Gait Components and Their Application to Gender Recognition

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***Abstract*—Human gait is a promising biometrics resource. In this paper, the information about gait is obtained from the motions of the different parts of the silhouette. The human silhouette is segmented into seven components, namely head, arm, trunk, thigh, front-leg, back-leg, and feet. The leg silhouettes for the front-leg and the back-leg are considered separately because, during walking, the left leg and the right leg are in front or at the back by turns. Each of the seven components and a number of combinations of the components are then studied with regard to two useful applications: human identification (ID) recognition and gender recognition. More than 500 different experiments on human ID and gender recognition are carried out under a wide range of circumstances. The effectiveness of the seven human gait components for ID and gender recognition is analyzed.**

***Index Terms*—Biometrics, gender recognition, human gait recognition, visual surveillance.**

I. Introduction

COMMERCIAL visual surveillance has many applications, e.g., in public transportation, banks, and car park monitoring systems. In these applications, human beings are usually among the main foci of attention. Therefore some kind of biometric information [20], [32] should be extracted from surveillance sequences to help in the classification and analysis of behavior.

Previously, biometric research has concentrated on human authentication and authorization, utilizing face images, fingerprints, palm prints, shoeprint, iris images, and handwriting, but these conventional biometric resources suffer from several limitations.

1) Distance between camera/scanner and people: At present, none of the aforementioned conventional biometrics can work well from a large distance. In visual surveillance, the distances between the cameras and the people under surveillance are often large. The camera may be set on the top of a building, in the ceiling of a corridor, or wherever a panorama of the surveyed area can be obtained. In these situations, it is almost impossible to acquire the detailed conventional biometric information.
2) People (user) cooperation: This is often required to capture conventional biometric information. For example, a scanner may be provided to obtain a fingerprint or a palm print. The scanner must be used in the correct way. The requirements are even stricter for iris recognition because it is necessary to look through an eyepiece. Most of the current face databases have been built with the participants' cooperation. For these applications, people are normally the users of the system.
3) People's (user) attention in authentication and authorization: Previous work on conventional biometrics resources has focussed on the recognition rate, but paid less attention to other aspects, e.g., manners. For instance, it might not be polite to ask a person to stare at a camera that is used to capture iris patterns. Even worse, when something goes wrong with the system, the person has to repeat the action.

For visual surveillance applications, the earlier conventional biometrics resources are difficult to utilize, and human gait provides an interesting alternative. A gait describes the manner of a person's walking. It can be acquired at a distance, and if necessary, without the walker's cooperation or knowledge.

Human gait information was analyzed first in surgery [29] and psychology [11], [18]. In surgical applications, a patient's gait pattern was a basis for choosing an appropriate medical treatment (in this case, the data were gained at a close range). Murray [29] classified pathologically abnormal gaits into several groups for suitable treatments. This classification was achieved by comparing a patients' gait patterns with normal gait patterns obtained from a control group. Johansson reported in [18] that walking subjects could be recognized on the basis of their gaits alone. In the scope of computer science, some early efforts to recognize a person by gait are introduced in [5], [23], and [30]. Many other efforts have also been spent on gait information processing [2], [4], [6], [9], [10], [12], [19], [22], [38], and since then, gait silhouette information has been widely utilized, e.g., in [8], [14], [21], [37], and [39]. Human gait recognition (HGR) has applications not only in visual surveillance but also in human computer interaction, access control, human motion analysis [1], [7], and identification [32]. Some important surveys along with detailed comparisons of different algorithms can be found in [1], [13], [16], and [27].

Human gait is affected by certain factors, including physical characteristics of people and environmental factors, such as:

Manuscript received January 21, 2007; revised May 25, 2007 and August 25, 2007. This paper was recommended by Associate Editor Z. Wang.

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Digital Object Identifier 10.1109/TSMCC.2007.913886

1) camera factors, such as viewpoint [31], affect the measurement of the gait (and do not normally affect the gait itself); 2) time elapsed [31], [34] is also a key issue in visual surveillance; 3) the walking figure's carrying status [35] and clothing such as clothes and shoes [31]; 4) kinematics features such as walking speed [33], bounciness, and rhythm [24], note that qualities such as bounciness and rhythm are properties of the gait itself; and 5) other factors, such as injury, disguise, image quality [25], observer' familiarity with the people under surveillance, lighting, background, and walking surface. The human ID dataset [32] studied several of these factors and provided baseline algorithms for researchers. So far, how to measure the effect of each factor or combination of factors is still an open issue.

Any one factor may be correlated with other factors. For example, a change in a walking surface or a shoe type may cause a change in speed. These correlations between different factors can be very significant because the different components of a person's gait have wide variations as compared with conventional biometrics, e.g., a person's hand could touch his leg or head. These large variations are not found in conventional biometrics, e.g., we cannot move the eyes below the nose—in other words, the relative positions of the eyes and nose on the face can vary only over a small range. The larger variations in gait make the gait difficult to measure, but at the same time, indicate that a large amount of information might be recovered from the gait. From the aforementioned examples, we can understand that the correlations between the different gait factors/components are very significant for human recognition and gender recognition.

In this paper, we first separate human gait into seven components, and then, perform human gait recognition first based on the entire human gait silhouette, then on each of the seven components individually, and finally, on certain combinations of the seven components. The results show that the gait is helpful for efficiently and effectively recognizing people. Moreover, human gait not only shows the distinctive moving silhouette of a human body, but also reflects the walker's physical situation and even his or her psychological state. Therefore, after studying different components of the human silhouette and their contribution to human gait recognition, we also studied the effectiveness of these components for human gender recognition, which has useful applications in commercial visual surveillance.

The rest of the paper is organized as follows. Section II introduces the human gait modeling scheme, and describes the segmentation of the human silhouette into seven components. Section III introduces the dataset utilized for the experiments. The use of gait for human recognition and gender recognition is studied in Sections IV and V, respectively. Finally, the conclusion is drawn in Section VI.

II. Human Gait Modeling

We segment the averaged gait image into seven components according to the usually segmentation method as shown in Fig. 1.The first component is the head; the second component is the arm (it also includes the breast); the third component is the trunk (different from traditional "trunk," the trunk in this paper excludes the breast); the fourth component is the thigh (it also includes the hip); the fifth component is the front leg; the sixth component is the back leg; and the seventh component is the feet. The front-leg and back-leg are included as separate components because of the bipedal walking style. During walking, the left-leg and the right-leg come to front/back by turns. The resulting partition is shown in Fig. 2.

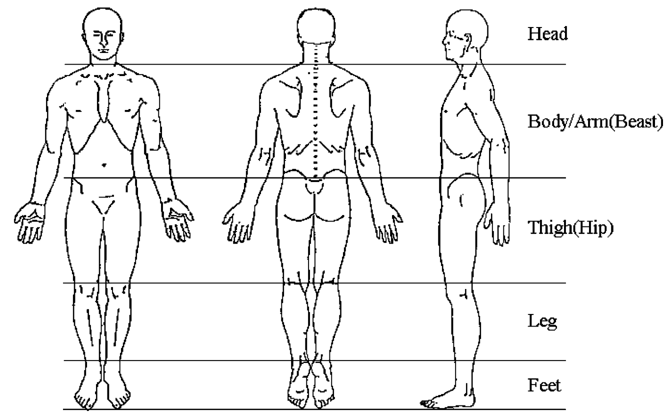

Fig. 1. Three-sided human view (adapted from http://www.vbflorida.com/htmassage/clientinfoform.cfm with minor changes).

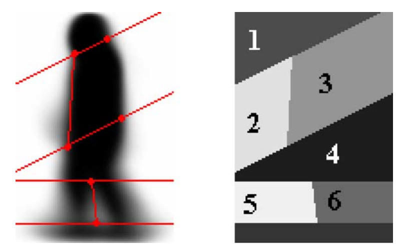

Fig. 2. Averaged human gait image partition model (the bottom component is part 7).

The averaged gait image partition model is constructed by the following steps.

1) Calculate the mean image of all averaged gait images in the gallery set (Fig. 4 shows sample images for *average gait*; Table I describes probe and gallery sets, and Section IV-A describes how to obtain the averaged gait image) [32].
2) Select six control points according to Fig. 2. Here, two points are marked on the mean image of all averaged gait images in the gallery to locate the head; two points are marked to locate the arm (including breast) and trunk; one point is marked to indicate the thigh (with hip); and one point is marked to indicate the feet. The six control points are shown in the left subfigure of Fig. 2.
3) Use lines to connect the relevant pairs of points to partition the mean image into seven parts. The connections between the points are shown in the left subfigure of Fig. 2, and the resulting segmentation is shown in the right subfigure of Fig. 2.

Fig. 3 the seven templates are shown in white. The subfigures from left to right can extract head, arm (with breast), trunk, thigh (with hip), front leg, back leg, and feet, respectively, from an averaged gait image.

TABLE I
TWELVE PROBE SETS FOR CHALLENGE EXPERIMENTS, IN WHICH H, I, AND J FOCUS ON THE *CARRYING* STATUS (BF)

Experiment (Probe)	# of Probe Sets	Male/Female	Difference between Gallery and Probe Set
A (G, A, L, NB, M/N)	122	85/37	View
B (G, B, R, NB, M/N)	54	38/16	Shoe
C (G, B, L, NB, M/N)	54	38/16	View and Shoe
D (C, A, R, NB, M/N)	121	85/36	Surface
E (C, B, R, NB, M/N)	60	39/21	Surface and Shoe
F (C, A, L, NB, M/N)	121	85/36	Surface and View
G (C, B, L, NB, M/N)	60	39/21	Surface, Shoe, and View
H (G, A, R, BF, M/N)	120	85/35	Briefcase
I (G, B, R, BF, M/N)	60	41/19	Briefcase and Shoe
J (G, A, L, BF, M/N)	120	85/35	Briefcase and View
K (G, A/B, R, NB, N)	33	26/7	Time, Shoe, and Clothing
L (C, A/B, R, NB, N)	33	26/7	Time, Shoe, Clothing, and Surface

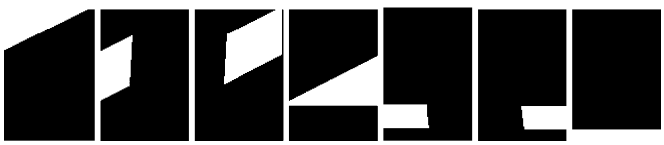

Fig. 3. Seven templates are shown in white. The subfigures from left to right can extract head, arm (with breast), trunk, thigh (with hip), front-leg, back-leg, and feet, respectively, from an AGI.

The segments shown in the right subfigure of Fig. 2 correspond to the seven templates in Fig. 3. The image segment corresponding to a given template is extracted from an averaged gait image by placing the template on the gait image and selecting all the pixels in the gait image corresponding to the high values in the template. By this means, the complement to a selected component can also be obtained. The subfigures in Fig. 3 from left to right correspond to seven components shown in the right subfigure in Fig. 2. They are head, arm (with breast), trunk, thigh (with hip), front-leg, back-leg, and feet, respectively.

III. BRIEF REVIEW OF THE USF GAIT DATABASE

The experimental images were taken from the University of South Florida (USF) HumanID outdoor gait (people–walking–sequence) database that has been built and widely utilized for vision-based gait recognition. It consists of 1870 sequences from 122 subjects. For each of the subjects, there exist the following covariates: change in viewpoint (left or right), change in shoe type (A or B), change in walking surface (grass or concrete), change in carrying condition (*carrying* a briefcase or no briefcase), and change in elapsed time (May or November) between sequences being compared. All these covariates are important for different aspects/applications. Probably, the effect of a covariate is more cleanly captured by its impact on the match scores, and it can possibly be measured by testing two probe sets that differ in only one factor. Herein, the silhouette data are normalized in USF HumanID, and the alignment has already been done.

There is a set of 12 predesigned experiments [32] for algorithm comparison. For classifier training, the database provides a gallery, which was collected in May, with the following covariates: grass, shoe type A, right camera, and no briefcase, which includes several new subjects in November. The gallery set has 122 individuals, of which 85 are males and 37 are females. The averaged gait image (with size 128×88 and provided by the USF database) contains the human gait information available to the classifier. Examples from the gallery set are given in Fig. 4. For algorithm testing, 12 probe sets are constructed according to the 12 predesigned experiments. Detailed information about the probe sets is given in Table I.

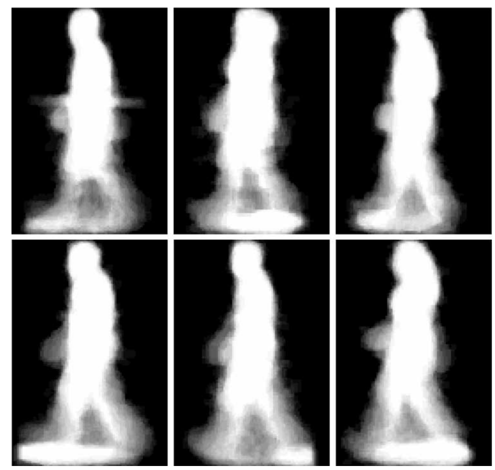

Fig. 4. AGIs in the gallery set.

IV. EXPERIMENTS ON HGR

Human gait is an important biometric for identification. Current research on gait recognition is usually based on an averaged gait image or a silhouette sequence, or a motion structure model. The movements of the different components (e.g., head, arm, and thigh) in the averaged gait image have not been studied closely.

In the following, the gait recognition algorithm is briefly described. Then, we describe a series of experiments to demonstrate the impact of each component on gait recognition. Finally, experimental results are analyzed.

A. Human Gait Recognition

Fig. 4 shows some examples of average gaits (AGs), which demonstrate that AGs could be used for gait recognition and gender recognition, because different people have different

TABLE II
RANK 1 EXPERIMENTAL RESULTS FOR HUMAN GAIT RECOGNITION

	0	1	∼1	2	∼2	3	∼3	4	∼4	5	∼5	6	∼6	7	∼7
A	83	34	77	27	78	43	80	30	81	34	84	34	80	25	84
B	85	54	83	54	83	74	85	72	83	46	89	35	83	35	87
C	67	26	65	15	67	26	69	28	65	13	67	19	65	19	67
D	24	6	23	6	21	9	21	4	31	8	21	3	20	5	14
E	24	2	21	3	22	14	22	5	26	5	26	7	24	3	22
F	9	3	9	3	8	3	11	5	8	5	11	7	9	2	12
G	16	3	17	3	10	9	16	3	16	7	14	2	12	5	12
H	51	53	45	35	42	61	44	3	78	30	47	12	53	42	40
I	48	43	41	21	47	60	40	3	66	14	48	10	47	29	38
J	42	29	33	9	38	34	36	4	47	11	42	13	41	11	32
K	0	6	0	9	0	15	0	9	0	0	3	0	3	0	12
L	6	0	3	9	3	6	0	3	6	0	6	0	6	0	12

The first column contains the ID for 12 probes and the other columns contain the recognition rates when the different parts of the body are used for gait recognition. "0" presents the averaged gait images. "1," "2," "3," "4," "5," "6," and "7" refer to the recognition of gait using head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. "∼1," "∼2," "∼3," "∼4," "∼5," "∼6," and "∼7" refer to the recognition of gait using the averaged gait image without head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. The table entries are percentages.

AGs. The AG is the mean image (pixel by pixel) of silhouettes *over a gait cycle* within a sequence of images. As suggested in [26], a sequence of images is partitioned into a series of subsequences according to the gait period of length N_{Gait}. Then, the binary images (silhouettes) within one cycle (a subsequence) are averaged to yield AGs by means of $AG_i|_{i=1}^{\lfloor T/N_{\mathrm{Gait}}\rfloor} = (\sum_{k=iN_{\mathrm{Gait}}}^{k=(i+1)N_{\mathrm{Gait}}-1} S(k))/N_{\mathrm{Gait}}$, where $S(k)$ stands for the k silhouette, as stated earlier, a binary image. As an average value, AG is very robust against any errors in individual frames, so we choose the AG to represent a gait cycle. One sequence yields several AGs and the number of AGs depends on the number of gait cycles in the sequence. In the following experiments, the AGs provide the data for gait recognition.

The distance defined between the gallery sequence and the probe sequence is defined as in [26] by

$$\mathrm{Dist}\left(\mathrm{AG}_P^{\mathrm{Method}}, \mathrm{AG}_G^{\mathrm{Method}}\right) = \mathrm{Median}_{i=1}^{N_P}\left(\min_{j=1}^{N_G}\left\|\mathrm{AG}_P^{\mathrm{Method}}(i) - \mathrm{AG}_G^{\mathrm{Method}}(j)\right\|\right) \quad (1)$$

where $\mathrm{AG}_P^{\mathrm{Method}}(i)|_{i=1}^{N_P}$ is the ith projected AG in the probe data and $\mathrm{AG}_G^{\mathrm{Method}}(j)|_{j=1}^{N_G}$ is the jth projected AG in the gallery. Equation (1) uses the median of the Euclidean distances between the averaged silhouettes from the probe and the gallery sequences.

The difference between (1) and the gait recognition measure developed by Liu *et al.* [26] is that we choose a template to pop out only the relevant component for recognition. The algorithm is shown in Fig. 5. We first segment each sequence in the gallery set (training set) into a few subsequences where each subsequence is a complete gait cycle. We then calculate the averaged gait image for each subsequence of images and use the template to select a component or its complement from each averaged gait image. The same procedure is carried out on the probe set (test set). Finally, the similarities are calculated between: 1) a testing sample of average gait image (AGI) from the probe set (it could be a part or several parts of the entire AG) and 2) all AGIs stored in the gallery set. Then, this sample from the probe set is recognized by (1).

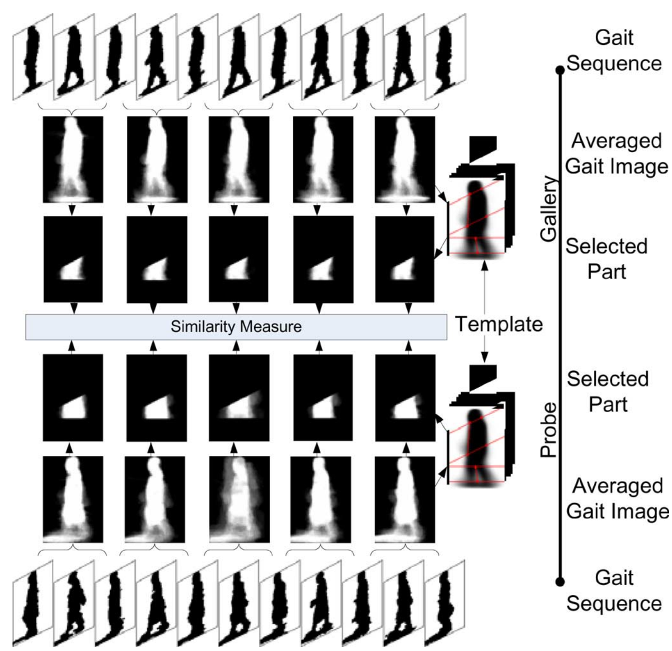

Fig. 5. Extraction of the average gait and the similarity measure.

B. Experimental Results

We first conduct 15 groups of experiments to examine the effectiveness of the averaged gait image, each component of the averaged gait image, and the complement of each component for gait recognition. Table II lists the recognition rates. Note that different from the data set provided in Table I, we here focus on the contribution of different parts/component of human AGI to human recognition.

We also conduct a number of experiments to examine the cooccurrence effects of pairs of components on the gait recognition. It would be difficult to conduct experiments on all 252 pairs and get useful information from them. Therefore, we only conduct experiments on pairs of two parts, which may possibly reduce the recognition rates or may not impact the recognition rate compared to the performance obtained by using the

TABLE III
RANK 1 EXPERIMENTAL RESULTS FOR HUMAN GAIT RECOGNITION

Probe	Experimental Results
A	{82 | (5,7)}
B	{83 | (3,5)}, {87 | (3,7)}, {89 | (5,7)}
C	{65 | (2,3)}, {70 | (2,5)}, {70 | (2,7)}, {72 | (3,5)}, {69 | (3,7)}, {70 | (5,7)}
D	
E	{28 | (4,5)}, {24 | (4,6)}, {28 | (5,6)}
F	{9 | (1,3)}, {8 | (1,5)}, {8 | (1,6)}, {12 | (1,7)}, {11 | (3,5)}, {11 | (3,6)}, {10 | (3,7)}, {10 | (5,6)} {14 | (5,7)}, {13 | (6,7)}
G	{17 | (1,3)}, {12 | (1,4)}, {14 | (3,4)}
H	{82 | (4,6)}
I	{59 | (4,5)}
J	{43 | (4,5)}
K	{3 | (1,3)}, {12 | (1,7)}, {3 | (2,6)}, {9 | (2,7)}, {3 | (3,5)}, {3 | (3,6)}, {12 | (3,7)}, {15 | (4,7)} {6 | (5,6)}, {6 | (5,7)}, {15 | (6,7)}
L	{6 | (4,5)}, {6 | (4,6)}, {15 | (4,7)}, {6 | (5,6)}, {21 | (5,7)}, {18 | (6,7)}

The table has 12 rows, where each row corresponds to one of the 12 probes. In each row, the element $\{a|(i,j)\}$ means the recognition rate is a when the ith and the jth component are removed. Index $i(j)$, "1," "2," "3," "4," "5," "6," and "7" refer to the recognition based on the averaged gait image without head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. For example, the element "{82 | (5,7)}" in the first row indicates that the rank 1 recognition rate of probe A is 82% when we remove the front-leg (fifth component) and feet (seventh component) from the averaged gait image. The table entries are {percentages|(gait parts #, gait parts #)}.

whole averaged gait image (i.e., we only select pairs for which strong effects are expected). For example, in probe A, both the fifth component and the seventh component have a negative impact on the recognition rate, while the complement of the fifth component and the complement of the seventh component can improve the recognition rate. Therefore, we need to investigate the performance when we remove both the components from the averaged gait image. All results from the examination of co-occurrence effects are shown in Table III.

C. Discussion

We first evaluate the effect of each component on gait recognition, as shown in Table II. We deem that a component has a positive effect on gait recognition if the recognition rate is significantly reduced when the component is removed from the averaged gait image. A component has a negative impact on gait recognition if the recognition rate is significantly increased when the component is removed from the averaged gait image. Otherwise, we deem that the component has little effect on the gait recognition. For example, the head has a positive impact for the probe A test, because the recognition rate is 77 if we remove the head from the averaged gait image and the recognition rate is 83 if we use all components for recognition. The front-leg has a negative contribution for the probe A test, because the recognition rate is 84 without the front-leg, and the recognition rate is 83 with all components for recognition. The trunk has little effect on the recognition rate in probe B because the recognition rate is the same with or without the trunk. A full analysis of the results is given in Table IV.

The preliminary analysis in Table IV and the experimental results in Tables II and III are summarized by the following observations listed in Table V for all probes.

The following conclusions are drawn from Table V. For person identification, head, arm, trunk, and back-leg usually provide the best discriminating information. The inclusion of the front-leg usually reduces the recognition rate. When the probe set differs from the gallery set in terms of walking surface or the carrying of a briefcase, the inclusion of the thigh reduces the recognition rate. Otherwise, the inclusion of the thigh usually increases the recognition rate. The usefulness of the feet for recognition is unclear.

V. EXPERIMENTS ON HGR

Gender recognition has received a fair amount of attention in the psychophysical and computer vision literature, especially in the case of gender recognition based on the face. There are relatively few gait-based studies. In [17], a human face image is treated as a vector, and independent component analysis (ICA) is then applied to reduce the dimension of the data space. A support vector machine (SVM) is used to further improve the classification performance. The SVM is also used in [28] for gender recognition based on face images. In [36], an input image is coarsely divided into face, hair, and clothing regions, and a model is learned independently for each region. The final classification of the face image is made by using a Bayesian approach. Local regions are used for gender recognition in [3]: the similarity values between N local regions and M face images in the training set are used as features, PCA is used to reduce the dimension of the feature space and remove the noise, and then an SVM or Fisher linear discriminant analysis (LDA) is used for the final classification. The algorithm achieves high recognition accuracy on a database with 13 000 frontal or nearly frontal face images. In the future, locality preserving projections (LPP) [15] could be the basis of an algorithm to

TABLE IV
PRELIMINARY EVALUATION OF THE IMPACT OF EACH COMPONENT ON HUMAN GAIT RECOGNITION

ID		1	2	3	4	5	6	7
A	View	+	+	+	+	–	+	–
B	Shoe	+	+	N	+	–	+	–
C	View and Shoe	+	N	–	+	N	+	N
D	Surface	+	+	+	–	+	+	+
E	Surface and Shoe	+	+	+	–	–	N	+
F	Surface and View	N	+	–	+	–	N	–
G	Surface, Shoe, and View	–	+	N	N	+	+	+
H	Briefcase	+	+	+	–	+	–	+
I	Briefcase and Shoe	+	+	+	–	N	+	+
I	Briefcase and View	+	+	+	–	N	+	+
K	Time, Shoe, and Clothing	N	N	N	N	–	–	–
L	Time, Shoe, Clothing, and Surface	+	+	+	N	N	N	–
	#{–}	1	0	2	5	5	2	5
	#{N}	2	2	3	3	4	3	1
	#{+}	9	10	7	4	3	7	6

"1," "2," "3," '4," "5," "6," and "7" refer to recognition based on head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. "+" indicates that the component has a positive impact on gait recognition; "−" indicates that the component has a negative impact on gait recognition; and "N" indicates that the component has little impact on recognition. "#{−}," "#{N}," and "#{+}" indicate respectively the number of "−," "N," and "+" in a column.

TABLE V
OBSERVATIONS FROM EXPERIMENTS

ID	Observations from experiments
A	Head, arm, trunk, thigh, and back-leg are important for recognition. Front-leg and feet both reduce the recognition rate. If the front-leg and the feet are both removed from the averaged gait image, then the recognition rate is reduced.
B	Head, arm, thigh, and back-leg are useful for recognition; front-leg and feet both reduce the recognition rate; and trunk has little effect on the recognition rate. If the front-leg and the feet are removed, the recognition rate increases. In this experiment, because shoe type is one of the ways in which the probe set differs from the gallery, the feet can reduce the recognition rate.
C	Head, thigh, and back-leg increase the recognition rate. The arm and the feet have little effect on the recognition rate. Trunk reduces the recognition rate. If trunk and front-leg are both removed from the averaged gait image, then the recognition rate increases.
D	Thigh reduces the recognition rate when the surface is changed in the probe set. The other components increase the recognition rate.
E	Head, arm, trunk, and feet increase the recognition rate. Thigh and front-leg both reduce the recognition rate when surface and shoe are changed together in the probe set. Back-leg has little effect on the recognition rate. If the front-leg and thigh are both removed from the averaged gait image, then the recognition rate increases.
F	Arm increases the recognition rate. Head and back-leg both have little effect. Front-leg and feet both reduce the recognition rate. If thigh and feet are both removed, then the recognition rate is (12). The thigh has little effect on the recognition rate. On removing both the front-leg and the feet together, the recognition rate is (14).
G	Arm, front-leg, back-leg, and feet increase the recognition rate. The head reduces the recognition rate. The other components have little effect.
H	Head, arm, trunk, front-leg, and feet all increase the recognition rate. Thigh and back-leg both reduce the recognition rate. If the front leg and feet are both removed from the averaged gait image, then the recognition rate increases. In this experiment, the probe set contains a person carrying a briefcase. The measurement of the gait of the thigh is affected, to the extent that the recognition rate increases if the thigh is omitted.
I	Head, arm, trunk, and back-leg all increase the recognition rate. Thigh can reduce the identification rate. While, the front leg does not affect the identification rate, i.e., no more than a small variation in the recognition rate. This experimental result can be compared with the result for probe B, as it has an incremental change. From B, it can be seen that feet and front leg both reduces the recognition rate when the shoe type differs between the probe set and the gallery set. Therefore, the recognition rate is measured without thigh, front leg, and feet. It is found that the recognition rate is that same as that obtained when the thigh only is omitted.
J	Head, arm, trunk, and back-leg all increase the recognition rate. The thigh and the front leg both have little effect on the recognition rate. If the thigh and front-leg are both removed from the averaged gait image, then the recognition rate is 43. If the thigh only is removed, the recognition rate is (47). Therefore, the front-leg provides some contribution to the recognition rate.
K	Head, arm, trunk, and thigh all increase the recognition rate. If the thigh, feet or back-leg and feet are removed from the averaged gait image, then the recognition rate achieves the highest point (15). If the thigh, back-leg, and feet are removed together, then the recognition rate is (12).
L	Head, arm, and trunk all increase the recognition rate. Feet reduce the recognition rate. The other components have little effect on the recognition rate. If the front-leg and feet are removed from the averaged gait image, then the recognition rate achieves its highest value (21).

select features for subsequent gender classification, e.g., by an SVM. LPP has been proposed to discover the nonlinear structure of data, which lie on or nearly on a low-dimensional manifold embedded in a high-dimensional space.

In this paper, we show that the averaged gait image can be used for gender recognition. An examination of Fig. 6 shows that the averaged gait images for males and females differ in several ways, for example: 1) for the arm (with breast) component, the breast area of females is not so flat as that of males; 2) for the trunk component, the back neck area is more curved for males than for females, possibly because males tend to have less hair than females; and 3) difference on all other

TABLE VI
EXPERIMENTAL RESULTS FOR HUMAN GENDER RECOGNITION FROM AVERAGED GAIT IMAGES

	0	1	~1	2	~2	3	~3	4	~4	5	~5	6	~6	7	~7
A	98	85	98	86	96	89	93	85	98	73	98	74	98	80	95
B	98	91	100	83	98	91	94	80	98	74	98	76	98	70	98
C	96	93	96	72	96	87	91	80	96	76	94	76	96	74	93
D	82	71	86	71	84	78	86	68	82	69	80	73	85	64	84
E	84	76	74	64	79	78	79	64	83	67	81	66	81	55	76
F	76	80	83	71	78	81	76	73	73	65	75	66	76	57	81
G	74	74	81	64	78	81	74	76	72	67	78	57	71	50	69
H	92	84	92	76	91	81	89	70	88	70	89	68	88	76	92
I	84	88	93	76	81	81	84	71	88	66	84	66	86	69	86
J	93	88	92	85	92	86	87	59	94	71	90	64	94	76	86
K	94	88	91	82	97	85	97	76	97	73	91	76	97	67	94
L	82	82	76	76	82	82	82	82	67	79	73	70	76	48	79

The first column contains the IDs for the 12 probes and the other columns contain the recognition rates for different parts. Column "0" lists the averaged gait images. "1," "2," "3," "4," "5," "6," and "7" indicate that gender is recognized by head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. "∼1," "∼2," "∼3," "∼4," "∼5," "∼6," and "∼7" indicate that gender is recognized by the averaged gait image without head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. The table entries are percentages.

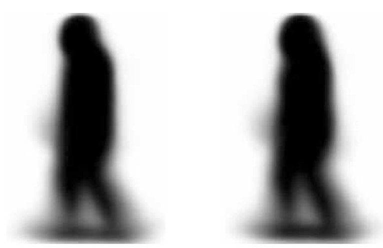

Fig. 6. Male versus female. The left subfigure is the mean image of all male averaged gait images, and the right subfigure is the mean image of all female averaged gait images.

gait parts/components, e.g., the front-leg component, the dark area of the lower part is wider for females. The performance of the averaged gait-image-based gender recognition is impressive compared with the normal human ability to recognize gender using motion information.

In the following, the averaged gait-image-based gender recognition algorithm is described briefly. Then, we conduct experiments to demonstrate the impact of each component on gender recognition. Finally, an analysis of the experimental results is given.

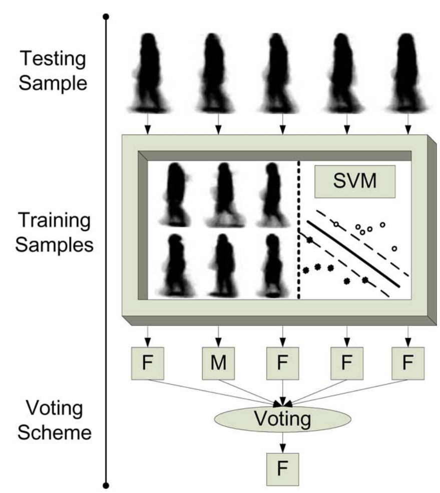

Fig. 7. SVM-based gender recognition algorithm. The five images at the top of the figure are the AGIs of a sequence, which represents a person's gait. The block in the middle of the figure with some averaged gait images represents the training set and the SVM classifier. The blocks at the bottom of the figure represent the voting scheme. The test sample represented by the five averaged gait images is classified as female.

A. AGI-Based Gender Recognition

The gender recognition procedure is shown in Fig. 7. In the gallery, we first segment each sequence into a subsequences such that each subsequence corresponds to a complete walking period. We then calculate the averaged gait image and use the template to select a part or its complement in all subsequences in the gallery and probe sets. We train a linear SVM classifier based on the averaged gait image, a selected part, or its complement. The averaged gait image, a selected part, or its complement of a sample in a probe is classified by the trained SVM. Finally, a voting scheme is used to obtain the final decision.

B. Recognition Performance

We first conduct 15 groups of experiments to examine the performances of the averaged gait image, each component of the averaged gait image, and the complement of each component for gender recognition. Table VI shows the recognition rates.

We also conduct a number of experiments to examine the cooccurrence effects of pairs of parts on gender recognition. It would be difficult to conduct experiments on all 252 pairs and get useful information from them. Therefore, we only conduct experiments on pairs of parts, which can reduce the recognition rate or have little effect on the recognition rate. Then, whether the omission of the two parts causes a reduction in the recognition rate will be examined later. For example, in probe A, the first part, the fourth part, the fifth part, and the sixth part have little effect on the recognition rate, because the complements of these components do not reduce or improve the recognition rate. We investigate the recognition rates when both of the selected parts are removed from the averaged gait image. All the results from these experiments are shown in Table VII.

TABLE VII
EXPERIMENTAL RESULTS FOR GENDER RECOGNITION FROM AVERAGED GAIT IMAGES

Probe	Experimental Results
A	{97 | (1,4)}, {98 | (1,5)}, {98 | (1,6)}, {98 | (4,5)}, {98 | (1,6)}
B	{98 | (1,2)}, {100 | (1,4)}, {98 | (1,5)}, {100 | (1,6)}, {96 | (1,7)}, {96 | (2,4)}, {98 | (2,5)} {94 | (2,6)}, {96 | (2,7)}, {98 | (4,5)}, {98 | (4,6)}, {98 | (4,7)}, {98 | (5,6)}, {98 | (5,7)} {94 | (6,7)}
C	{96 | (1,2)}, {96 | (1,4)}, {96 | (1,6)}, {93 | (2,4)}, {96 | (2,6)}, {94 | (4,6)}
D	{86 | (1,2)}, {77 | (1,3)}, {83 | (1,4)}, {80 | (1,6)}, {82 | (1,7)}, {84 | (2,3)}, {82 | (2,4)} {81 | (2,6)}, {84 | (2,7)}, {80 | (3,4)}, {85 | (3,6)}, {83 | (3,7)}, {76 | (4,6)}, {86 | (4,7)} {84 | (6,7)}
E	
F	{81 | (1,2)}, {69 | (1,3)}, {79 | (1,6)}, {74 | (2,3)}, {77 | (2,6)}, {72 | (3,6)}
G	{78 | (1,2)}, {59 | (1,3)}, {81 | (1,5)}, {79 | (2,3)}, {76 | (2,5)}, {76 | (3,5)}
H	{92 | (1,4)}, {93 | (1,7)}, {86 | (4,7)}
I	{74 | (1,3)}, {90 | (1,4)}, {88 | (1,5)}, {91 | (1,6)}, {90 | (1,7)}, {84 | (3,4)}, {86 | (3,5)} {83 | (3,6)}, {83 | (3,7)}, {91 | (4,5)}, {88 | (4,6)}, {81 | (4,7)}, {84 | (5,6)}, {84 | (5,6)} {84 | (6,7)}
J	{94 | (4,6)}
K	{94 | (2,3)}, {97 | (2,4)}, {97 | (2,6)}, {91 | (2,7)}, {97 | (3,4)}, {94 | (3,6)}, {91 | (3,7)} {97 | (4,6)}, {97 | (4,7)}, {97 | (6,7)}
L	{79 | (2,3)}

The table has 12 rows, where each row corresponds to one of the 12 probes. In each row, the element $\{a|(i, j)\}$ means the recognition rate is a when the ith and the jth component are removed. Index $i(j)$, "1," "2," "3," "4," "5," "6," and "7" indicate that gender recognition is based on the averaged gait image without head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. For example, the element "{97 | (1,4)}" in the first row indicates that the rank 1 recognition rate of probe A is 97% when the head (first component) and thigh (fourth component) are removed from the averaged gait image. The table entries are $\{$percentages|(gait parts #, gait parts #)$\}$.

TABLE VIII
PRELIMINARY EVALUATION OF THE IMPACT OF EACH COMPONENT ON GENDER RECOGNITION

ID		1	2	3	4	5	6	7
A	View	N	+	+	N	N	N	+
B	Shoe	–	N	+	N	N	N	N
C	View and Shoe	N	N	+	N	+	N	+
D	Surface	–	–	–	N	+	–	–
E	Surface and Shoe	+	+	+	+	+	+	+
F	Surface and View	–	–	N	+	+	N	–
G	Surface, Shoe, and View	–	–	N	+	–	+	+
H	Briefcase	N	+	+	+	+	+	N
I	Briefcase and Shoe	–	+	N	–	N	–	–
J	Briefcase and View	+	+	+	–	+	–	+
K	Time, Shoe, and Clothing	+	–	–	–	+	–	N
L	Time, Shoe, Clothing, and Surface	+	N	N	+	+	+	+
	#{–}	5	4	2	3	1	4	3
	#{N}	4	3	4	4	3	4	3
	#{+}	3	5	6	5	8	4	6

"1," "2," "3," "4," "5," "6," and "7" indicate that gender recognition is based on head, arm, trunk, thigh, front-leg, back-leg, and feet, respectively. "$+$," indicates that the component has a positive effect on gender recognition; "$-$," indicates that the component has a negative effect on gender recognition; and "N," indicates that the component has little effect on gender recognition. "#$\{-\}$," "#$\{$N$\}$," and "#$\{+\}$" refer respectively to the number of "$-$," "N," and "$+$" in a column.

C. Discussion

The following observations and conclusions are drawn from Tables VI and VII. In the case of Table VI, we deem that a component has a positive effect on gender recognition if the recognition rate decreases when the component is removed from the averaged gait image. A component has a negative effect on gender recognition if the recognition rate is increased when the component is removed from the averaged gait image. Otherwise, we deem that the component has little effect on gender recognition. For example, the arm has a positive effect for the probe A test, because the recognition rate is 96 if the arm is removed from the averaged gait image and the recognition rate

TABLE IX
OBSERVATIONS FROM EXPERIMENTS

ID	Observations from experiments
A	Arm, trunk, and feet are useful for gender recognition. The other parts have little effect on gender recognition.
B	Arm is the most important component for gender recognition; the head can reduce the recognition rate; the remaining components have little effect on the recognition rate. Without head and thigh or head and back-leg, the gender recognition rate can be improved to 100.
C	Trunk, front-leg, and feet are useful for gender recognition. The other components have little effect on gender recognition.
D	Front-leg produces a large increase in the gender recognition rate. Thigh has a negligible effect on gender recognition. The other components can reduce the gender recognition rate.
E	All components can increase the gender recognition rate.
F	Thigh and front-leg increase the gender recognition rate. Arm, trunk, back-leg, and feet have negligible effects on gender recognition. Head reduces the gender recognition rate. Without the head, the recognition rate takes its highest value (83).
G	Thigh, back-leg, and feet increase the gender recognition rate. Head reduces the recognition rate. The other components have only small effects on the recognition rate. Without head, the recognition rate takes its highest value (81).
H	Without feet or head, the performance is stable. The removal of feet and head both improve the recognition rate and keep it stable.
I	Arm increases the gender recognition rate. Head reduces the recognition rate. The other components have negligible effect on the recognition rate. If the head is removed from the averaged gait image, then the recognition rate takes its highest value (93).
J	Head, arm, trunk, front-leg, and feet increase the recognition rate. Thigh and back-leg reduces the recognition rate. If we remove the thigh, back-leg, or both of them (three cases) from the averaged gait image, the recognition rate achieves the highest point (94).
K	Head and front-leg both increase the gender recognition rate. Back-leg and feet both reduce the recognition rate. The components have only a negligible effect on the recognition rate. If we remove back-leg, feet, or both of them (three cases) from the averaged gait image, the recognition rate achieves the highest point (97).
L	Head, thigh, front-leg, back-leg, and feet all increase the gender recognition rate. The other components have only a negligible effect on the recognition rate.

is 98 if all components are used for the recognition. The head has a negative effect for the probe B test, because the recognition rate is 100 without the head and the recognition rate is 98 if all components are included. The thigh has little effect on the recognition rate for probe A because the recognition rate is same with or without trunk.

Based on the preliminary analysis in Table VIII and the experimental results in Tables VI and VII, we make the following observations listed in Table IX for all probes.

The following conclusions are drawn from Table IX. Trunk and front-leg usually increase the gender recognition rate. When the probe set is different from the gallery set in terms of surface, arm reduces the recognition rate, and when the probe set is different from the gallery set in terms of briefcase, thigh reduces the recognition rate. Otherwise, arm and thigh usually increase the recognition rate. The head, back-leg, and feet have only negligible effects on the gender recognition rate.

VI. CONCLUSION

With strong empirical evaluation, this paper first focuses on the idea of using silhouette-based gait analysis for gender recognition—in details, the application of human gait information to human recognition and gender recognition has been studied. The following has been demonstrated.

1) The gait of the head, arm, trunk, and back-leg are important for averaged gait-based human recognition.
2) The inclusion of the gait of the front-leg usually reduces the recognition rate.
3) The contributions of the feet to recognition are not clear.
4) The inclusion of the gait of the thigh reduces the recognition rate when the probe set is different from the gallery set in terms of walking surface or the carrying of a briefcase.
5) The gaits of the trunk and front-leg are usually important for gender recognition.
6) The gaits of the head, back-leg, and feet are not helpful for gender recognition.
7) The gaits of the arm and thigh reduce the gender recognition rate when the probe set is different from the gallery set in terms of walking surface or the carrying of a briefcase.

Gait analysis is difficult because of the wide variety of movements of the different parts of the body, but at the same time the experiments suggest that a large amount of useful information can be obtained from gait, e.g., according to our experiences, if one falls down on the street, the change of his feet silhouette component has a large probability to lead a change of other components. The AGI has been shown to be effective for both human ID recognition and gender recognition. Nevertheless, the AGI ignores the temporal information that is intuitively useful for understanding a gait. Our future work will focus on the robust extraction and modeling of the dynamic properties of a walking sequence, and then, use these properties for dynamic gait analysis.

ACKNOWLEDGMENT

The authors would like to thank the Associate Editor and all reviewers for their constructive comments.

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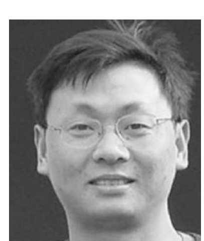

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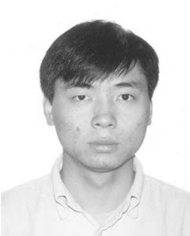

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