A Study on Gait-Based Gender Classification

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***Abstract*—Gender is an important cue in social activities. In this correspondence, we present a study and analysis of gender classification based on human gait. Psychological experiments were carried out. These experiments showed that humans can recognize gender based on gait information, and that contributions of different body components vary. The prior knowledge extracted from the psychological experiments can be combined with an automatic method to further improve classification accuracy. The proposed method which combines human knowledge achieves higher performance than some other methods, and is even more accurate than human observers. We also present a numerical analysis of the contributions of different human components, which shows that head and hair, back, chest and thigh are more discriminative than other components. We also did challenging cross-race experiments that used Asian gait data to classify the gender of Europeans, and vice versa. Encouraging results were obtained. All the above prove that gait-based gender classification is feasible in controlled environments. In real applications, it still suffers from many difficulties, such as view variation, clothing and shoes changes, or carrying objects. We analyze the difficulties and suggest some possible solutions.**

***Index Terms*—Appearance-based features, gait analysis, gender classification, human silhouette.**

I. Introduction

Gender plays an important role in social communication. Many social interactions depend greatly on correct gender perception. Gender classification is a task in which humans excel. If a computer can recognize gender, it will be very helpful in many applications. For example, gender classification can improve surveillance systems' intelligence, analyze customers for store managers, allow robots to perceive gender, etc.

Automatic gender classification can be based on face [1], voice [2], or gait [3]. Among these, we consider gait, which is a particular way or manner of walking, and has become an attractive biometric feature detectable at a distance [4]. Some researchers have done pioneering work on gender classification [5]–[7]. Gait-based gender classification is still immature. Because of its unique advantages of being noncontact, noninvasive, and easily acquired at a distance, it is gaining increasing interest from researchers.

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In the earlier gait-based gender classification settings, trackers are attached to the main joints of the body, and sometimes the subjects are even asked to wear swimsuits [8]. These measures are inconvenient and not user-friendly. In real applications, it is unreasonable to attach trackers on all subjects. Some other methods try to build a human walking model from images. However, building a robust human movement model is relatively difficult.

Appearance-based gait features can be easily acquired and have lower computational cost than model-based ones. In this correspondence, we first describe an experiment that asks human participants to recognize the gender of moving human silhouettes. Then the human knowledge is extracted and used to improve appearance-based gender classification. We also analyze the contributions of different parts of the human body to find the discriminative body parts. Some challenging and interesting experiments on cross-race gender classification are also carried out and achieved encouraging results. Like gait recognition, gait-based gender classification suffers from some variations such as view angle variation, clothing and shoes changes. In this correspondence, we also suggest solutions for some of these variations.

In the remainder of the correspondence, Section II summarizes related work on gender classification. Section III describes the experiments with human observers. The gait feature and the classifier are introduced in Section IV. Section V presents the experimental results and analysis, includes cross-race gender classification. Section VI introduces some variations which can affect gender classification performance and suggests possible solutions. Section VII concludes the correspondence.

II. Related Work

Much gender classification work published in the literature is based on face [1], [9]–[11] or voice [2], [12]. The SexNet proposed in [1] is pioneering work in gender recognition; it is a back-propagation neural network trained for face-based gender classification. Its average error rate was 8.1%, and compared favorably to humans, who averaged 11.6%. It proved that computer vision-based gender classification is feasible.

Gait features can also be used for gender classification and some prominent researchers have worked on it. An early gait-based-gender classification is developed by Kozlowski and Cutting [5]. In their experiments, point-light displays are attached to the major joints of persons. Human observers can classify the gender from the displays with 63% accuracy. They also found that point-lights from dynamic sequences were sufficient for gender classification, but static point-lights are insufficient. Some other studies [7], [8] have also used point-light displays for the gender classification task. Unlike the earlier studies that they use human observers to recognize gender, Davis and Gao [7] use point-light displays in an automatic method. The method proposed in [7] uses an adaptive three-mode PCA to extract feature from point-light displays; the correct classification rate (CCR) in a 40 subjects database (20 females and 20 males) is 95.5%. They also recruited 15 observers to recognize gender by watching moving point-light displays on a computer monitor. The CCR is 69% and within the range of the results in [5], [8]. From the previous work, we can see that high CCRs cannot be obtained by human observers when using point-light displays. On the contrary, computer algorithms can achieve higher CCRs as shown in [7].

Body sway, waist-hip ratio, and shoulder-hip ratio are also indicative of a walker's gender [13]. Males tend to swing their shoulders more than their hips, and females tend to swing their hips more than their shoulders. Males normally have wider shoulders than females, and females normally have thin waists and wider hips. It is not easy to accurately extract these kinds of features from videos.

Human silhouettes can be used for gender classification. Some researchers have developed new methods based on human silhouettes. In [6], Lee and Grimson employ features from moving human silhouettes for gender classification. Each silhouette in a sequence is divided into seven regions and an ellipse is fit to a region. The centroid, the aspect ratio of the major and minor axes of the ellipse, and the orientation of the major axis of the ellipse are taken as features. The method of Lee and Grimson achieves a CCR of 84.5% in a database of 24 subjects (ten females and 14 males). Similar to Lee and Grimson's method, Huang and Wang also use ellipse features for gender classification [14]. The difference is that Huang and Wang combine multiview features to improve the performance. Shan *et al.* fuse gait and face to improve gender discrimination and achieve 97.2% in a large database [15]. Unlike Lee's and Huang's methods, in [16], the gait signature was represented as a sequential set of 2-D stick figures. Each 2-D stick figure is extracted from a human silhouette and contains head, neck, shoulder, waist, pelvis, knees, and ankles. The classifier is a support vector machines, and the CCR is 96% for 100 subjects (84 males and 16 females).

Detailed analysis of human body components can be found in [3]. Human silhouettes are separated into seven components to analyze the contribution of each component to gender classification. The seven components are head, arm, trunk, thigh, front leg, back leg, and feet. Over 500 experiments are carried out under different circumstances, including different views, shoes, walking surfaces, etc. The effectiveness of the seven components is analyzed using the experimental results. This comprehensive experimental study on human body components gives many useful suggestions. According to our study, hair style and chest are two important body components for gender classification. However, in [3], the hair component is divided into head component and trunk component. Chest sometimes can be divided into the arm component (for fat persons), and sometimes into the trunk component (for slim persons). To study the effectiveness of different components, it is better to set the segmentation borders in the areas where both males and females are the same, such as the center of the trunk. Besides a more reasonable segmentation, we give a more detailed analysis at the pixel level in this correspondence.

The previously introduced methods are based on human dynamic movement or silhouettes, and the background and clothing texture are all removed. Different from these methods, Cao *et al.* proposed a new method which recognizes gender from static full body images [17]. They use the Histogram of Oriented Gradients (HOG) [18] as the feature, and Adaboost and Random Forest algorithms as classifiers. A 75.0% accuracy is achieved for 600 images. This shows that texture is discriminative in gender classification, and it is further discussed in Section VI.

Most current research does not pay much attention to this question: Which contributes more to gender classification: human body shape or motion? In [19], McDonnell *et al.* state that motion is more dominant than shape information when using point-light displays, and conversely, shape is more influential than motion when using silhouettes. The question is also investigated in our experiments.

III. Gender Classification By Human Observers

Before the analysis on automatic gender classification, we present an interesting human knowledge-based gender classification to investigate how humans recognize gender and what kind of features contributes more to classification: static (body shape) or dynamic (the movement of legs and arms).

In this correspondence, we designed an experiment for human observers to recognize gender. The human silhouettes in the CASIA Gait Database (Dataset B) [20] were shown on a computer screen at a rate of 25 frames per second, the same rate at which the video were recorded. The participants were asked to recognize the gender without time limitation. The upper body silhouettes convey more static information than the lower body silhouettes. In order to analyze the contribution of static and dynamic information, the body images are divided into upper body images and lower body images (Fig. 1) for experiments.

(a) Lower body (b) Upper body (c) Whole body

Fig. 1. Lower, upper, and whole body silhouettes used in the experiment.

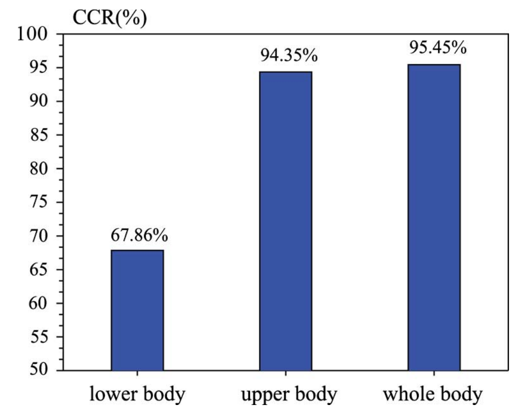

Fig. 2. Correct classification rates by human observers.

Forty-four volunteers (36 males and 18 females) participated in the experiment. The average accuracy achieved by these 44 participants are 67.86% for the lower body silhouettes, 94.35% for the upper body silhouettes and 95.45% for the whole body silhouettes (Fig. 2). From the experimental results with human observers, it can be seen that the upper body contributes more than the lower body to gender classification. The lower body achieved a very low classification accuracy, since coin flipping can achieve 50%. It seems that humans are more sensitive to static body shape information than to dynamic information.

We also surveyed the participants to get more information on the contribution of different body components. Several options, specifically, head and hair style, chest, back, waist and buttocks, thickness of legs, movement of legs, swing of arms and movement of the body, were given to the participants, and they were asked to evaluate the effectiveness of these options, and give a score from 0 to 5. Score 0 means no help on gender classification, and 5 means this option is very important. The average scores are listed in Table I. The two most important parts for gender classification are head/hair style and chest. They both belong to the upper body. Furthermore, human observers do not think that dynamic information (movement of legs, arms and whole body) help gender classification as much as static information. The survey is consistent with the experimental results in Fig. 2.

IV. Proposed Method

A. Feature Extraction

Human gait representation can be roughly divided into two categories. One is model-based gait features [21], [22], such as height, frequency, angle between two thighs. To robustly extract these model-

Fig. 3. Gait energy image (right one) is the average of silhouettes in a gait cycle.

TABLE I
DIFFERENT OPTIONS AND THEIR EFFECTIVENESS ON GENDER CLASSIFICATION

Option	Average score
Head and hair style	4.71
Chest	3.93
Back	2.07
Waist and buttocks	1.86
Thickness of legs	2.57
Movement of legs	2.57
Swing of arms	1.64
Movement of the body	1.86

based features is a challenging task, so another set of features, appearance-based features, has been widely used. Currently, many gait analysis and recognition methods are appearance-based [23]–[26]. These gait features are mostly used in gait recognition, but they can also be used in gait-based gender classification. The gait energy image (GEI) [23] feature is chosen in our experiments for gender classification.

In our experiments, all videos were captured by fixed cameras. Human silhouettes can be extracted by background subtraction and thresholding. The method in [24] is used to segment human silhouettes from image sequences. The sizes of the silhouettes are not unique, and the silhouettes have to be normalized to the same size.

If we use all silhouettes in a gait cycle as feature, the feature dimension will be very high. The gait energy image (GEI) can greatly reduce gait feature dimension. GEI, also called average silhouette, is a kind of statistical feature. It was proposed by Bobick and Davis in [27], used for gait recognition by Han and Bhanu in [23], and used for gender classification by Li *et al.* in [3]. GEI has been reported to be a good feature in gait recognition because it is robust to silhouette errors and noise. GEI is defined as

$$F(i,j) = \frac{1}{T}\sum_{t=1}^{T} I(i,j,t) \tag{1}$$

where T is the number of frames in the sequence $I(i,j,\cdot)$, $I(i,j,t)$ is a binary silhouette image at frame t, i, and j are the image coordinates. The silhouettes in a gait cycle and the GEI are shown in Fig. 3.

B. Combining Human Knowledge

Experiments by human observers show that the contributions of different body component vary. We can use the scores in Table I to improve performance.

Each GEI in our experiments is segmented into five components: head and hair, chest, back, waist and buttocks, and legs (Fig. 4). Because there is overlap between arms and trunk area, here arms are mostly taken into the waist and buttocks component. Unlike the segmentation in [3], the borders between the different components lie in the inner part of the GEI because pixel values there are almost the same for males or females.

Since each component has different effectiveness, we would like to give different weights to different components. The weights

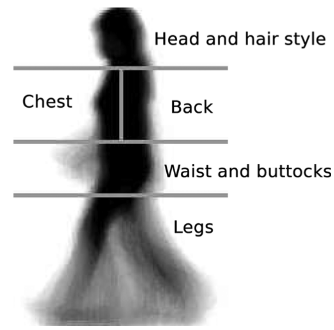

Fig. 4. GEI is segmented into five components: head and hair, chest, back, waist and buttocks, and legs. (Here darker pixels indicate greater intensity).

$[w_1, w_2, \ldots, w_5]$ can be the scores in Table I. Only the first five scores for static features are used here. The scores are normalized as follows:

$$w_i' = \frac{5 \cdot w_i}{\sum_{j=1}^{5} w_j}.$$

This makes the average of w_i' be 1. So the weighted feature can be

$$\mathbf{v} = [w_1' \cdot \mathbf{v}_1, w_2' \cdot \mathbf{v}_2, \ldots, w_5' \cdot \mathbf{v}_5]$$

where $\mathbf{v}_i$ is the feature of the ith component.

C. Classifiers

Because gender classification is a two-class problem, and support vector machines (SVMs) [28] excel in two-class problems with few samples, we employed SVMs in our experiments to evaluate the potential of gait-based gender classification. SVMs is also known as maximum margin classifier. It can simultaneously minimize the empirical classification error and maximize the geometric margin between different classes. A linear hyperplane can be found in a higher dimensional space to separate different classes. The feature vectors that are closest to the hyperplane are called *support vectors*, meaning that the hyperplane is supported by these support vectors and the positions of other vectors do not affect the hyperplane.

Given a set of labeled samples $(\boldsymbol{x}_i, l_i), i = 1, 2, \ldots, n$, where $\boldsymbol{x}_i \in R^N$ and $l_i \in \{-1, +1\}$, SVMs need the solution of the following optimization problem [28]

$$\begin{aligned} \min_{\boldsymbol{w},b,\xi} \quad & \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{n}\xi_i \\ s.t. \quad & l_i(\boldsymbol{w}^T\phi(\boldsymbol{x}_i) + b) \geq 1 - \xi_i \\ & \xi_i \geq 0 \end{aligned} \tag{2}$$

where C is the penalty parameter of the error term, and ϕ is a function that maps feature vectors into a higher dimensional space. Then SVMs can find a linear hyperplane in the higher dimensional space to separate different classes. The kernel function $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is defined as

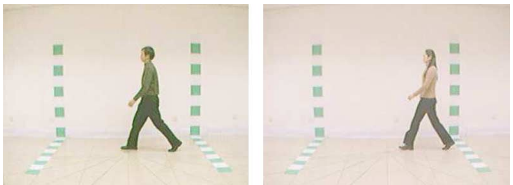

Fig. 5. Male (left) and female (right) images from the CASIA Database.

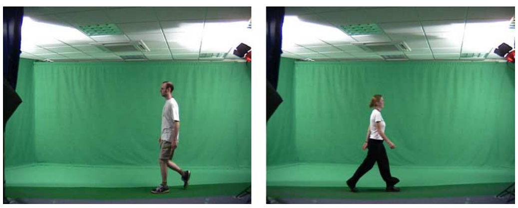

Fig. 6. Male (left) and female (right) images from the Soton Database.

$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \phi(\boldsymbol{x}_i)^T \phi(\boldsymbol{x}_j)$. We choose the linear kernel in our experiments as in [3].

V. Experiments and Analysis

To evaluate the performance of the proposed method, we use a dataset containing 62 subjects for our experiments. Unlike the analysis on human body components by human observers, a detailed statistical analysis is presented below. In addition, a challenging experiment, cross-race gender classification, is designed to discover the potential of gait in gender classification.

A. Databases

We choose the CASIA Gait Database (Dataset B) [20] for our experiments. In our cross-race experiments, the Soton Large Gait Database [29] is also included.

There are 124 subjects (93 males and 31 females) in the CASIA Database (Dataset B), and most subjects are Asians. Since gender classification is a two-class problem, it is better to use equal number of subjects for different genders to avoid bias. All the 31 females and 31 randomly selected males are used in the experiments. There are six video sequences for each subjects; altogether there are 372 sequences. All selected data were captured from the side view with normal clothes and without any bag as shown in Fig. 5.

The Soton Large Gait Database [29] contains 115 subjects. All the video sequences in the database were taken with a stationary indoor camera and the subjects walked along a straight path (Fig. 6). There are 15 European female subjects in this database, and we select the 15 European female subjects and 15 European male for our experiments. Like the CASIA Database, six sequences are involved for each subject.

B. Experimental Results

In the experiments using the CASIA Database, *m-fold cross-validation* [30] is used to evaluate different gait features and classifiers. The gait data for the 62 subjects is divided into 31 disjoint sets (*31-fold*). The data in each set are from a male and a female. One set is taken as testing data and the remaining 30 sets as training data. This ensures that data from the same subject will not be in both the test set and the training set. All 31 possible combinations are considered in the *m-fold cross-validation*, and the experimental result (correct classification rate) is the average of all these 31 combinations.

TABLE II
Correct Classification Rates Using the CASIA Database (Dataset B)

Method	Dataset	CCR
Lee and Grimson [6] [a]	25 males and 25 females	85.0%
Huang and Wang [14] [b]	25 males and 25 females	85.0%
Li *et al.* [3] [c]	31 males and 31 females	93.28%
44 human observers	31 males and 31 females	95.47%
Proposed method	31 males and 31 females	95.97%

[a] Implemented by Huang and Wang in [14].

[b] Implemented by Huang and Wang in [14].

[c] Implemented by us according to [3].

The experimental results are listed in Table II. The methods of Lee and Huang are implemented by Huang and Wang in [14]. The experimental protocol is slightly different from that of the other two methods. The results by Lee and Huang are listed here for reference. The other two methods, proposed by Li *et al.* [3] and our proposal, have the same experimental protocol. The results show that our proposed method outperforms the other three methods. The correct classification rate is even slightly higher than that achieved by human observers.

In the experiments with human observers, the feature used is silhouettes shown to the observers at a rate of 25 FPS. The information contains not only static body shape information, but also dynamic information. The feature used in the proposed method eliminates temporal information, but achieves higher accuracy.

C. Contributions of Human Body Components

We want to discover which part of the body, or what components of the feature, contribute more to gender classification. In [3], Li *et al.* separate human silhouettes into seven components and analyze the contribution of different components. The seven components are head, arm, trunk, thigh, front-leg, back-leg, and feet. The problem in [3] is how to choose the ratio of each component, e.g., is 1/6 or 1/7 of the silhouette feet? Here, we extend the analysis by considering each pixel in the silhouette image as a component.

In our method, analysis of variance (ANOVA) is applied to analyze the gait features. The ANOVA F-statistic is a measure to evaluate different features' discriminative capability. The greater the F-statistic value, the better the discriminative capability. The F-statistic is calculated as follows [31]:

$$\mathsf{F} = \frac{\frac{1}{c-1}\sum_{i=1}^{c} n_i(\overline{x}_i - \overline{x})^2}{\frac{1}{n-c}\sum_{i=1}^{c}\sum_{j=1}^{n_i}(x_{ij} - \overline{x}_i)^2} \tag{3}$$

where x_{ij} is the j^{th} sample of class i, c is the number of classes, n_i is the sample number of class i, $n = \sum_{i=1}^{c} n_i$, $\overline{x}_i$ is the mean of samples in class i, and $\overline{x}$ is the mean of $\overline{x}_i$.

We use the F-statistic to analyze which body components contribute more in GEI. Since x in (3) is a pixel, the set of F values can be represented by a matrix. The calculated F-statistic values are shown in Fig. 7. Higher pixel value (whiter) means better discriminative capability.

Fig. 7 shows that the hair style is a great difference between males and females. Another aspect is the back component because females normally have thinner body trunks. The thigh component is also discriminative. The chest component is not as discriminative as the back

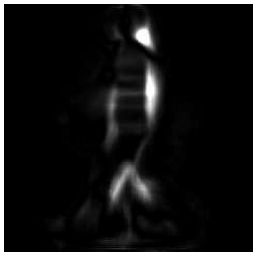

Fig. 7. F-statistic values.

TABLE III
CROSS-RACE EXPERIMENTAL RESULTS (CORRECT CLASSIFICATION RATE)

Asian training data, European test data	European training data, Asian test data
87.15%	87.90%

component. However, human observers stated that the chest was more important (Table I). It seems that human perception is different from computer perception.

D. Cross-Race Experiments

Many biometric features are differ between races. For example, the appearance of European faces is different from Asian or African faces. In iris images, the overall statistical measurement of iris texture is correlated with genes on a large scale [32]. Some experiments are designed to investigate the potential for cross-race gender classification

In the CASIA Database, almost all subjects are Asians. In contrast, only about 1/5 of the subjects in the Soton Database are Asians, and most subjects are Europeans. The data in the two databases were collected with different devices and under different conditions. Surely, it is a challenging task when the training set and test set are from different databases, especially from different races. Two experiments are designed. In the first experiment, the 62 Asian subjects (31 males and 31 females) from the CASIA Database in previous experiments are taken as training data, and the 30 European subjects (15 males and 15 females) from the Soton Database are taken as test data. In the second experiments, the European subjects are taken as training data, and the Asian subjects are taken as test data. The feature and classifier used in the cross-race experiments are the same as in the previous experiments. The experimental results are listed in Table III.

There are many different factors that can affect the performance. Besides race, clothing is also different because the CASIA Database was created in a different season than the Soton Database. The data collection devices are different. Even with these challenges, CCRs above 87% are achieved. This indicates that gender classification across different races is feasible.

VI. APPLICATIONS AND CHALLENGES

Gait-based gender classification can improve a computer's perception capability, and it can be used in a wide range of applications, including security, commercial and other applications. Some typical applications are listed below.

- **Intelligent visual surveillance.** An intelligent visual surveillance system is expected to track moving objects, classify them into different classes, detect abnormal behaviors, etc. Gait-based gender classification can be used to divide the pedestrians into two categories, male and female. With gender information, searching for a suspect in a large video database can be sped up. Moreover, different prior probability values can be assigned to detect different genders in abnormal behavior.
- **Customer statistics.** With cameras mounted in supermarkets, gender classification technology can help the managers know which gender is more interested in some products. Combined with object tracking technology, the walking routes of different genders can also be followed. Thus, products can be placed at the location and time that customers experience them. Gender classification help the managers know more about their customers and provide better service to them.
- **Robots.** Personal robot is becoming a hot research topic. It is expected that personal robots can live with humans as partners. Because many interactions among humans depend on gender, a robot with gender perception capability can interact more naturally and comfortably with humans.
- **Video games.** Gait analysis according to genders, rather than gender classification directly, can be used in video games to increase their realism. Different genders have different gait patterns. Applying different gait patterns to different virtual characters according to their genders noticeably improve the sense of reality.

As in gait recognition [33], there are still many challenges in gait-based-gender classification. As gait-based gender classification is normally used in uncontrolled environments, there are many variations which can negatively affects on the performance. Some common variations are:

- **View angle.** When a human body is captured by a camera from a different view angle, some body parts will be occluded. To reduce the effect of view angle variation, one possible solution is to track each body part (hands, arms, head, etc.) and recover the 3-D human body model.
- **Clothing and shoes.** In contrast to gait recognition, clothing and shoes maybe possibly improve gender classification performance because clothing and shoes styles differ according to gender. Moreover, clothing texture may also be helpful in gender classification, as in the method of [17].
- **Carrying condition.** Sometimes walking persons carry something, normally a bag, which occludes some body parts. One solution is to remove carried objects from human bodies and estimate the original body images, but this is difficult. Another possible solution is to recognize the carried object type first, and then use it to help recognize the gender.

VII. CONCLUSION

Gait-based gender classification is a new and interesting topic. In this correspondence, a gender classification method which combines human knowledge with image features is proposed. The proposed method achieves good results, and the correct classification rate is even higher than that achieved by human observers. Cross-race gender classification also conditions encouraging results despite different races, clothing, and capture conditions. All these results prove that gait can be employed to recognize gender at a distance. By analyzing the discriminatory capability of different body components, We found that hair, back, chest and thigh components are more discriminant that other components.

In the proposed method, no temporal information is used for gender classification. As indicated by the survey (Table I), dynamic information also has positive effects in gender classification. In the future, we will fuse dynamic information and static information for gender classification. We will also study the effects of view direction, clothing, carrying condition, and other factors on gait-based gender recognition.

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