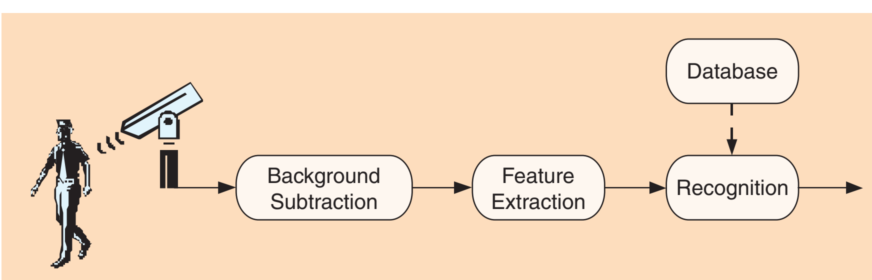
Despite the differences among walking styles, the process of walking is similar for all humans. A typical sequence of stances in a gait cycle is shown in Figure 1. A detailed analysis of gait phases can be found in [13]. For simplicity, we consider the following four main walking stances [14]: right double support (both legs touch the ground, right leg in front), right midstance (legs are closest together, right leg touches the ground), left double support, and left midstance. Although some other definitions would also be appropriate, in this article we define a gait cycle as the interval between two consecutive left/right midstances. The interval between any two consecutive midstances is termed half cycle. The time interval in which a gait cycle is carried out is called the gait period, whereas the walking frequency is termed the fundamental gait frequency.

A GENERIC GAIT RECOGNITION SYSTEM

Gait recognition is a multistage process (see Figure 2). It is important that *gait capturing* is performed in environments where the background is as uniform as possible. Moreover, since gait recognition algorithms are not, in general, invariant to the capturing viewpoint, care must be taken to conduct capturing from an appropriate viewpoint. Preferably, the walking subject should be walking in a direction perpendicular to the optical axis of the capturing device since the side view of walking individuals discloses the most information about their gait. Once a walking sequence is captured, the walking subject is separated from its background using a process called *background subtraction*. A critical step in gait recognition is *feature extraction*, i.e., the extraction, from video sequences depicting walking persons, of signals that can be used for recognition. This step is very important since there are numerous conceivable ways to extract signals from a gait video sequence, e.g., spatial, temporal, spatiotemporal, and frequency-domain feature extraction. Therefore, one must ensure that the feature extraction process compacts as much discriminatory information as possible. Finally, there is a *recognition* step, which aims to compare the extracted gait signals with gait signals that are stored in a database. Apart from the apparent usefulness of gait analysis in biometric applications, gait has several important nonbiometric applications that are summarized in the "Nonbiometric Applications of Gait" sidebar.

PREVIOUS WORK

The study of gait as a discriminating trait was first attempted a few decades ago from a medical/behavioral viewpoint [16], [17]. Later, several attempts were made to investigate the gait recognition problem from the perspective of capturing and analyzing gait signals [18]–[22]. Most recent work investigating the appropriateness of gait as a biometric for human identification has taken place in the context of the HumanID project sponsored by the U.S. Defense Advanced Research Project Agency (DARPA). Each of the participating institutions has established its own database of sequences depicting humans walking.



[FIG2] General block diagram of a gait recognition/authentication system.

Such sequences are termed gait sequences. A list of the most widely known databases of gait sequences is presented in Table 1.

The techniques used for gait recognition can be divided into two categories: holistic (feature/appearance based) and model based. Techniques that address the gait recognition problem using only sequences of binary maps of walking human silhouettes are of much interest since they do not presume the availability of any further information, such as color or grey-scale information, which may not be available or extractable in practical cases. The main focus of algorithms is the tracking of silhouettes, analysis of the tracked silhouettes for feature extraction purposes, and recognition using the extracted features.

Although several approaches for gait analysis and recognition will be discussed in the following sections, we here present some representative techniques as an introduction. A baseline method was proposed by the University of South Florida [23]. It was tested on a gait database that is tailored to the study of the impact of several factors, such as viewpoint, footwear, and surface, on the performance of a gait recognition algorithm. (An extended version of the USF/NIST database is also available.) The simple baseline methodology was intended to serve as a reference for other experiments on the same database.

The deployment of motion fields in gait recognition was investigated in [21] and [24]. Although both methods reported good results on their own databases, they presume the availability of texture information, which must be used for the accurate computation of the motion fields. In [25]–[28], several feature extraction techniques were proposed based on the calculation of projections, contours, or other such features from gait silhouettes. A comparison among different features will be presented later in this article.

In [29], a comparison is provided of several techniques for improving the quality of silhouettes extracted from video sequences depicting humans walking. The silhouettes were extracted using a model-based method that produces silhouettes that have fewer noise pixels and missing parts. The resulting sequences were tested with the model-based algorithm in [30], and the overall system was shown to improve on the baseline system in [23].

To the authors' judgement, the most promising approach for gait recognition is based on the formation, by means of averaging similar frames, of a limited number of representative frames for each sequence. This process seems to capture all structural information in a gait sequence while implicitly yielding denoised frames that can be used directly for recognition. This approach is taken in [31] and [32]. In [31], the recognition is based on the comparison of such templates, whereas in [32], the templates are derived in the context of training an exemplar-based hidden Markov model (HMM) that additionally takes

NONBIOMETRIC APPLICATIONS OF GAIT

Human gait recognition and analysis is a promising technology with possible applications in numerous sectors of our society, including security surveillance applications such as characterization of motion for identification and authentication of individuals, and recognition and detection of suspicious or impostor behavior in video surveillance. However, there are significant nonsecurity-related applications, e.g., detection of postural disturbances due to mobility disorders or aging [33] and optimal technique strategies in sports.

The analysis of gait signals finds important applications in the clinical rehabilitation of patients of stroke or spinal cord injuries. Of particular interest are devices for functional electrical stimulation (FES)-assisted walking [34], which provides appropriate stimulation sequences to injured patients. The challenge here is to control the timing of the stimulation based on inputs from peripheral nerves [35] to achieve natural walking.

Moreover, gait pattern analysis is also used in devices for the automatic robotic rehabilitation of patients, e.g., for treadmill training. In this case the device plays the role of a physiotherapist to injured persons. If the injured person is able to actively contribute to the motion, the gait pattern that determines the motion of the device can be adaptively changed to the motion provided by the patient [36].

Another application of gait analysis is in the design of walking biped robots, where achieving stability and maintaining stability on different surfaces [37] or while ascending and descending stairs demands careful design of the walking process. Finally, gait analysis finds applications in the animation and computer game industry, in which the presentation of realistic walking persons is very important.

[TABLE 1] DATABASES USED FOR GAIT RECOGNITION.

DATA	URL	SUBJECTS	PARAMETERS
USF/NIST	WWW.GAITCHALLENGE.ORG	71	VIEWPOINT, SURFACE, SHOE
CMU	WWW.HID.RI.CMU.EDU	25	VIEWPOINT, WALKING SPEED, CARRIED OBJECT
SOTON	WWW.GAIT.ECS.SOTON.AC.UK	118	VIEWPOINT, TREADMILL, INDOORS/OUTDOORS
SHAPE OF MOTION	PAGES.CPSC.UCALGARY.CA/~BOYD/GAIT/GAIT.HTML	6	—
GATECH	WWW.CC.GATECH.EDU/CPL/PROJECTS/HID/	20	VIEWPOINT, INDOORS/OUTDOORS
CASIA	WWW.SINOBIOMETRICS.COM	20	VIEWPOINT
MIT	WWW.AI.MIT.EDU/PROJECTS/GAIT/	25	TIME

into account the gait dynamics. All methods in this class yield state-of-the-art performance.

GAIT ANALYSIS FOR FEATURE EXTRACTION

For the study of gait analysis, we assume that the walking subject has been extracted from a gait sequence using standard image processing techniques. Henceforth, we focus on feature extraction from background-subtracted sequences. Below, we divide gait analysis techniques into model based and holistic. Furthermore, we summarize the approaches for the reduction of the dimensionality of the original feature vectors.

GAIT CYCLE DETECTION

An important part of the gait analysis process is gait cycle detection, i.e., the partitioning of a gait sequence into cycles that depict a complete walking period. In almost all approaches seen thus far in the literature, the detection of gait cycles is achieved using a time series corresponding to a measure extracted from a sequence (e.g., the sum of foreground pixels of silhouettes). This signal is usually very noisy and requires processing before its analysis. In [21], although no explicit cycle partitioning was attempted, a method using linear prediction was proposed for fitting a sinusoidal signal to the noisy extracted signals. This method could be readily used for cycle partitioning. In [32], an adaptive filter was used to filter the foreground sum signal prior to the calculation of the gait cycles using the minima of this signal. In [38], the autocorrelation of the foreground sum signal was taken to calculate the walking period and compute the coefficients of an optimal filter for the denoising of the sum signal. Figure 3(a) shows the foreground sum signal $sum(t)$ with respect to time, and Figure 3(b) represents the correlation between signal samples $sum(t_1), sum(t_2)$ with respect to the time difference $|t_1 - t_2|$. By observing the autocorrelation peaks in Figure 3(b), it is easy to determine the walking period and partition the signal in Figure 3(a) into gait cycles. In general, there are several efficient methodologies for partitioning gait sequences into gait cycles; henceforth, we assume that such a partitioning is available to the gait recognition system.

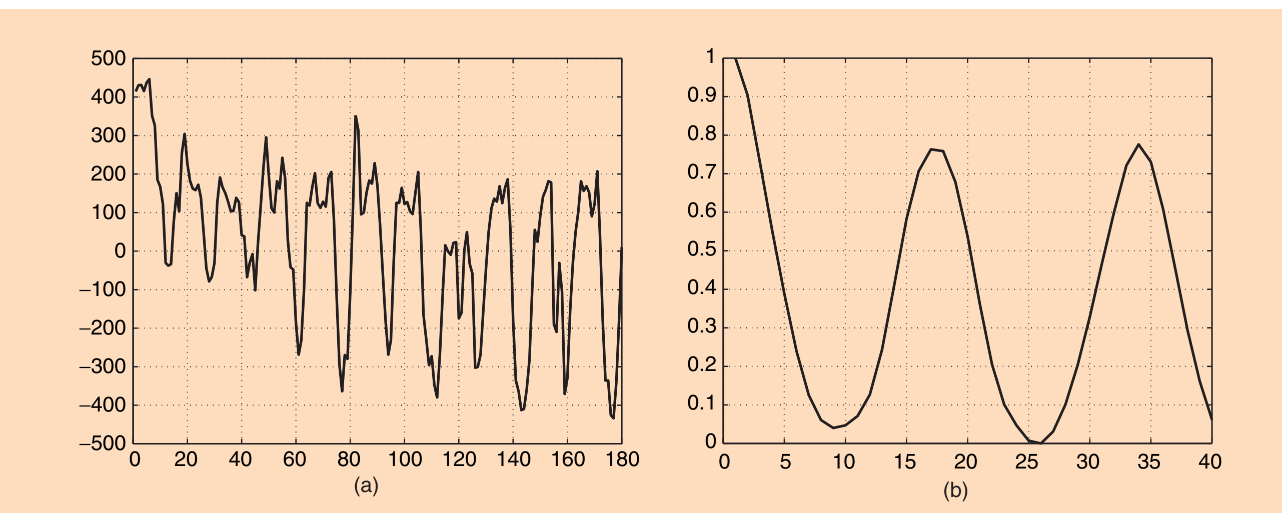
MODEL-BASED APPROACHES

Model-based approaches employ models whose parameters are determined using processing of gait sequences [30], [39], [40], [41]. Unlike holistic approaches, model-based approaches are, in general, view and scale invariant. This is a significant advantage over the holistic approaches since it is highly unlikely that a test gait sequence and a reference sequence will be captured from identical viewpoints. However, since model-based approaches rely on the identification of specific gait parameters in the gait sequence, these approaches usually require high-quality gait sequences to be useful. Moreover, other hindrances such as self-occlusion of walking subjects may even render the computation of model parameters impossible. For this reason, a multicamera gait-acquisition system would be more appropriate for such techniques.

A multiview gait recognition method was proposed in [39] using recovered static body parameters, which are measurements taken from static gait frames. Gait dynamics are not used. The static parameters used in [39] are the height, the distance between head and pelvis, the maximum distance between pelvis and feet, and the distance between the feet [Figure 4(a)]. The static parameters are view invariant, which makes them very appropriate for recognition applications.

In [30], the silhouette of a walking person was divided into seven regions. Ellipses were fit to each region [Figure 4(b)] and region feature vectors were formed, including averages of the centroid, the aspect ratio, and the orientation of the major axis of the ellipse. Another feature vector that was tested included the magnitude and phase of a Fourier transform of the time series of the above ellipse parameters.

In [40], a model-based feature analysis method was presented for the automatic extraction and description of human gait for recognition. The method generated a gait signature using a Fourier series expansion of a signal corresponding to the hip



[FIG3] (a) Foreground sum signal (normalized). (b) Autocorrelation.

rotation [Figure 4(c)]. In [41], a more detailed model was proposed using ellipses for the torso and the head, line segments for the legs, and a rectangle for each foot [Figure 4(d)].

HOLISTIC APPROACHES

Unlike model-based approaches, holistic solutions operate directly on the gait sequences without assuming any specific model for the walking human. For example, in [21], **optical flow** was used to extract moving subjects from gait sequences. Subsequently, several scalar descriptors were extracted from a gait sequence, and the relative phases of the periodic signals corresponding to different descriptors were used for recognition.

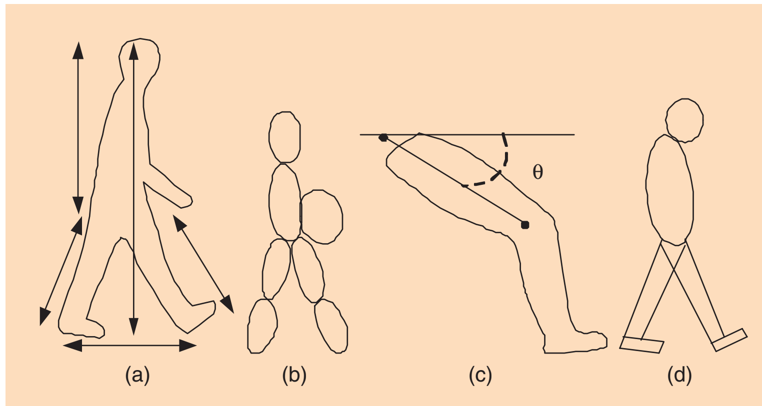
A very interesting class of holistic techniques merely employs binary maps (silhouettes) of walking humans. Such techniques are particularly suited for most practical applications since color or texture information may not be available or extractable. The **contour of the silhouette** is probably the most reasonable feature in this class. It can be used directly [27], or it can be transformed to extract Fourier descriptors [42]. However, in practice, this feature relies heavily on the accurate identification of contour pixels and for this reason, algorithms that use this feature do not perform well when they are applied to noisy silhouettes. In addition, the extraction of the contour feature is computationally more complex than most of the features in this class.

The **width of silhouette** was proposed in [43] as a suitable feature for gait feature extraction. The width $w[i]$ of silhouette is the horizontal distance between the leftmost and rightmost foreground pixels in each row i of the silhouette [Figure 5(a)]. Although the calculation of width signals imposes minimal processing load on a gait system, algorithms that use this feature are vulnerable to spurious pixels that often render the identification of the leftmost and rightmost pixels inaccurate. For this reason, the authors in [43] propose a postprocessing technique to smooth and denoise the feature vectors prior to their deployment in gait recognition. The bottom of Figure 5(a) presents the width of silhouette with respect to time. As expected, the width coefficients that exhibit the greatest variance are the coefficients derived from the leg and arm area (bottom and middle of the figure). It should also be noted that shadows result in inaccurate computation of the width coefficients in the feet area.

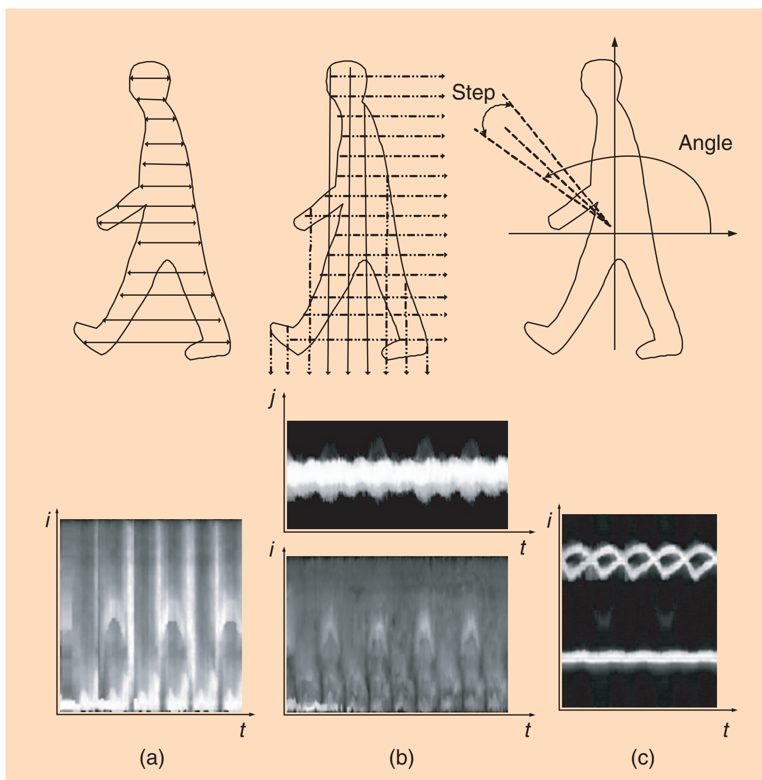
Henceforth, we assume that each gait sequence is composed of several binary silhouettes, denoted as $s[i, j],\ \ i = 0, \ldots, M-1,\ \ j = 0, \ldots, N-1,$ where M, N denote the number of rows and columns of the silhouette, respectively. Let

$$s[i, j] = \begin{cases} 1 & \text{if } (i, j) \text{ belongs to the foreground} \\ 0 & \text{otherwise.} \end{cases}$$

Using the above definitions, the **horizontal and vertical projections of silhouettes** [25] are expressed as



[FIG4] Graphical representation of parameters used in model-based approaches. (a) Distances used as static parameters in [39], (b) ellipse fitting in silhouette regions [30], (c) hip rotation model [40], and (d) model using a combination of shapes [41].



[FIG5] Some features extracted from binary silhouettes for gait recognition. On the bottom row, examples of these representations are shown with respect to time: (a) width of silhouette, (b) vertical (top) and horizontal (bottom) projections, and (c) angular representation.

$$p_h[i] = \sum_{j=0}^{N-1} s[i, j], \quad i = 0, \ldots, M-1 \tag{1}$$

$$p_v[j] = \sum_{i=0}^{M-1} s[i, j], \quad j = 0, \ldots, N-1. \tag{2}$$

The efficiency of this feature is based on the fact that it is sensitive to silhouette deformations since all pixel movements are reflected in the horizontal or vertical projection [Figure 5(b)]. Although this feature is similar to the width of silhouette (note the similarity between the width vector and the horizontal projection vector), it is more robust to spurious pixels. An additional advantage is that it is fast and can be computed in real time. However, an important consideration here is that the silhouettes must be centered prior to the computation of the feature since misplaced silhouettes will result in shifted projections.

An **angular transform** of the silhouette was proposed in [28]. The angular transform divides the silhouettes into angular sectors and computes the average distance between foreground pixels and the center (i_c, j_c) of the silhouette [Figure 5(c)]

$$\mathcal{A}(\theta) = \frac{1}{N_\theta} \sum_{(i,j)\in\mathcal{F}_\theta} s[i, j]\sqrt{(i-i_c)^2 + (j-j_c)^2}, \tag{3}$$

where θ is an angle, $\mathcal{F}_\theta$ is the set of the pixels in the circular sector $[\theta - (\Delta\theta/2), \theta + (\Delta\theta/2)]$, and N_θ is the cardinality of $\mathcal{F}_\theta$. The transform coefficients were shown to be a linear function of the silhouette contour. This feature is, in general, robust since it obviates the need for detection of contour pixels. The bottom of Figure 5(c) displays the transform coefficients with respect to time. As seen, most information is concentrated in the leg area (appearing on the plot as rings).

The *silhouette* itself was used in several algorithms as a feature. Prior to their deployment, the silhouettes in a gait sequence should be appropriately scaled and aligned. In most cases, it appears that the silhouette is at least as efficient as the low-dimensional features that can be extracted from a silhouette. This is intuitively expected since the feature extraction step is a lossy operation, i.e., in general, the silhouette cannot be reconstructed from the feature. However, the silhouette feature leads to systems of high complexity, whereas feature extraction could dramatically reduce complexity. Since there is some information in a silhouette that is apparently useless for recognition (e.g., the interior of the body), we believe that there are efficient features that will perform at least as well as the silhouette feature. In our pursuit for the ideal feature, the silhouette feature provides a useful target for gait performance.

The advantages and disadvantages of all presented features are summarized in Table 2.

FREQUENCY TRANSFORMATION OF FEATURE TIME SERIES

Regardless of the way in which a vector of features $\mathrm{f}(t)$ is extracted from each frame (i.e., for each t) of a gait sequence, we can always go a step further. All features extracted thus far from each of the frames in a gait sequence form a time series. Since walking is a periodic activity, the Fourier analysis of the time-domain gait signals is a very appealing approach as most discriminative information is expected to be compacted in a few Fourier coefficients, providing a very efficient gait representation. Therefore, taking the Fourier transform of the feature vector series $\mathrm{f}(t)$

$$\mathrm{F}(k) = \frac{1}{T}\sum_{t=0}^{T-1} \mathrm{f}(t)e^{-j\frac{2\pi}{T}kt}, \tag{4}$$

where T is the walking period, yields a new representation that is related to the frequency content of the originally extracted features. The new representation can serve as a gait signature, which is appropriate for direct comparison between gait sequences. The frequency-domain extraction of gait signatures

[TABLE 2] SUMMARIZATION OF THE ADVANTAGES AND DISADVANTAGES OF THE PRESENTED HOLISTIC AND MODEL-BASED FEATURES.

	HOLISTIC FEATURES	
FEATURE	**ADVANTAGES**	**DISADVANTAGES**
CONTOUR	SENSITIVE TO STRUCTURAL DIFFERENCES	HIGH COMPLEXITY, LOW ROBUSTNESS
WIDTH	SENSITIVE TO STRUCTURAL DIFFERENCES, LOW COMPLEXITY	LOW ROBUSTNESS
PROJECTIONS	ROBUSTNESS, LOW COMPLEXITY	COARSE STRUCTURAL REPRESENTATION
ANGULAR	ROBUSTNESS	COARSE STRUCTURAL REPRESENTATION
RELATIVE PHASES	COMPACT REPRESENTATION, SCALE INVARIANCE	COMPLICATED DETERMINATION OF PHASES
SILHOUETTE	LOSSLESS REPRESENTATION	LEADS TO HIGH-COMPLEXITY SYSTEMS
	MODEL-BASED FEATURES	
FEATURE	**ADVANTAGES**	**DISADVANTAGES**
STATIC PARAMETERS	VIEW INVARIANT, COMPACT REPRESENTATION	DIFFICULT CAPTURING (REQUIRES CAMERA CALIBRATION)
ELLIPSE PARAMETERS	COMPACT REPRESENTATION	LOW ROBUSTNESS
HIP ANGLE	COMPACT REPRESENTATION	LOW ROBUSTNESS
COMBINATION OF SHAPE PARAMETERS	COMPACT REPRESENTATION	LOW ROBUSTNESS

has advantages over the time-domain approach. Specifically, since the transform is calculated in increments of the angular frequency $2\pi/T$, signals extracted from gait sequences with different walking periods are directly comparable. In practice, however, not all frequency components are useful for recognition. This is why there are methods that use only the magnitude and phase of the Fourier transform at the fundamental walking frequency [30], [44].

In [44], it was stated that all motions in a gait cycle share the same fundamental frequency, and a system was proposed which uses optical flow for measuring shape oscillations. A significant conclusion reached in [30] was that frequency signatures yielded superior performance in cases where the compared gait sequences were captured on different days (and, therefore, the structural information alone was not reliable). This provides an additional motive for investigating frequency-domain features.

In the experimental assessment section, we will evaluate the performance of a simple scheme based on the direct transformation of features. In this system, the entire feature time series is expressed as a *single* complex feature vector through application of (4). In Figure 6, we display such a representation using silhouettes.

DIMENSIONALITY REDUCTION

A natural question arises in the context of gait analysis: How much information do we need to extract from a gait sequence in order to capture most discriminative information?

On the temporal axis, it appears that shape information can be captured using four or five characteristic frames [14], [32] or feature vectors. However, the frames or feature vectors themselves could be represented in a more compact way. Since several of the elements in the feature vectors, extracted using the techniques in the previous sections, usually contain information that does not contribute to the purpose of recognition, methodologies such as principal component analysis (PCA) [43], [24], [27] or linear discriminant analysis (LDA) [24] are used to retain only the important elements of the original feature vector. Analysis of variance (ANOVA) can also be used for the identification of the significant components in a gait feature vector. Several works achieve good performance using holistic features of dimension as low as 100. On the other hand, feature vectors consisting of model parameters would carry more information than feature vectors extracted using a holistic method. This is the reason why, for model-based approaches, the required coefficients might be fewer provided that the model parameters can be determined accurately (which is the real challenge in model-based approaches).

PATTERN MATCHING AND CLASSIFICATION

Once gait information is extracted from gait sequences and the associated feature vectors are formed, the actual recognition/classification task must be performed. Two main approaches can be taken, namely, a template-based approach or a stochastic approach. In both cases, an appropriate distance metric between feature vectors must be initially defined. The classical Euclidean distance is the measure that is used in most gait recognition applications. Other measures are the inner product distance [32] and the number of "ones" in the binary difference between frames [23]. A variety of other distance measures may also be used [45]; however, in this work, we use the classical Euclidean distance in the implementations of the presented gait methodologies.

TEMPLATE MATCHING

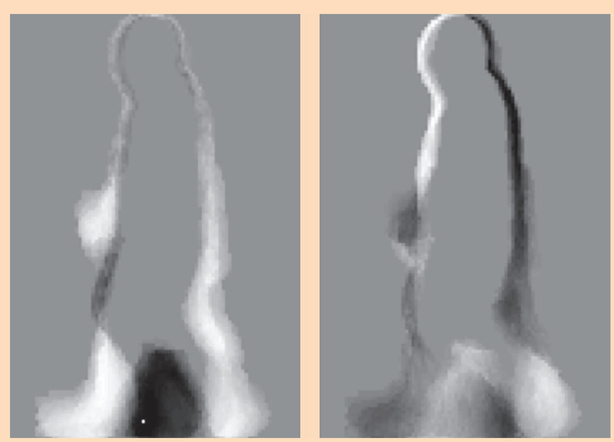
The main concern in calculating distances between different gait representations (templates) is whether we compare corresponding quantities in the two representations. In case of *frequency templates* (e.g., harmonic components computed using Fourier analysis), the calculation of the distance between two templates is straightforward since the correspondence between frequency components in different templates is obvious. In this case, a frequency component in one template should be compared with the component in the same spectral position in the other template.

In the case of *spatial templates*, the gait representation is a *sequence of features* that must be compared with another sequence of features. When the fundamental walking periods T_1 and T_2 of the two sequences are not equal, their cumulative distance over a gait cycle is defined as

$$D_{12} = \frac{1}{U}\sum_{t=1}^{T} u(t) D(\mathrm{f}_1(w_1(t)), \mathrm{f}_2(w_2(t))),$$

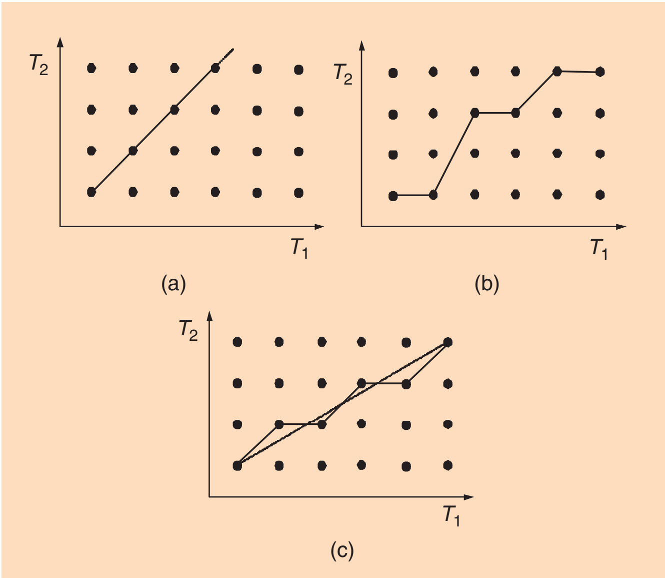
where the pairs $(w_1(t), w_2(t))$ define a warping function, $u(t)$ is a weighting function, $U = \sum_{t=1}^{T} u(t)$, and $D(\cdot)$ denotes the distance between the feature vectors at time t. Based on the characteristics of the warping function, we can distinguish three approaches for the calculation of distances between feature sequences.

The **direct matching** approach can be regarded as a brute-force attempt to match a pattern consisting of feature vectors (derived from frames in a gait cycle) by sliding it over a sequence of feature



(a) (b)

[FIG6] **Frequency signatures: a complex silhouette template computed as the Fourier transform of the gait sequence at the fundamental frequency. (a) Real part and (b) imaginary part.**



[FIG7] Approaches for the matching of different sequences. (a) Direct, (b) dynamic time warping, and (c) linear time normalization.

vectors of the reference sequence to find the position that yields the minimum distance. This is the approach taken in the baseline method created at USF [23]. However, this approach is clearly not suitable for a gait recognition system since it implicitly assumes that the periods of the gait cycles in the test and reference sequences are identical. Therefore, two sequences depicting the same person walking at different speeds would appear dissimilar.

The use of **time normalization** [46] is a more reasonable approach since reference and test sequences corresponding to the same subject may not necessarily have the same gait period. Consequently, if recognition is to be performed by template matching, some kind of compensation would have to be applied during the calculation of the distance. To this end, *dynamic time warping* (DTW) [46] can be used to calculate the distance between a test sequence and a reference sequence. Using DTW [43], [38], all distances between test and reference frames are computed and the total distance is defined as the accumulated distance along the minimum-distance path (termed the optimal *warping path*). Another option is to use *linear time normalization*. Experiments demonstrate that linear time normalization rivals the performance of DTW. This conclusion is in contrast to our intuitive expectation based on speech recognition paradigms, in which DTW was reported to be *much* more efficient than linear time normalization [46]. The above approaches for template matching are depicted in Figure 7.

Having computed the distances between a test subject and all subjects in a reference database, the recognition decision is taken as

$$\text{identity}(i) = \arg\min_j D_{ij},$$

where D_{ij} denotes the cumulative distance between the ith test subject and the jth reference subject. This means that the identity of the test subject is assumed to be the identity of the reference subject with which the test subject has the minimum distance.

STATISTICAL APPROACH: HMMS

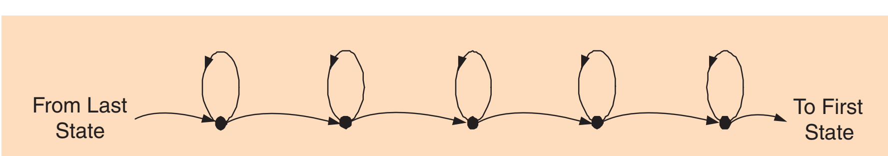
Using the template matching approaches outlined in the previous section, the extent of similarity between walking styles is quantitatively described using distances based on a distance metric. This is a disadvantage; on one hand, such distances may not have a clear interpretation whereas, on the other hand, the pattern of states related to the succession of stances during walking is not explicitly taken into account. For the above reasons, stochastic approaches such as HMMs [47] can also be used for gait recognition [32], [48]. In practical HMM-based gait recognition, each walking subject is assumed to traverse a number of stances (see Figure 8). In other words, each frame in a gait sequence is considered to be emitted from one of a limited number of stances. The a priori probabilities, as well as the transition probabilities, are used to define models λ for each subject in a reference database. For a test sequence of feature vectors $\tilde{f}_i$, the probability that it was generated by one of the models associated with the database sequences can be calculated by

$$P\left(\tilde{f}_i/\lambda_j\right), \quad j = 1, \ldots, N,$$

where N is the number of subjects in the reference database. The subject corresponding to the model yielding the higher probability is considered to be identical to the test subject, i.e.,

$$\text{identity}(i) = \arg\max_j P\left(\tilde{f}_i/\lambda_j\right), \quad j = 1, \ldots, N.$$

The HMM-based methodology is, in many aspects, preferable to other techniques since it explicitly takes into consideration not only the similarity between shapes in the test and reference sequences, but also the probabilities with which shapes appear and succeed each other in a walking cycle of a specific subject.



[FIG8] A left-to-right hidden Markov model for gait recognition.

EXPERIMENTAL ASSESSMENT

To evaluate the efficiency of the main gait analysis and recognition approaches that were presented previously, we considered several features, as well as both the template matching and statistical approaches for the recognition stage. Although there are several gait databases for the evaluation of the main approaches, as summarized in Table 1, we used the USF database, which is used by most researchers in the gait community for reporting results. Prior to testing, we aligned the silhouettes to the center of the frames to give a fair comparison with features that are not translation-invariant.

We tested several features and recognition methods. We considered only holistic features here since they generally outperform the model-based features (see, e.g., [49] for a comparison) and they are more interesting from a signal processing perspective. For the evaluation of the efficiency of features, we formed feature vectors of appropriate size. The size of the width vector [43] was equal to the vertical dimension of the silhouettes. The width vector was filtered with a three-tap low-pass filter since this approach was reported to yield better results. The *projections* vector [25] was generated as a concatenation of the horizontal and vertical projections and, therefore, its size was set equal to the sum of the horizontal and vertical dimensions of the silhouettes. For the *angular feature*, we calculated the transform coefficients in circular sectors of 5°. This yielded 72-dimensional feature vectors.

In this section, we report results in terms of cumulative match scores. To calculate these scores, we conduct multiple tests using multiple test sequences. Each test sequence is compared to the sequences in the reference database (for each test sequence there is only one correct match in the reference database), and the sequences in the reference database are ranked according to their similarity with the test sequence. As proposed in [50], rank-n performance is calculated by measuring the percentage of tests in which the correct subject appears in the top n matches. The results, rank-1 and rank-5 scores averaged over all test sets in the gait challenge database, are tabulated in Table 3. It is seen that features that do not depend on the detection of boundary pixels offer the best performance. Despite the fact that the database on which the features were tested was quite noisy, experiments on less noisy conditions demonstrate that these features would still be superior, occasionally with a narrower margin. In any case, the noisy conditions should be considered as the general rule in gait recognition since only in laboratory environments is it possible to achieve perfectly clean silhouettes.

All features were combined and tested with several recognition methodologies. Although the *frequency signatures* constitute features derived from time-domain features, here we treat the frequency-domain approach as a recognition method that computes the Fourier transform of the feature time series at the walking frequency and compares the resultant components using a Euclidean distance. For *DTW* and *linear time normalization*, the distance between test and reference gait sequences was computed by taking the median of the distances from all combinations between cycles in the reference and test gait sequences. For testing the performance of HMMs for gait recognition, we implemented the algorithm in [48]. In the *structural matching* approach, we computed for each subject the minimum cumulative distance of gait frames to the exemplars determined using the HMM model. This experiment was intended to show how much of the performance of the HMM approach is due to the computation of structural similarities and how much is due to the exploitation of gait dynamics.

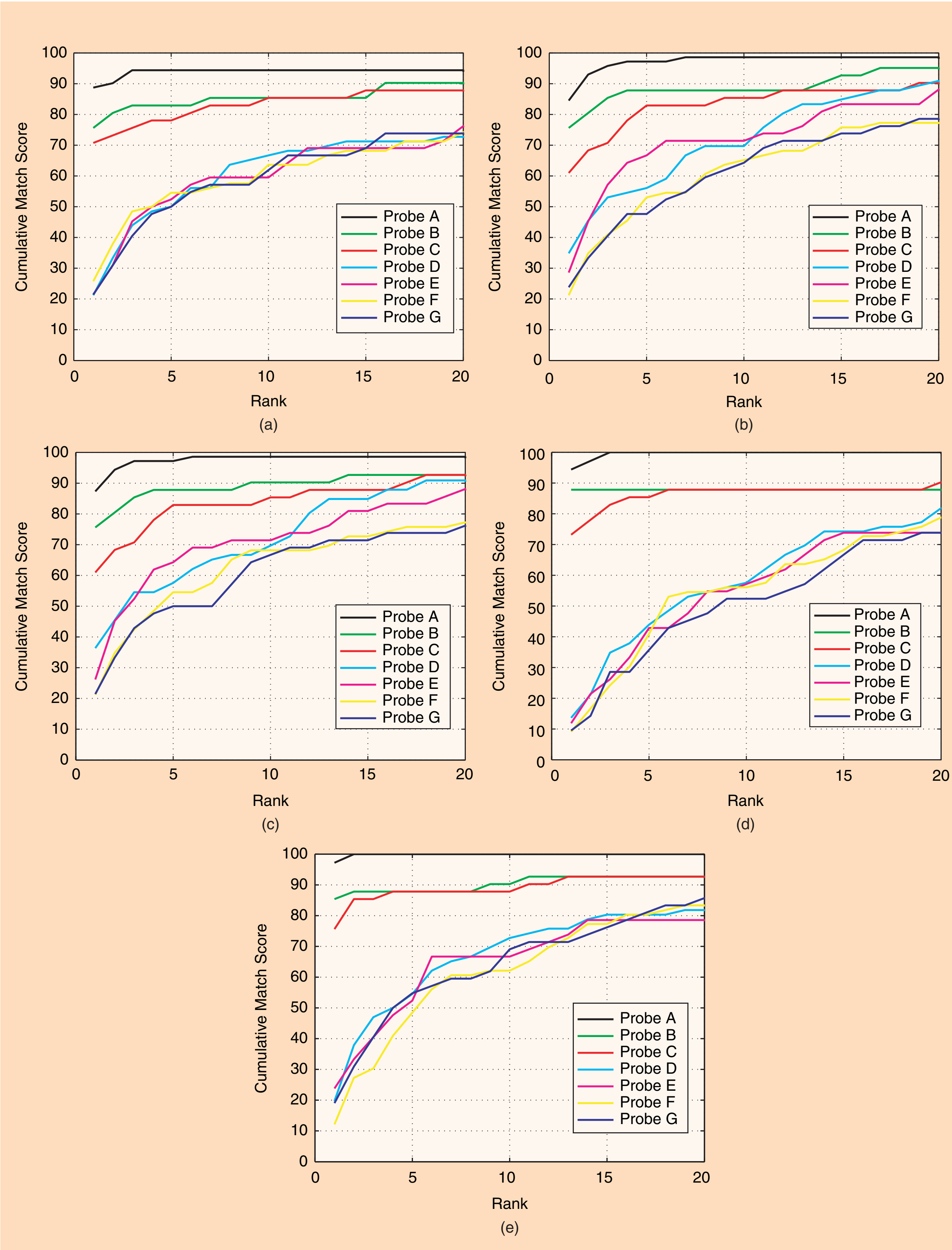
Complete cumulative match score curves are shown in Figure 9 for recognition based on frequency signatures, DTW, linear time normalization, HMMs, and structural matching. As seen, the *frequency signature* approach is quite efficient despite the fact that it is the least complicated of all approaches in our comparison. Since the determination of similarity between frequency signatures is direct, i.e., there is no need to find the correspondences in two compared frequency representations, the savings in computational complexity is considerable and the approach appears to be rather appealing.

In general, the *DTW* and the *linear time normalization* approaches perform roughly the same. As mentioned in the previous section, this is a rather unexpected result since, in the context of speech recognition, it was reported [46] that DTW performed clearly better than linear time normalization. A possible explanation might lie in the fact that, in the case of gait, recognition using these methods seems to be based predominantly on structural similarities between compared sequences and/or that the gait dynamics can be captured equally well by the linear and the nonlinear normalization processes.

The results derived using the *structural matching* approach disclose the importance of shape in gait recognition. We see that, although gait dynamics are ignored, with this approach the performance of the system is generally good in comparison to the rest of the approaches. It also reinforces our belief that current approaches for gait recognition primarily depend on structure rather than on gait dynamics. The performance of the system deploying HMMs is better than that achieved using structural matching. However, the performance gain is not very impressive, and this makes us believe that there might be other more appropriate ways to exploit gait dynamics.

[TABLE 3] RESULTS OBTAINED FOR SEVERAL COMBINATIONS OF FEATURES AND RECOGNITION METHODS. AVERAGES OF *RANK*-1 (R1) AND *RANK*-5 (R5) SCORES OVER ALL SETS OF THE GAIT CHALLENGE DATABASE ARE REPORTED.

FEATURE	**WIDTH [43]**		**PROJECTIONS [25]**		**ANGULAR [28]**		**SILHOUETTE**		**AVERAGE**	
	R1	R5	R1	R5	R1	R5	R1	R5	R1	R5
FREQUENCY-DOMAIN DISTANCE	21	42	26	45	20	41	46	66	28	49
DYNAMIC TIME WARPING	26	49	33	56	36	59	47	70	36	59
LINEAR TIME NORMALIZATION	28	49	35	55	36	60	46	74	36	59
HIDDEN MARKOV MODELS	34	51	36	49	36	62	45	70	38	58
STRUCTURAL MATCHING	33	50	35	47	36	60	43	62	37	55
AVERAGE	28	48	33	50	33	56	45	68	—	—



[FIG9] Cumulative match scores for different recognition approaches using the silhouette feature. (a) Frequency signature, (b) dynamic time warping, (c) linear time normalization, (d) structural matching, and (e) hidden Markov models.

For the evaluation of the impact of capturing condition variations to the performance of the gait recognition system, we report detailed results on the USF database. As seen in Table 4, the performance of the gait recognition system is satisfactory when there are changes in shoe or/and viewpoint. However, in cases of excessive viewpoint differences between reference and test sequences, the distortions on the extracted feature vectors would be considerable and, unavoidably, this would have a detrimental effect on recognition performance. Clearly, the performance of most tested algorithms suffers when a change in surface is involved. This is an important conclusion, and it imposes some limitations on the capturing process appropriate for a gait recognition system, i.e., surface variations should be avoided. The complete cumulative match scores are displayed in Figure 9. As seen, in most cases, the correct subject was with high confidence in the top ten matches (out of a total of 71 subjects in the reference database). This provides a strong indication that, even if gait is currently not able to achieve reliable exact recognition, it can be readily used in a multibiometric system as an efficient filter prior to the utilization of some other biometric.

SUMMARY AND CONCLUSIONS

This article was intended to provide an overview of the basic research directions in the field of gait analysis and recognition. The recent developments in gait research indicate that gait technologies still need to mature and that limited practical applications should be expected in the immediate future. At present, there is a potential for initial deployment of gait for recognition in conjunction with other biometrics. However, future advances in gait analysis and recognition—an open, challenging research area—are expected to result in wide deployment of gait technologies not only in surveillance, but in many other applications as well. We hope that this article will expose the gait analysis and recognition problem to the signal processing community and that it will stimulate the involvement of more researchers in gait research in the future.

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[TABLE 4] THE IMPACT OF DIFFERENCES IN CAPTURING CONDITIONS TO THE PERFORMANCE OF GAIT RECOGNITION SYSTEMS USING THE USF/NIST (GAIT CHALLENGE) DATABASE. THE AVERAGE OF RESULTS FOR ALL RECOGNITION METHODS USING THE SILHOUETTE FEATURE IS REPORTED.

PROBE	DIFFERENCE	RANK-1	RANK-5
A	VIEW	90	98
B	SHOE	80	87
C	SHOE, VIEW	68	83
D	SURFACE	25	53
E	SURFACE, SHOE	21	57
F	SURFACE, VIEW	18	51
G	SURFACE, SHOE, VIEW	18	46

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