Investigating the Separability of Features from Different Views for Gait Based Gender Classification

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Abstract

In this paper, we investigate the efficiency of different view angles when classifying gender with gait biometrics for the first time. A gait database is built for this purpose in which walking videos are recorded at seven different views for each subject. Then, we employ a robust gait representation method to extract gait features. The class separability of these features from different view angles are analyzed and compared. A set of experiments are designed to evaluate the performance of gait based gender classification along with the changes of view angle. The experimental results show that 0^0 and 180^0 are the worst view angles in this two-category case and the 90^0 view dose not perform the best, unlike it takes the best performance in gait recognition.

1. Introduction

Gait is an identifying feature of a person that is determined by his/her weight, limb length, and habitual posture. Hence, it is reasonable to use gait as a biometric measure in individual recognition and classification. Gender classification is an important visual task for human beings because a typical social category is gender. We know from experience that people often recognize the gender of others by simply observing the way they walk. Moreover, psychophysical studies have proved this fact as shown in [10].

In recent years the gait based gender classification technique has been paid more and more attention because gait has the advantages of being non-contact, non-invasive and easily acquired at a distance. Lee and Grimson [7] proposed a gait silhouette appearance representation and apply it to gender classification task in a database including 23 males and 2 females. They showed that the distinction between genders is consistent with a linear boundary. A later study [8] by Yoo et al. utilized a large gait database, consisting of 84 males and 16 females. Likewise, they demonstrated the strong gender discriminatory ability of human gait. The common limiting points of all related studies on gait based gender classification are that only the lateral view of human walking is used in these experiments and that there exists a big difference between the quantity of males and females in these gait databases.

For a further study on gait based gender classification, we want to make a comparison of the separation ability of different views on determining gender. Since such study has not been done before, we propose a framework that includes a gait database, class separability analysis and a set of experiments. Our database contains walking data captured from seven different view angles and a similar number of males and females.

The rest of this paper is organized as follows. Section 2 describes the gait database. Separability analysis is presented in Section 3, and experiments are shown in Section 4. Section 5 concludes this paper.

2. Database

2.1. Overview of other gait databases

Many gait databases have been established during the development of gait recognition. The earlier databases, such as UCSD database, MIT AI Gait Data, CASIA Gait Dataset A [2], Georgia Tech Database [3], CMU Mobo Database [4] and HID-UMD Dataset I, consists of a small number of subjects less than fifty. Later, larger gait databases containing more than one hundred subjects have been set up. These large

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databases include Soton Database [5], Gait Challenge Database [1] and CASIA Gait Dataset B [2]. Even though some covariates such as viewing angle change, shoe type change and carrying condition change etc. have been considered in these large databases, they were built for human identification. The obvious quantity difference between males and females can impact the performance of gender classification.

2.2 IRIP Gait Database

Our gait data were captured in an indoor laboratory scenario. Simple background was used to simplify silhouette segmentation, as we do not focus on human detection or segmentation in this framework. Eight cameras were placed at different angles recording the movement of a person. These cameras are divided into two groups each of which consists of four cameras and forms a 1/4 circle, as shown in Figure 1.

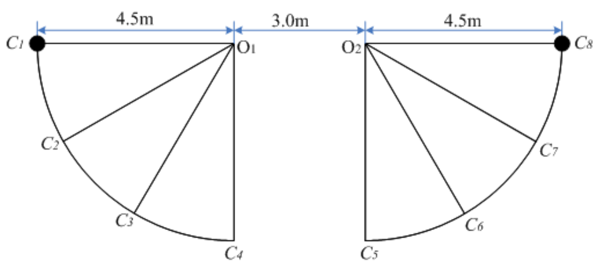

Figure 1. Cameras setup

During the course of data collection, every participant was asked to walk along the straight line between camera C_1 and C_8, which are denoted by two black points in Figure 1, from left to right and then return, repeating five times. Thus, every camera recorded five left-to-right and five right-to-left walking video sequences for each person. Meanwhile, we label camera C_8 with the 0^0 view, C_7 with the 30^0 view, till C_1 with the 180^0 view. Camera C_4 and C_5 have the same view angle.

The frame rate is 25 fps. There are three gait cycles at least in every sequence. For the purpose of increasing evaluation capacity on classification, we try to make the similar number of male and female subjects. Eventually, our gait database contains 32 male and 28 female volunteers in all.

Last, we name our database as IRIP Gait Database.

3. Separability Analysis of Features from Different Views

With the side view of human gait, previous researches have proved that gait is an effect biometric feature to classify gender. In this section, we will compare the class separability among different views.

3.1 Feature Extraction

At the beginning of our analysis task, we need a gait representation method to extract those compact and useful features. For the independence of cloth color or texture information, silhouettes of walking humans are extracted by background subtraction firstly. The method in [9] is used to segment human silhouettes from image sequences. Then, we seek to a representation that not only contains enough discriminative features but also has a lower computation cost. The spatio-temporal gait representation proposed in [6] is sensitive to silhouette deformations and robust to spurious pixels. So it is very suitable to analyze the impact of view changing. Moreover, it can be computed in real time. Therefore, we take this representation into account and make a little improvement.

In [6], for a sequence of silhouette images $b(x, y, t)$ indexed spatially by pixel location (x, y) and temporally by time t, the author forms two new 2D images $F_R(x,t)$ and $F_C(y,t)$. Considering the periodicity of gait, we form these two images only from a gait cycle of silhouettes instead of the whole sequence to reduce redundancies. This is our enhancing point for this method. Hence, the end value of t is the number of silhouettes included in one gait cycle, denoted by N_{gait}.

The silhouettes are normalized to be the same size and centered before feature acquisition. Define a silhouette as $s[i, j]$, $i = 0,1,..., M-1$, $j = 0,1,..., N-1$, where M, N denote the number of rows and columns of the silhouette, respectively. Let

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

With the above definitions, the horizontal and vertical projection of silhouettes [6] can be expressed as

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

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

Consequently, two projection vectors can be defined as follows:

$$H = \{p_h[0], p_h[1],......, p_h[M-1]\}$$

$$V = \{p_v[0], p_v[1],......, p_v[N-1]\}$$

Here, one gait cycle has N_{gait} silhouettes. Therefore, the aforementioned image $F_R(x,t)$ is formed by N_{gait} H vectors arranged by columns. Likewise, N_{gait} V vectors form the image $F_C(y,t)$. Figure 2 shows these images F_R and F_C at different view angles from a sample.

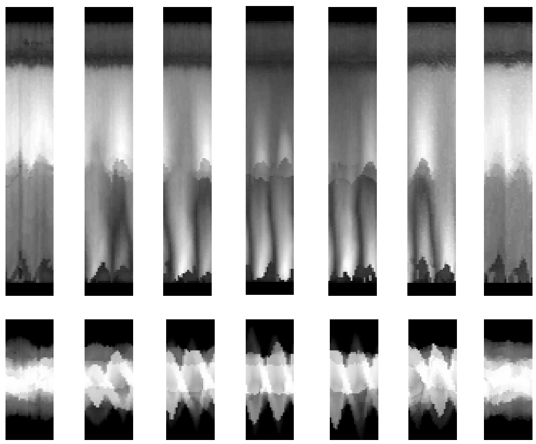

Figure 2. An example of images F_R and F_C. Columns from left to right present different view angles: $0^0, 30^0, 60^0, 90^0, 120^0, 150^0, 180^0$. F_R images are listed on top row and their corresponding F_C images are shown on bottom row.

N_{gait} is calculated through the autocorrelation of the foreground sum signal. As different people may have different walking period, we resize all F_R and F_C images using bicubic interpolation to the same width (the end value of t i.e.). Then, PCA is used to retain only the important elements of F_R and F_C images. Finally, for each pair of F_R and F_C images, we combine their PCA results into one vector and use it as the feature vector that we intend to extract from a gait sequence.

3.2 Comparison of separability for different view angles

We want to know the extent of the separation between male and female sets with the extracted features and further, which of view angle can result in a better separation. Since gender classification is a two-class problem, we can resort to the well-known Fisher linear discriminant. Given the within-class scatter matrix S_W and the between-class scatter matrix S_B, the Fisher criterion function can be written as:

$$J(w) = \frac{w^t S_B w}{w^t S_w w} \quad (2)$$

While the vector w maximizes $J(\bullet)$, we can gain the best separation between two projected sets. The solution for the w that optimizes $J(\bullet)$ is:

$$w = S_W^{-1}(m_1 - m_2) \quad (3)$$

where m_i $(i = 1,2)$ denotes the sample mean.

For each view angle, we compute the maximum value of $J(\bullet)$. The results are listed in Table 1. Note that we only use the gait sequences of left-to-right walking direction and we choose the sequences for the 90^0 view only from camera C_5.

View angle	Maximum $J(\bullet)$
0^0	5.52
30^0	16.23
60^0	15.33
90^0	11.64
120^0	12.80
150^0	10.95
180^0	5.87

Table 1. The maximum values of $J(\bullet)$

From these values, it is easy to draw the conclusion that the 0^0 and 180^0 views have the worst separability. As illustrated in Figure 1, the 0^0 view is the frontal view when the walking direction is from left to right. The view angle turning to side view obtains the best separation at 30^0 and 60^0. Other view angles also have better separability than 0^0 and 180^0.

4. Experiments

We design a set of experiments to evaluate the effect of view angle on gender classification. There are seven different views available in our gait database. Because camera C_4 captured the walking videos in the same view as camera C_5, we leave these videos from C_4 for later experiments. Thus, each sample has five sequences from one view angle. In all, there are $60 \times 5 = 300$ sequences for each view angle in our experiments.

We trained and tested support vector machines on our gait features gained in above section under different view angles. For making the best of our samples, we used the leave-one-out approach. Given the sequences from a view angle, we trained SVM 60 separate times, each time using the training set from which a different single subject including 5 sequences had been deleted. Each resulting SVM classifier was tested on these deleted 5 sequences and the sum of 60 numbers of correct classified sequences was used to calculate the correct classification rate.

The linear kernel and the 3_{rd} degree polynomial kernel have been employed in SVM training respectively. These experimental results are listed in Table 2.

View angle	Kernel type	
	linear	polynomial
0^0	78.7%	79.7%
30^0	90.3%	91.0%
60^0	91.7%	82.7%
90^0	90.3%	78.0%
120^0	88.3%	85.3%
150^0	84.0%	83.0%
180^0	82.3%	78.3%

Table 2. SVM gender classification results

According to the analysis of separability in Section 3, the classification accuracy of the 0^0 view and 180^0 view should be the lowest. Table 2 just shows the expected results under either kernel. When the kernel type is linear, the performance of the 30^0 view and the 60^0 view is also consistent with the values shown in Table 1, which indicate the extent of class separation for different view angles. However, for the 90^0 view, a lower value in Table 1 corresponds to a higher correct classification rate under the linear kernel type in Table 2. Such inconsistency is hard to be avoided because the implementation of SVM with linear kernel differs from the Fisher linear discriminant criterion.

Additionally, from Table 2, we can find that even though the correct classification rates of the 0^0 view and 30^0 view are approximate between the two kernels, the linear kernel performs better than the polynomial kernel for all other views. At last, the fact that the view angles less than 90^0 have better accuracy than the angles more than 90^0 proves that the front part of the body contains more abundant gender information.

5. Conclusions

In this paper, we have presented a comprehensive evaluation of various view angles for determination of gender from human gait. A gait database consisting of walking videos captured at seven view angles has been set up for this task. Both the analysis of class separability and the results of our classification experiments demonstrate the obvious difference in the contribution for gait based gender classification when the view angle changes. We find from all the results that the 0^0 view and 180^0 view perform the worst and the oblique view in front of a person is most helpful when recognizing gender. Besides, this study can act as a significant reference in many fields, such as visual surveillance applications, psychophysical research and so on.

6. Acknowledgement

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