Biometrics System based on Human Gait Patterns

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Abstract— **Today's commercially available biometric systems show good reliability. However, they generally lack user acceptance. In general, people favour systems with the least amount of interaction. Using gait as a biometric feature would lessen such problems since it requires no subject interaction other than walking by. Consequently, this would increase user acceptance. And since highly motivated users achieve higher recognition scores, it increases the overall recognition rate as well. 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. This article outlines the application of gait technologies for security and other purposes. Gait analysis and recognition can form the basis of unobtrusive technologies for the detection of individuals who represent a security threat or behave suspiciously.**

Index Terms— **Gait Recognition System, Holistic Approach, Model Based Approaches, Pattern Recognition**

I. INTRODUCTION

Gait is not a new topic in research and scientific literature. It has been investigated and examined in various aspects over the past decades. On the one hand, research was inspired by medical applications to track rehabilitation or as a diagnostic tool. On the other hand, research was also driven by the sport shoe industry. Murray conducted in 1967 [37] a systematic study to fully characterize the coordinated movement patterns of the various parts of the body that constitute the walking act. His empirical investigation was based on a relatively large sample set of 60 normal men in wide ranges of age and height. He obtained the walking patterns with reflective targets attached to specific anatomical landmarks which he illuminated with a strobe-light flashing 20 times per second. The study suggests that gait is a unique personal characteristic, if all gait movements are considered; this indicates that gait could be used as a promising feature for biometric authentication.

Later, in 1977, Cutting and Kozlowski [38] empirically showed that recognizing friends by their gait is indeed a surprisingly simple task for humans; even when stripped from all familiarity cues such as clothing and hairstyle. Light sources mounted on joints that are prominent during the act of walking were sufficient for identification. It is noteworthy that people recognized others not by using static properties such as height but dynamic aspects such as amount of arm swing, rhythm of the walker, bounciness, or

the length of steps. But what seems to be an easy task for humans must not necessarily apply to computers.

Although those early results were encouraging and promising, gait has not been proposed as a biometric feature until recently. Possible reasons might encompass the lack of reliable and inexpensive sensors as well as the lack of processing power to handle the huge amount of data.

All of the aforementioned methods and approaches can be roughly divided into two groups. Namely, the model-free and the model-based approaches. Model-free approaches have no underlying three-dimensional representation of a walking person and mainly rely on statistical properties of the acquired gait data. Conversely, the model-based methods have a model of the human body, or at least part of it, that is fit to every frame of the walking sequence. In order to fit the model in the frame, static parameters such as the limb lengths, body height, body width as well as dynamic parameters such as the angular velocities and walking speed need to be estimated. 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, ear and foot pressure [2]. 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 [3]. The combination of gait with face recognition was examined in [4] and [5]. In [5], 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.

II. TERMOLOGY

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 [6]. For simplicity, we consider the following four main walking stances [7]: 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.

III. A GENERIC GAIT RECOGNITION SYSTEM

Gait recognition is a multistage process (see Fig 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.

Fig. 1. Different silhouette stances during a gait cycle.

IV. SUMMARY ON PREVIOUS WORK

The study of gait as a discriminating trait was first attempted a few decades ago from a medical/behavioral viewpoint [8], [9]. Murase and Sakai developed [Murase96] a method to efficiently calculate the spatio-temporal correlation for model-free moving object recognition. To lower the computational cost of the spatio-temporal correlation they reduced the dimension of the input vectors with an orthogonal transformation and performed the correlation in the resulting low-dimensional parametric eigenspace representation. This general approach can be applied not only to gait but to other moving object recognition problems as well.

In 1997 Addlesse et al. proposed in [39] an Active Floor system. They used an array of four by four load cells to measure the force, perpendicular to the floor, exerted by a walking person. To characterize the footsteps a Hidden Markov Model (HMM) was trained using data acquired from 15 different individuals. The best HMM-configuration achieved a recognition rate of 91 %.

In [40], Little and Boyd theorized an alternate video based method. Their description of the spatial distribution of optical flow yields model-free frequency and phase features whose variation over time is periodic. The relative phase difference among these periodic signals is repeatable for particular subjects and varies between subjects and can thus be used as a biometric feature.

Huang et al. suggested two different approaches in their publications using characteristics extracted from video sequences. The first approach is based on spatial templates [41] of the subject's binarized silhouette, whereas the second uses temporal-templates [41-42, 44-45] of the silhouette. In both cases a combination of an Eigenspace Transformation (EST) and Canonical Space Transformation (CST) [43] are applied to reduce data dimensionality and to circumvent the singularity problem that occurs in the CST, when the number of elements in the feature vector is higher, than the number of feature vectors in the training set.

In [46], Nash et al. proposed a new model-based technique to allow the automated determination of human gait characteristics. Their technique employs a parametric two-line model representing the lower limbs. To speed up the search of the parameter space, they used a genetic algorithm (GA) based implementation of the Velocity Hough Transform (VHT) rather than an exhaustive search. Although their approach is promising, the accuracy of the estimated hip rotation patterns is still insufficient for biometric purposes.

Meyer et al. described in [47] a system based on statistical models that performs automatic classification of different gaits from grey-level image sequences. In particular, they can differentiate between walking, running, hopping, and limping. To extract the trajectories of the different body parts they used statistical models. The classification is performed with discrete Hidden Markov Models (HMM).

A different approach was followed by Orr and Bawd [48] who proposed a method using simple parameters extracted from the ground reaction force profiles (GRF). To characterize each footstep profile, they propose ten features (mean value of the profile, its standard deviation, length of the profile, area under the profile, x-y-coordinates of the two maximum points and the minimum point). The poor recognition rate of this simple approach limits its applicability for low-security environments only. However, the method is perfectly suitable for its intended purpose in the Aware Home Research Initiative (AHRI).

In September 2000, the DARPA launched the HumanID program with 26 individual projects and research groups involved from the USA, Germany, and England. The goals of the project are to develop non cooperative, multimodal surveillance technologies for identifying humans at a distance under day/night, and all-weather conditions. The HumanID program has two phases: The initial 2 years of Phase I will end in late 2002 with a major evaluation. Phase II lasts another 2 years and continues research with the most promising approaches identified in the technology assessment at the end of Phase I.

Although most of the research projects are still in an early stage, some groups have already published preliminary results.

Recently, Bobick and Johnson published two papers [49,50] where they proposed a multi-view method that recovers body and stride parameters of the subjects as they walk. In particular they estimate four static distances: the vertical distance between the head an the foot, the distance between the head and the pelvis, the maximum distance

between the foot and the pelvis, and finally the maximum distance between the left and right foot during the double support phase. Instead of reporting percent of correct matches from a limited database (20 subjects), they introduced a novel confusion metric that allowed them to predict how their static body parameters discriminate even in a large population.

Gene Greneker's group at the Georgia Tech Research Institute is working on a radar device that can be used to record the human gait signature over a distance of up to 120 meters.

J. Shi's research group at the Carnegie Mellon University has already published a technical report [51] detailing the capturing of 25 individuals walking on a treadmill in the CMU 3D room. The subjects performed four different activities: slow walk, fast walk, inclined walking, and walking with a ball while being filmed using six color cameras with different viewing angels.

J. Phillips et al. from the NIST14 will publish a proposal [52] of a reference implementation of a biometric system using gait analysis. This baseline algorithm will be used to characterize the conditions under which the problem of identifying/authenticating people using gait is solvable Later, several attempts were made to investigate the gait recognition problem from the perspective of capturing and analyzing gait signals [10]–[14]. 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. A baseline method was proposed by the University of South Florida [15]. 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.

The deployment of motion fields in gait recognition was investigated in [13] and [16]. 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 [17]–[20], 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 [21], 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 [22], and the overall system was shown to improve on the baseline system in [15]. To the authors' judgment, 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 [23] and [24]. In [23], the recognition is based on the comparison of such templates, whereas in [24], the templates are derived in the context of training an exemplar-based hidden Markov model (HMM) that additionally takes into account the gait dynamics. All methods in this class yield state-of-the-art performance.

V. GAIT CYCLE DETECTION

For the study of gait analysis, we assume that the walking subject has been extracted from a gait sequence using standard image processing techniques. 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 [13], although no explicit cycle partitioning was attempted, a method using linear prediction was proposed for fitting a sinusoidal signal to the noisy extracted signals. In [24], 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 [25], 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.
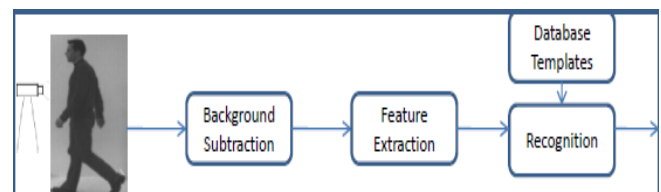

Fig. 2. Block Diagram of a Gait recognition/authentication system.

VI. MODEL BASED APPROACHES

Model-based approaches employ models whose parameters are determined using processing of gait sequences [22], [26], [27], [28]. 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.

A multiview gait recognition method was proposed in [26] using recovered static body parameters, which are measurements taken from static gait frames. Gait dynamics are not used. The static parameters used in [26] are the height, the distance between head and pelvis, the maximum distance between pelvis and feet, and the distance between the feet [Figure 3(a)]. The static parameters are view invariant, which makes them very appropriate for recognition applications. In [22], the silhouette of a walking person was divided into seven regions. Ellipses were fit to each region [Figure 3(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. In [27], 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 rotation [Figure 3(c)]. In [28], 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 3(d)].
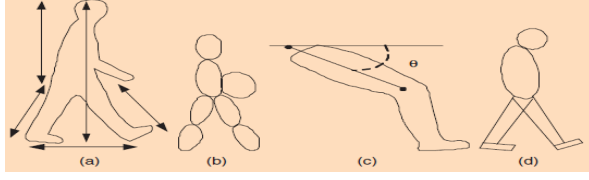

Fig. 3. Graphical Representation of parameters used in model-based approaches. (a) Distance used as static parameters in [26], (b) Ellipse fitting in silhouette regions[22], (c) Hip rotation model [27] and (d) Model using a combination of shapes[28].

VII. Model Free Approaches

Model free solutions operate directly on the gait sequences without assuming any specific model for the walking human. 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 [19], or it can be transformed to extract Fourier descriptors [29].The width of silhouette was proposed in [30] 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 4(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 [30] propose a postprocessing technique to smooth and denoise the feature vectors prior to their deployment in gait recognition. 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.

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

Using the above term, the horizontal and vertical projection of silhouettes [17] are expressed as

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

$$p_v[j] = \sum_{i=0}^{M-1} s[i, j], j = 0,1,\ldots N - 1 \qquad (2)$$

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 4(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 angular transform of the silhouette was proposed in [20].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 4(c)].

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

where, θ is an angle, F_θ is the set of the pixels in the circular sector $[\theta - (\Delta\theta / 2), \theta + (\Delta\theta / 2)]$ and $.$ is the cardinality of F_θ. The transform coefficients were shown to be a linear function of the silhouette contour.
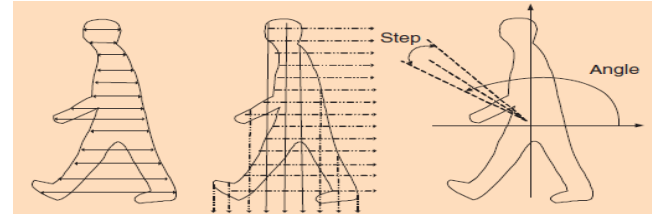

Fig. 4. Features extracted from binary silhouettes for gait recognition (a) Width of silhouette, (b) Vertical and Horizontal Projections and (c) Angular representation.

TABLE I: Advantages & Disadvantages of The Holistic and Model Based Approaches

HOLISTIC APPROACH		
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 APPROACH		
FEATURE	ADVANTAGES	DISADVANTAGES
STATIC PARAMETERS	View Invariant, Compact Representation	Difficult Capturing
ELLIPSE PARAMETERS	Compact Representation	Low Robustness
HIP ANGLE	Compact Representation	Low Robustness
COMBINATION OF SHAPE PARAMETERS	Compact Representation	Low Robustness

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.

VIII. FREQUENCY TRANSFORMATION OF FEATURE 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 f*(t)*.

$$F(K) = \frac{1}{T} \sum_{t=0}^{T-1} f(t) e^{-j\frac{2\pi}{T}Kt} \qquad (4)$$

where T is the walking period, yields a new representation that is related to the frequency content of the originally extracted features. 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 [22], [31]. In [31], 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 [22] 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. In Figure 6, we display such a representation using silhouettes.
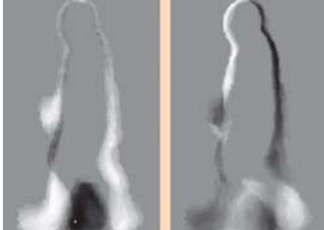

Fig. 5. Frequency signatures: a complex silhouette template computed as the Fourier transform of the gait sequence at the fundamental frequency. (a) Real part and (b) imaginary part.

IX. 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 [7], [24] or feature vectors. 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) [30], [16], [19] or linear discriminant analysis (LDA) [16] 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.

X. 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 [24] and the number of "ones" in the binary difference between frames [15]. A variety of other distance measures may also be used [32]. However, in this work, we use the classical Euclidean distance in the implementations of the presented gait methodologies.

TABLE II: IMPACT ON AVERAGE RESULTS DUE TO DIFFERENCE IN CAPTURING CONDITIONS

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

XI. 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 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

$$D_{12} = \frac{1}{U} \sum_{t=1}^{T} u(t) D(f_1(w_1(t)), f_2(w_2(t))),$$

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 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 [15]. The use of time normalization [33] 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) [33] can be used to calculate the distance between a test sequence and a reference sequence. Using DTW [30], [25], 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*. Having computed the distances between a test subject and all subjects in a reference database, the recognition decision is taken as

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

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.

XII. STATISTICAL APPROACH: HMMS

Stochastic approaches such as HMMs can also be used for gait recognition [24]. In practical HMM-based gait recognition, each walking subject is assumed to traverse a number of stances. 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, the probability that it was generated by one of the models associated with the database sequences can be calculated by

$$P(f_i / \lambda_j), j = 1, 2 \dots N$$

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.

$$identity(i) = \arg\max_j P(f_i / \lambda_j), j = 1, \dots N$$

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.

XIII. 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 III, 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 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 [30] 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 [17] 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 [36], 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 IV. 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.

TABLE III: LIST OF 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

TABLE IV: RESULTS OBTAINED FOR SEVERAL COMBINATIONS OF FEATURES & RECOGNITION METHODS OVER ALL SETS OF GAIT DATABASE CLASSIFIED INTO RANK-1 (R1) AND RANK-5(R5).

FEATURE	WIDTH		PROJECTION		ANGULAR		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 Wrapping	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	-	-

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 [35]. 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 6 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 [34] 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 discloses 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.

XIV. CONCLUSION

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.
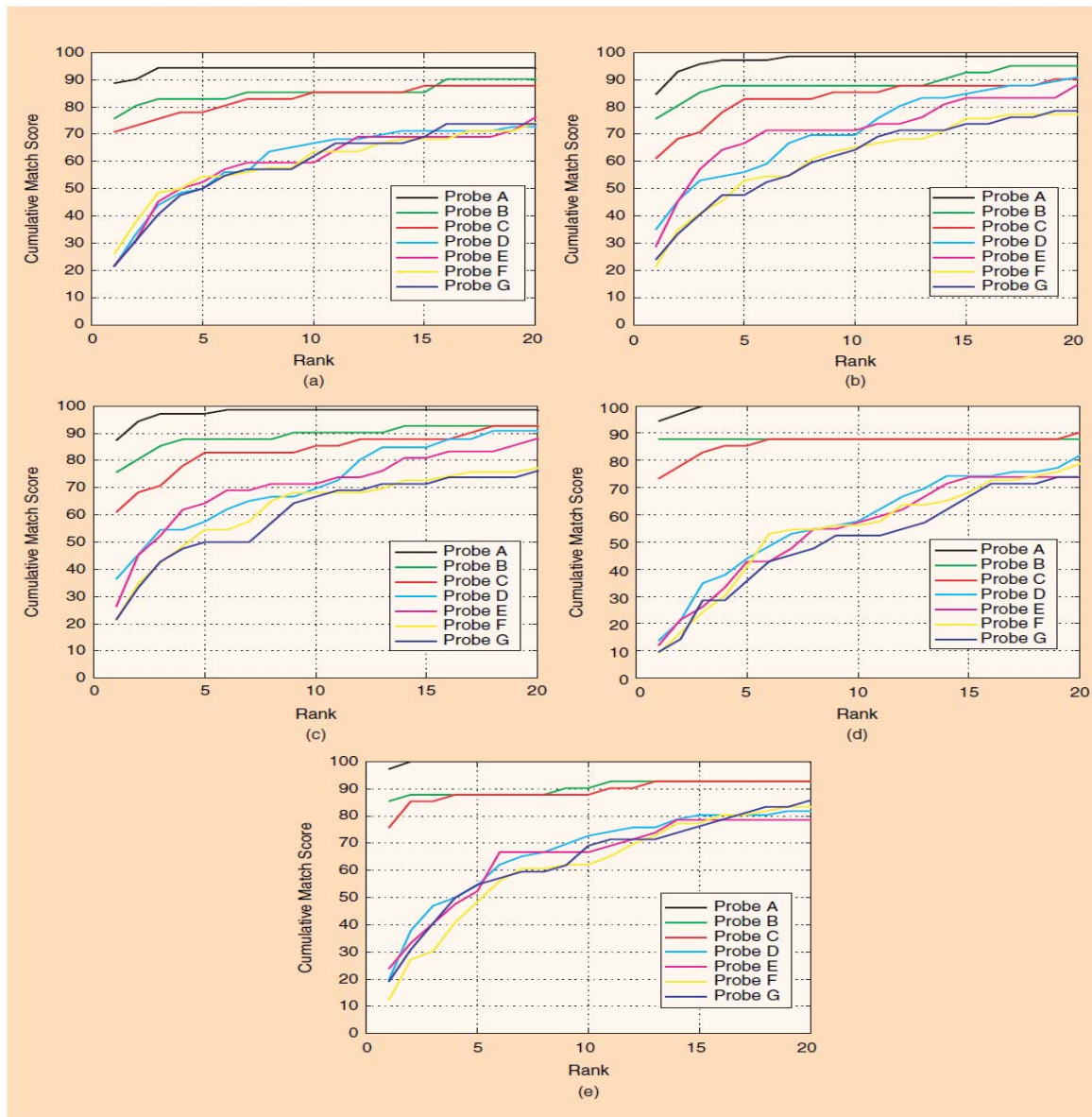
Fig. 6. Cumulative match scores for different recognition approaches using the silhouette feature. (a) Frequency signature, (b) dynami time warping, (c) linear time normalization, (d) structural matching, and (e) hidden Markov models.

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