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HUMAN GENDER RECOGNITION USING GAIT-BASED LOCAL ZIGZAG PATTERN

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Abstract. *Human gait is a useful biometric feature for human identification because the gait features can be captured at a distance in uncontrolled scenarios. Automatic gender recognition from the gait-based images has received much attention because it has a wide range of applications, including biometric identification, security control, and intelligent surveillance. One critical step for gait-based human gender recognition is to properly and accurately extract gait features from the images. In this paper, we propose a human gender recognition method based on the gait energy image and the local Zigzag pattern. The local Zigzag pattern is first applied to the gait energy image, and then the most discriminative features from the image are extracted. Finally, these features are classified by the support vector machine. Experiments on the CASIA gait database (Dataset B) are provided to illustrate the feasibility of the proposed approach.*

Keywords: Gender recognition, Gait energy image, Local Zigzag pattern, Support vector machine

1. **Introduction.** Gender plays an important role in social communication. Many social interactions depend greatly on correct gender perception. In the last few years, much gender classification work published in the literature is based on face or voice. Recently, with the growing demands in recognition and classification of the long-range surveillance video, gait has become a hot research topic. Gait is one of the well recognized biometric features widely used for human identification. Particularly, it can assist to effectively recognize people at a distance. Moreover, gait is hard to be disguised or concealed. Therefore, using gait information has more advantages than face or voice for gender recognition. A lot of work has been devoted to studying the human gait analysis and applying this knowledge to human recognition and gender classification.

Li et al. [1] proposed an appearance-based approach which utilizes the gait silhouette information for gender recognition. The human silhouette is segmented into seven components, namely head, arm, trunk, thigh, front-leg, back-leg, and feet. Each of the seven components and a number of combinations of the components are then studied with regard to two useful applications: human identification recognition and gender recognition. Yu et al. [2] presented 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. Hu et al. [3] proposed a supervised modeling approach for gait-based gender classification. Different from traditional temporal modeling methods, male and female gait traits are competitively learned by the addition of gender labels. Shape appearance and temporal

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dynamics of both genders are integrated into a sequential model called mixed conditional random field, which provides an open framework applicable to various spatiotemporal features. Sabir et al. [4] proposed a gender classification method based on gait features by fusing three different modalities. These modalities are spatio-temporal model, leg motion detection, and statistical wavelet model. These features have different characteristics to be used in the gait-based gender recognition system. In order to fuse three sets of features, they used three types of fusion methods (feature fusion, score fusion, and voting fusion). Generally, like most pattern recognition problems, the feature extraction in the image-based gender recognition problem is crucial to the whole classification process. Wang et al. [5] proposed a novel texture descriptor called local block difference pattern (LBDP) to extract more detailed gender information while enhancing the discriminative capability. The LBDP has been successfully applied in the gait-based gender classification. El-Alfy and Binsaadoon [6] presented a method for gait-based gender recognition using fuzzy local binary patterns. They adopt the gait energy image (GEI) representation to alleviate the computation and storage overhead of traditional spatio-temporal recognition approaches. GEI is a single image that summarizes the spatio-temporal characteristics of the human walking and conserves motion temporal properties over a gait cycle. Choudhary et al. [7] proposed a hybrid approach by fusing GEI with spatio-temporal parameters for the gender classification. The dimensions of GEI are reduced and five temporal parameters are calculated and concatenated with the reduced GEI. Mawlood and Sabir [8] proposed a gender classification method based on human gait features using wavelet transform and investigated the problem of non-neutral gait sequences. They also investigated a new set of feature based on the GEI and the gait entropy image (GEnI). Isaac et al. [9] formulated a gait-based gender classification algorithm that delineates the gait instance as a sequence of poses or frames. The algorithm predicts the gender of each frame that constitutes the gait instance and makes the decision of whether the subject is male or female based on majority voting. Gillani et al. [10] proposed a three-stage method for gender classification and age estimation using the largest available inertial sensors human gait dataset.

To recognize the human gender in a gait image can be viewed as a texture classification problem. In addition to extracting the discriminative textural features, the selection of a good classifier is also crucial for texture classification. From Bayes classifiers to neural networks, there are many possible choices for an appropriate classifier. Among these, the support vector machine (SVM) [11, 12, 13, 14] would appear to be a good candidate because of their ability to generalize in high-dimensional spaces, such as spaces spanned by texture patterns.

Due to its discriminative power and low computational complexity, the LBP [15] and its variants have become a very popular texture descriptor used for classification in different applications of computer vision, image analysis, and pattern recognition [16, 17, 18, 19, 20, 21, 22, 23, 24]. Inspired by the Zigzag scanning of discrete cosine transform coding technique, a novel texture descriptor named as local Zigzag pattern (LZP) [25] is proposed. It ignores the local binary structure of LBP by considering the local spatial Zigzag structure of a texture image. In this paper, we use the GEI as the gait template, and then the block-based LZP descriptor is applied on the GEI subblocks to extract distinctive texture features from those areas separately. The main advantage of our approach is that it can simultaneously capture pixel-level and region-level texture features for the classification. We use the SVM to classify the texture features for gender recognition. Experimental results and comparisons demonstrate the feasibility of the proposed approach.

The remainder of this paper is organized as follows. In Section 2, the basic concepts of GEI and LZP are introduced, and then the proposed approach is described. The experimental results and discussions are given in Section 3. The conclusions are summarized in Section 4.

2. **Methodology.** The feature extraction phase represents a key component of any pattern recognition system. In this paper, a novel texture descriptor, LZP, was applied to a GEI to extract the most discriminate features.

2.1. **Gait representation.** There have been a number of gait representation techniques proposed in the literature. In this paper, the GEI feature is chosen in our approach for gender recognition. Using background subtraction techniques, the walking subjects can be extracted from the original image sequences to derive binary silhouette image sequences. To make the gait representation insensitive to the distance between the camera and the subject, we have to perform silhouette preprocessing procedure including size normalization and horizonal alignment. If all silhouettes in a gait cycle are considered as feature, the feature dimension will be very high. The GEI can greatly reduce gait feature dimension. It has been demonstrated that GEI is less sensitive to noise and able to achieve highly competitive results compared to alternative representations. Figure 1 shows the sample silhouette images in a gait cycle from one person, and the right most image is the corresponding GEI.

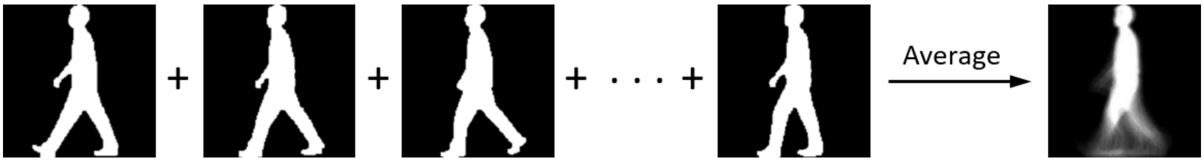

FIGURE 1. Gait energy image is the average of silhouettes in a gait cycle.

The gray-level GEI [26] is defined as

$$G(x, y) = \frac{1}{N} \sum_{t=1}^{N} B(x, y, t), \tag{1}$$

where N is the number of frames in the gait sequence, x and y are the image coordinates, and $B(x, y, t)$ is a binary silhouette image at frame t in the gait sequence.

2.2. **Local Zigzag pattern.** Local image feature descriptors play a key role in texture classification tasks. However, some traditional descriptors are deficient to capture the local intrinsic structure of images. Recently, LBP has gained more attentions due to its simplicity and excellent performance in texture analysis. The basic idea behind LBP is that the LBP histogram contains information about the distribution of local micropatterns over the whole image. However, two drawbacks of LBP are 1) it is not very robust against local changes in the texture, and 2) it may not work properly for noisy images or on flat image areas of constant gray level [16]. In order to overcome the aforementioned shortcomings of the existing LBP operator, a novel feature descriptor named LZP is proposed [25].

Unlike LBP that considers two possible relations of a pixel with its neighborhood, the LZP is a local texture descriptor which considers the relation between two neighboring pixels by the Zigzag scanning order. Let a pixel be at a certain location, considered as the center pixel $c = (x, y)$ of a local neighborhood composed of P equally spaced pixels on a circle of radius R. The LZP operator which is applied to the center pixel c can be expressed as:

$$LZP_{P,R}(c) = \sum_{i=0}^{7} s(g_i - g_{i+1}) \times 2^i, \tag{2}$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}, \tag{3}$$

where g_i is the gray value of the pixel p_i. In a 3×3 pixel block, the code is generated by comparing its adjacent pixel according to the Zigzag scanning order as shown in Figure 2.

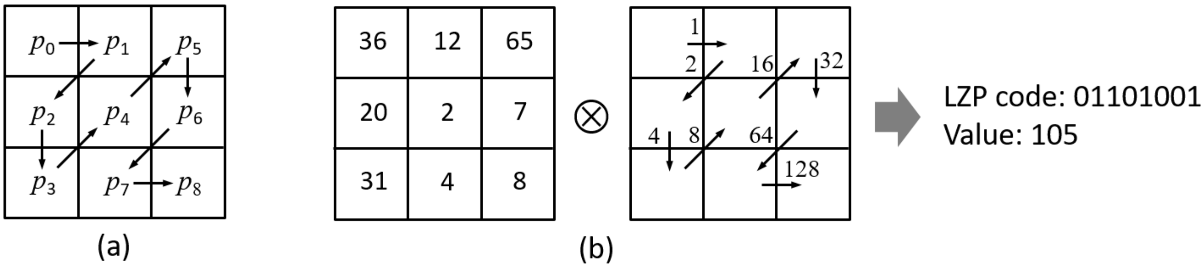

FIGURE 2. LZP code and value computation: (a) Local Zigzag structure of a patch; (b) illustration of the coding scheme of LZP

2.3. **The proposed approach.** In order to retrieve the grayscale difference information with the spatial relationship of the image content, the GEI is spatially divided into several non-overlapping regions, where each region has the same size commonly. After that, we apply the LZP operator on every pixel in every region. Then, the histogram of every region is extracted by collecting the occurrence of LZP codes. Finally, all histograms computed from different blocks are concatenated into a single histogram sequence to represent the feature vector of a given image. The concatenated feature vector provides a better gait feature representation and describes the image content accurately. Assume that a GEI is divided into M regions $\{R_1, R_2, \ldots, R_M\}$, the histogram of the GEI is formulated as follows:

$$H = \left(\left(h_0^1, h_1^1, \ldots, h_{L-1}^1\right), \ldots, \left(h_0^M, h_1^M, \ldots, h_{L-1}^M\right)\right), \tag{4}$$

$$h_l^j = \sum_{(x,y)\in R_i} f\{LZP(x,y) = l\}, \tag{5}$$

where $[0, \ldots, L-1]$ denotes the range of values in LZP map, and f is defined as:

$$f(A) = \begin{cases} 1, & \text{if } A \text{ is true} \\ 0, & \text{otherwise} \end{cases}. \tag{6}$$

After feature extraction, the next task is to classify the different texture patterns into distinct defined classes with a proper classifier. The SVM is a very powerful and versatile machine learning model [27]. It can be used for data classification or to solve the nonlinear regression problem. In our approach, to classify the crowd density with different texture pattern is performed by adopting an SVM.

SVM has been shown to be very effective because it has the ability to find the optimal separating hyperplane that gives the maximum margin between the positive and negative samples. Given a training set of labeled samples $\{(x_i, y_i), i = 1, \ldots, h\}$, where $x_i \in \mathcal{R}^n$ and $y_i \in \{+1, -1\}$, a new test data x is classified by:

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{h} \varphi_i y_i K(x_i, x) + c\right), \tag{7}$$

where φ_i are Lagrange multipliers of the dual optimization problem, c is a bias or threshold parameter, and $K(\cdot,\cdot)$ is a kernel function. In our work, we used the GPU-based LIBSVM [28] in all experiments.

3. **Experimental Results.** In the experiments, CASIA gait database (Dataset B) [29] is used to evaluate the performance of the proposed method. Dataset B consists of the data from 124 subjects (93 males and 31 females) under 11 viewing angles from 0° to 180°. For each subject there are six normal walking sequences conducted from every view angle. All selected data were captured from the side view with normal clothes and without any bag as shown in Figure 3.

FIGURE 3. Male (top) and female (bottom) images from the CASIA gait database

Since we adopt the block-based feature extraction strategy, the number of blocks is an important factor that influences the classification quality. We want to show that the appropriate block number is necessary to obtain better classification results. The results are presented in Table 1. As the observation in our previous work, it can be seen that the classification rate is improved generally as the block number is increased. However, a basic principle states that the number of blocks should be large enough so that the texture features can be represented reliably. On the other hand, it should be small enough to accurately describe the local textures of a gait image [30]. From the experimental result, in order to satisfy both classification accuracy and computation effort requirements, the appropriate number of blocks is 9×9 which can provide better classification performance.

TABLE 1. Classification rate (%) with different block numbers

Block numbers	2×2	3×3	4×4	5×5	6×6	7×7	8×8	9×9
Accuracy	98.52	97.85	99.33	99.33	99.46	99.47	99.46	99.60

In order to justify the performance of the proposed approach, we compare our approach with other methods in [2, 3, 4, 5]. In [2], the human knowledge is extracted and used to improve the gait-based gender classification. They also analyze the contributions of different parts of the human body to find the discriminative body parts. In [3], the methods of shape feature extraction and temporal Markov property modeling are included for gait-based gender classification. For the appearance part, the simply constructed shape descriptor preserves the essential pose information. For the temporal part, the mixed conditional random field models the periodic shape variations closely correlated with genders. In [4], a gender classification based on gait features is proposed. Three different gait features are constructed separately and fused together. The first feature is extracted from the spatial domain while the second and third features are extracted from the wavelet domain. A novel local texture descriptor called LBDP is proposed to extract more detailed discriminative information embedded in an image [5]. The proposed method derived mainly from the spirit of LBP with totally different encoding mechanism so that it can enhance the discriminative capability and remedy the intensity change problem encountered in LBP. The experimental results are shown in Table 2. It can be seen that all methods perform well on gait-based gender classification, but our approach provides significant higher accuracy than any other method.

Table 2. Performance comparison of different gait-based gender recognition methods

Method	Classifier	Recognition rate (%)
Yu et al. [2]	SVM	95.97
Hu et al. [3]	SVM	98.39
Sabir et al. [4]	SVM	96.47
Wang et al. [5]	SVM	97.31
Ours	SVM	99.60

4. **Conclusions.** Gender recognition from gait images has drawn a lot of attention in intelligent visual surveillance applications for security monitoring and management. Among the existing proposed methods for gait-based gender recognition, using the texture feature in the image is a simple but effective approach. In this paper, we apply the block-based local Zigzag pattern to extracting the texture features in GEI for gender recognition. Evaluations on CASIA gait database demonstrate that the proposed approach can obtain a significant improvement in classification performance. Further work of considering other more discriminative texture features into our approach is in progress.

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