Walker Recognition without Gait Cycle Estimation

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Abstract. Most of gait recognition algorithms involve walking cycle estimation to accomplish signature matching. However, we may be plagued by two cycle-related issues when developing real-time gait-based walker recognition systems. One is accurate cycle evaluation, which is computation intensive, and the other is the inconvenient acquisition of long continuous sequences of gait patterns, which are essential to the estimation of gait cycles. These drive us to address the problem of distant walker recognition from another view toward gait, in the hope of detouring the step of gait cycle estimation. This paper proposes a new gait representation, called normalized dual-diagonal projections (NDDP), to characterize walker signatures and employs a normal distribution to approximately describe the variation of each subject's gait signatures in the statistical sense. We achieve the recognition of unknown gait features in a simplified Bayes framework after reducing the dimension of raw gait signatures based on linear subspace projections. Extensive experiments demonstrate that our method is effective and promising.

Key words: Gait recognition, cycle estimation, PCA, LDA

1 Introduction

To some extent, gait characterizes personal moving styles, e.g., walking, running, and jumping. There have been many efforts to perform gait-based walker recognition. In brief, the prior work pertaining to gait recognition generally takes three steps to identify walkers: 1) localize moving people in video or image sequences; 2) estimate gait cycles and pinpoint the walking phase; and 3) recognize unknown pedestrians based on the time-aligned features extracted from images.

But we are sometimes confronted with two unfavorable situations when developing real-time gait recognition systems. First, the accurate estimation of gait cycles often devours much computational resource and does not adapt well to the requirement of online recognition. Second, the inconvenient acquisition of continuous gait sequences of multiple cycles makes it impractical to evaluate gait cycles; gait motion can dramatically vary after a long time and is just approximately cyclic in the short term. The two facts plunge us into a dilemma as to whether to proceed with the estimation of cycles of gait sequences or not. It is this dilemma that prompts us to reexamine gait recognition methods. This paper deals with the problem of walking people recognition at a distance. Rather than following the conventional route, we start from a statistical view on gait (just for recognition purpose), in the hope of bypassing the step of gait cycle estimation. From the perspective of security, this work is necessary.

The rest of this paper is as follows. Section 2 introduces related work. Then, we discuss technical details in Section 3 and justify our method in Section 4. Finally, Section 5 concludes this paper.

2 Related Work

Prior methods for gait recognition can be roughly clustered into two categories: the model-based category and the image appearance-based category. For example, Cunado et al. [3] used two inter-connected pendulums to model the kinematics of human legs and extracted magnitude and phase features in the frequency domain to differentiate subjects. Urtasun and Fua [12] further employed angle features in a 3D human physical model to describe the signatures of walking people. As opposed to the model-based methods, the work in [1, 7, 15] directly extracted different distance features from binary silhouette images for walker identification. Moreover, the research in [5, 8, 14] simplified the description of binary gait silhouettes within a cycle through averaging them and achieved satisfactory results. In particular, Sarkar et al. [10] established a baseline daytime gait database in an attempt to benchmark evaluation of gait recognition algorithms, and Tan et al. [11] created a large infrared night gait dataset in an effort to narrow the gap between daytime walker recognition and nighttime gait identification. However, it is still challenging to resolve the problems of how to balance the particularity of human structural models against the generality and how to extend the discriminative ability of appearance features across different harsh conditions.

The diligent efforts to shed light on cognitive principles deepen the insight into human perception of movement patterns. For instance, the body-inversion effect [9] showed that the perception of human body might be global. Surprisingly, a hemianopic patient AL [2] who lost the ability to recognize forms from motion could detect motion and distinguish static shape stimulus. Moreover, Downing et al. [4] figured out a region (EBA) in the lateral occipitotemporal cortex which focuses on the visual perception of appearance of human bodies (except face) and is not related to motion cues. Later, Jacobs and Pinto [6] showed that visual experience had a vital impact on identity perception, though disagreeing on the use of walking patterns for recognition. Meanwhile, Veeraraghavan et al. [13] concluded that shape cues play a more critical role in automatic gait recognition than those from motion. These findings reveal that the only use of global shape (or appearance) cues can achieve the human-recognition purpose; it seems that dynamic attributes are not suitable for discriminating walkers, since they

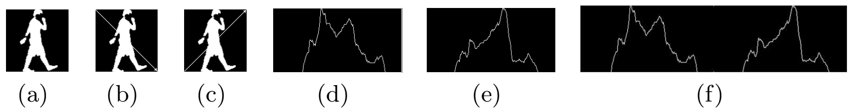


Fig. 1. NDDP illustration. (a) Normalized silhouette. (b) Positive diagonal direction. (c) Negative diagonal direction. (d) Curve for (b). (e) Curve for (c). (f) Curve concatenating (d) and (e).

are not reliable from the long-term perspective. This makes us rethink gait to form an alternative view on gait recognition.

3 Technical Details

In this paper, we consider human gait as a stochastic realization of one's static stances (or figures). It should be pointed out that we have employed this view for gait recognition in the form of equivalence constraints but did not provide extensive experiments to support this view. On the other hand, this paper uses this gait view in the Bayesian framework based on another gait representation, in the hope of justifying our view for gait recognition. Although this idea ignores the dynamic details in the human movement from the biomechanical point of view, it still grasps the more critical cues provided by human shapes for the recognition purpose. Assume that we have acquired human silhouettes. Then this paper will focus on gait representation, dimension reduction, and classification.

3.1 Gait Representation

This paper first normalizes each silhouette image to the same size of 32×32. Then, we project the size-normalized silhouette in the positive and negative diagonal directions, respectively. Meanwhile, it is easy to evaluate for each of the two directions a maximum value which indicates the maximal number of foreground pixels along that direction in this frame. Furthermore, the two maximums are used to normalize the respective projections. Finally, we concatenate the two normalized projections to represent human gait in the frame and refer to this representation as NDDP. It should be noted that a similar unnormalized diagonal representation is also able to describe human gait but is beyond the scope of this paper. Figure 1 illustrates the NDDP representation. The NDDP differs from [7] in that we are concerned with the relative number of foreground pixels in the dual diagonal directions whereas the authors in [7] are interested in the coarse number of foreground pixels in the single horizontal direction.

3.2 Dimension Reduction

We employ principal component analysis (PCA) and linear discriminant analysis (LDA) to achieve dimension reduction. The PCA projection matrix $U \in \mathbb{R}^{n \times d}$

can be derived from an intuitive, clear-cut geometric view. That is, we expect to search for a projection onto a subspace spanned by a group of orthonormal basis so that the transformed variables have as great the variance in each coordinate axis as possible—informative—and are implicitly uncorrelated. Suppose that U has the form $U = [u_1 \dots u_d]$ and that we have found $j-1$ axes $(u_1, \dots, u_{j-1})$. Now the aim is to seek the j-th axis u_j $(j \leq d)$. This problem can be formulated as (1):

$$\max_{u_j \in \mathbb{R}^n} var(u_j^T x) \quad s.t.\ u_j^T u_j = 1,\ u_k^T u_j = 0 \quad (k = 1, 2, \cdots, j-1) \tag{1}$$

where $x \in \mathbb{R}^n$ is the initial NDDP vector. It is trivial to prove that the optimal $u_1, \dots, u_d$ should correspond to the top d largest eigenvalues of the covariance (or correlation) matrix of x. This paper chooses d to be the minimum number of components of x which at least account for the proportion 95% of the total variation of x. Additionally, the LDA projection V can be expressed as the problem (2):

$$\max_V \frac{tr(V^T S_B^Y V)}{tr(V^T S_W^Y V)} \tag{2}$$

where S_B^Y and S_W^Y are inter- and intra-class scatter matrices, respectively. It is easy to obtain that the columns of V constitute the generalized eigenvectors of S_B^Y and S_W^Y. Similarly, we consider a fraction 98% of the generalized "variation" in an attempt to further reduce the dimension of gait features. Finally, we can gain a composition $P = U^T V^T$ which directly projects x in the original space X to $y = Px$ in the dimension-reduced space Y.

3.3 Classification

Unlike the only mean description of gait sequences, we exploit a normal distribution $x^i \sim N(\mu_i, \Sigma_i)$, $i = 1, 2, \dots, n_c$, where n_c is the number of subjects in the gait database, to express the i-th person's gait signatures with regard to our gait view. Then the transformed vector y^i has the distribution $y^i \sim N(P\mu_i, P\Sigma_i P^T)$. Assume that x_t^s $(t = 1, 2, \dots, M)$ is the raw feature vector of an unknown gait sequence S at the time t. In theory, we can recognize the identity in a brute force manner—combining every identified result for the sequence of silhouettes. However, this strategy involves huge computational resource. Instead, this paper employs the average $\bar{x}^s$ of feature vectors x_t^s in S to describe the unknown gait sequence S for the computational simplicity. The next is to map $\bar{x}^s$ to $\bar{y}^s$ with the P. In addition, our method incorporates the second-order moment (covariance) into the distance measure in a quasi-Bayesian fashion: $d_i^* = (\bar{y}^u - P\mu_i)^T (P\Sigma_i P^T)^{-1} (\bar{y}^u - P\mu_i)$. Finally, the nearest distance rule is used to judge the identity of the unknown walker in the gait sequence S.

4 Experiments

In order to validate the proposed method, we perform walker-recognizing experiments on three gait databases in an increasing order of the number of subjects:

Fig. 2. Sample gait images in the CMU Mobo Gait Database

Table 1. Five Experiments on the CMU Mobo Gait Database

Exp.	Gallery	Probe	Remarks
A	Slow	Slow	Within-condition
B	Fast	Fast	Within-condition
C	Ball	Ball	Within-condition
D	Slow	Fast	Across-condition
E	Fast	Slow	Across-condition

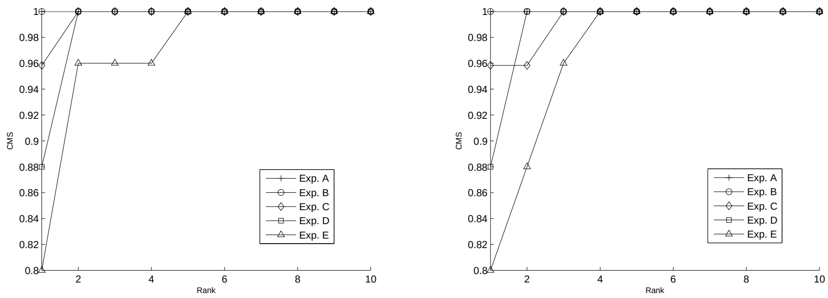
CMU Mobo Database [1], USF-NIST Gait Database [10], and CASIA Infrared Night Gait Dataset [11]. Meanwhile, we employ cumulative match score (CMS) [10] to assess recognition performance. Here the CMS value at rank k serves as an indicator of the fraction of probes whose leading k matches must include their real identities. In addition to the statistical estimation for Σ_i, our algorithm also replaces Σ_i with the global covariance matrix Σ estimated from training data for the computational convenience. We denote by D_G the distance measure which uses the plain estimates of Σ_i and by D_M the measure which utilizes the substitution of Σ for Σ_i. The following will give more experimental details.

4.1 CMU Mobo Gait Database

This database comprises gait sequences from 25 subjects and four kinds of walking patterns: slow walking, fast walking, slow walking at a certain slope, and slow walking with a ball. Figure 2 shows four sample gait images in the Mobo database. Five experiments designed for this database [7] are listed in Table 1. Table 2 presents the rank 1 performance of our approach and another two influential methods [7, 13]. We can see from Table 2 that our method can produce near 100 percent recognition rate for the 25 subjects when the training and testing data share the same moving attributes, that across-condition recognition is more difficult than the recognition in the within-condition case, and that our approach outperforms [7] and is conservatively comparable to [13] just using a simple model, despite neglect of dynamic cues. Furthermore, Figure 3 depicts the CMS curves of our method on this database. The CMS values at least illustrate the potential of our approach in the identification mode.

Table 2. Comparison of the Rank 1 Performance on the Mobo Gait Database

	A	B	C	D	E
HMM[7]	72%	68%	92%	32%	56%
SC[13]	100%	100%	92%	80%	84%
Ours(D_G)	100%	100%	96%	88%	80%
Ours(D_M)	100%	100%	96%	88%	80%



(a) CMS curve of D_G (b) CMS curve of D_M

Fig. 3. CMS curves of our method on the CMU Mobo Gait Database

4.2 USF-NIST Gait Database

We use the precomputed silhouettes for the May-2001-No-Briefcase dataset in the USF-NIST Gait Database [10]. The dataset used includes 74 individuals and considers the conditions across viewpoint, footwear, and ground surface. Figure 4 displays four example images in the USF-NIST database. Table 3 lists seven challenging experiments [10] on this dataset. Moreover, Table 4 compares our method with some well-known approaches [1, 7, 10, 15] in the literature.

Fig. 4. Sample gait images in the USF-NIST Gait Database

We can see from Table 4 that our model can produce a recognition rate close to 100 percent in the concurrent gait case (Exp. A) and that in the presence of disturbances on silhouette segmenting, the performance of our model begins to degrade as well as other algorithms' (this is an intrinsic flaw of appearance-based gait recognition algorithms). Moreover, our method is competitive with or comparable to the noted approaches on this gait database, in terms of both rank

Table 3. Seven Challenging Experiments on the USF-NIST Gait Database

Exp.	Probe[1]	Difference
A	(G, A, L)[71]	View
B	(G, B, R)[41]	Shoe
C	(G, B, L)[41]	Shoe,View
D	(C, A, R)[70]	Surface
E	(C, B, R)[44]	Surface, Shoe
F	(C, A, L)[70]	Surface, View
G	(C, B, L)[44]	Surface, Shoe, View

Table 4. Comparison of Recognition Performance on the USF-NIST Gait Database

	Algo.	A	B	C	D	E	F	G
Rank 1	CMU [1]	87%	81%	66%	21%	19%	27%	23%
	UMD [7]	91%	76%	65%	25%	29%	24%	15%
	USF [10]	79%	66%	56%	29%	24%	30%	10%
	NLPR [15]	70%	59%	51%	34%	21%	27%	14%
	Ours(D_G)	99%	83%	71%	20%	17%	14%	12%
	Ours(D_M)	100%	83%	68%	32%	24%	30%	31%
Rank 5	CMU [1]	100%	90%	83%	59%	50%	53%	43%
	UMD [7]	100%	81%	76%	61%	39%	46%	33%
	USF [10]	96%	80%	76%	61%	24%	45%	33%
	NLPR [15]	93%	83%	71%	64%	45%	39%	26%
	Ours(D_G)	100%	90%	90%	82%	79%	76%	74%
	Ours(D_M)	100%	93%	93%	80%	83%	79%	74%

1 and rank 5 values. In particular, our method has a much greater acceleration in CMS values. These not only exemplify the promising usefulness of our approach and but also indirectly give an experimental support for that our view on gait recognition is to some extent reasonable.

4.3 CASIA Infrared Night Gait Dataset

The previous two databases pay more attention to daytime gait patterns. Hence this paper employs the CASIA Infrared Night Gait Dataset [11] to diversify the gait recognition experiments. This dataset consists of 153 subjects' night gait sequences and allows for four walking cases: normal walking, slow walking, fast walking, and normal walking with a bag. Figure 5 illustrates sample night gait in the CASIA dataset. Table 5 presents four experiments on this dataset [11]. It should be noted that we use the entire gait sequences in this data collection, rather than a fraction of the data. Figure 6 shows CMS curves of our method for ranks up to 20.

We can notice from Fig. 6 that Exp. A has the best performance (almost 100% recognition rates), due to the similarity in walking attributes between

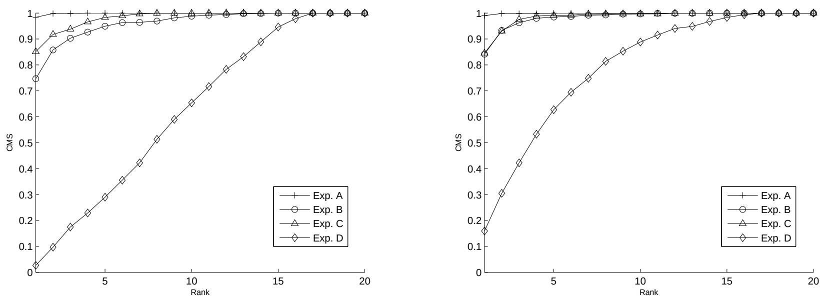
[1] The value in the bracket indicates the number of subjects in the test.

Fig. 5. Sample gait images in the CASIA Infrared Night Gait Dataset

Table 5. Four experiments on the CASIA Infrared Night Gait Dataset

Exp.	Gallery	Probe	#Gallery Seq.	#Probe Seq.
A	Normal	Normal	459	153
B	Normal	Fast	459	306
C	Normal	Slow	459	306
D	Normal	Bag	459	306

training and testing data. In addition, the changes in walking pace to some degree decline recognition accuracy largely because of the drastic departure of the means of feature vectors in some testing sequences from their corresponding training ones. Appearance variation can dramatically affect the precision of our recognition results; however, appearance-robust gait recognition is still not a well-resolved problem in the gait field. Nevertheless, the results favor the efficacy of our method with reference to the number of the subjects.



(a) CMS curve of D_G (b) CMS curve of D_M

Fig. 6. CMS curves of our method on the CASIA Night Gait Dataset

4.4 Discussions

In general, the measure d_i^* does not satisfy the distance definition and just serves as a simplified Bayesian classifier for the computational simplicity. Assuming that the prior distribution is uniform and that the volumes of eigenspaces of the subjects are equal (i.e., $|\Sigma_i|$ have the same value), we can obtain the D_G measure. Similarly, the much stronger assumption that all Σ_i are the same (homoscedastic) brings the D_M measure. The results indicate that both measures are sensible.

The aim of gait cycle estimation is to facilitate feature matching. As opposed to the conventional route, we make full use of features in static 2D shapes by combining the first- and second-order statistics to recognize walkers. A more promising scheme is to integrate posture cues into our method for recognition elaboration on a stance scale.

5 Conclusions

This paper has dealt with the problem of walker recognition in a simplified Bayesian framework. Experimental results show that our method is superior or comparable to the prior cycle-based algorithms. Our contribution is two-fold: One is that we propose the NDDP to characterize human gait patterns, and the other is that we explicitly incorporate second-order statistical cues into gait recognition and obtain an encouraging performance.

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