Conditional-Sorting Local Binary Pattern Based on Gait Energy Image for Human Identification

Chih-Hsien Hsia[1], Jen-Shiun Chiang[2], Yi-Jhe Dai[2], and Tien-An Lin[2]

[1] Department of Electrical Engineering
National Taiwan University of Science and Technology
Taipei, Taiwan
[2] Department of Electrical Engineering
Tamkang University
Tamsui, New Taipei City, Taiwan

Abstract — Gait recognition systems have recently attracted much interest from biometric researchers. This work proposes a new feature extraction method for gait representation and recognition. The new method is extended from the technique of Local Binary Pattern (LBP) by changing the sorting method of LBP according to the blend direction to create a new approach, Conditional-Sorting Local Binary Pattern (CS-LBP). After synchronizing and calibrating the gait sequence images, a cycle of images from the gait sequence can be captured to form a Gait Energy Image (GEI). We then apply the CS-LBP on GEI to derive different blend direction images and calculate the recognition ability for each blend direction image for feature selections. To solve the classification problem, the Euclidean distance and Nearest Neighbor (NN) approaches are used. With the experiments carried out on the CASIA-B gait database, our proposed gait representation has a very good recognition rate.

I. INTRODUCTION

Biometric identification techniques allow the identification of a person according to some geometric or behavioral traits that are uniquely associated with him or her. Commonly used biometrics includes face, iris, fingerprint, handwriting, palm shape, vena, and gait. An important limitation of most contemporary biometric identification systems is related to the fact that they require the cooperation of individual to be identified and some special capturing devices. Gait recognition is an emerging biometric technology which aims to identify individuals using their walking style. The apparent advantage of gait recognition in comparison to other biometrics is that it does not require the attention or cooperation of the observed subject. Gaits can thus be used in some situations when other biometrics might not be perceivable. Generally speaking, there are three steps in gait recognition: moving object tracking, gait feature extraction, and classification. Many proposed literatures [1]-[4] dedicate to the work of the second step. Gait recognition methods can be roughly classified into two major categories: model-based and appearance-based methods. The model-based methods [5]-[6] purpose to explicitly model the human body or motion, and the gait feature can be extracted by tracking the human body frame by frame. Generally, the feature extraction methods rely on the precise two-dimensional or three-dimensional model generation techniques to have a more accurate recognition result, and hence the calculation complexity of the model-based methods is relatively high [7]. The appearance-based methods for gait feature extraction use gait silhouettes directly without modeling the human body. Therefore, many gait recognition researchers made efforts on the appearance-based methods[8]-[9]. One of the most frequently used methods is

Gait Energy Image (GEI) [1], which represents the gait by using a single gray scale image obtained by averaging the silhouettes extracted over a complete gait cycle. This method is a really simple approach to get the complete gait information. In this research work we choose GEI as the based feature. Although there is wealth of information in GEI, how to extract useful features from GEI is worth developing [2]-[3]. The human movement is a progressive action; after the images are stacked into GEI, the result is an image with blend characteristics. Based on this factor, this research work proposes a new appearance-based method to extract these features. The new method is an extension from Local Binary Pattern (LBP). Here a new sorting method, Conditional-Sorting Local Binary Pattern (CS-LBP), is proposed, and in this approach the LBP is changed according to the direction of the blend. Based on the CASIA-B gait database [12], the experimental results of our proposed method demonstrate that it is very effective.

The rest of this paper is organized as follows. In Section II, related researches and GEI formation are described. Section III discusses the CS-LBP method and feature selection method. Section IV presents the experimental results and comparisons. Finally, Section V concludes this research work.

II. FEATURE EXTRACTION AND RELATED WORKS

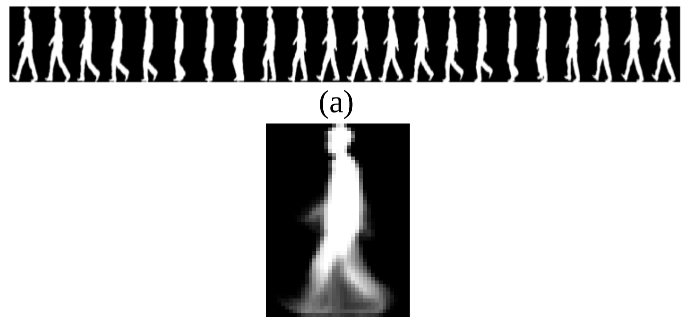
After the preprocessing operation, we have to locate one cycle within the gait sequence, and use GEI to describe the human gait, and then we have to apply the CS-LBP method on GEI to extract more characteristic features from GEI. Because of the image resolution, techniques of Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are utilized to achieve better recognition results.

A. Human Gait Representation Using Gait Energy Image

After the gait period is estimated, the GEI can be computed from the calibrated and normalized silhouettes by the following equation:

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

where $G(x,y)$ denotes the GEI intensity at location (x,y), N the gait period, and $I(x,y,t)$ the normalized and calibrated silhouette at time t. GEI is a simple and effective method to describe the gait features [1], and it can keep static and dynamic information at the same time. One example of GEI extraction is shown in Fig. 1.



(a)

(b)

Fig. 1. Gait energy image extraction: (a) Gait sequences, (b) GEI.

B. Local Binary Pattern

LBP was proposed by Matti *et al*. [10], and it was widely used in many pattern recognition researches, such as face recognition and texture recognition [10]-[11]. LBP is an operator to describe the surrounding of a pixel by generating a bit-code from the binary derivatives of a pixel. Generally, LBP considers the 3×3 surrounding of a pixel and generates a binary 1 if the value of a neighboring pixel is larger than that of the center pixel, otherwise it will generate a binary 0. Then it connects every binary value along the clockwise or counterclockwise direction from one neighbor as the starting point, and it will generate an 8-bit binary code, which is the final value of the LBP. The LBP cannot effectively represent the image feature because it lacks a meaningful sorting method. Based on this factor, a new sorting method is proposed to solve this problem.

III. CONDITIONAL-SORTING LOCAL BINARY PATTERN (CS-LBP)

A. Human Gait Recognition Using CS-LBP

The main task in gait recognition is the extraction of the appropriate and salient feature to effectively capture the gait characteristics. It is well known that human walking is a progressive movement; therefore, how to extract the progressive information is a critical issue. This work presents a modified LBP, Conditional Sorting-Local Binary Pattern (CS-LBP). The CS-LBP can be applied on GEI to extract many meaningful features. In the proposed approach, it first compares the surrounding neighbors with the middle pixel like the original LBP does. By dividing the neighbors into three blocks, high bit block, middle bit block, and low bit block, it then uses three graphics to represent each block (horizontal stripe, diagonal stripe, and vertical stripe). By this approach, eight sorting methods are defined for these three blocks as shown in Fig. 2. The horizontal stripe block corresponds to the most significant three bits of the 8-bit binary code (2^7, 2^6, 2^5), and the following equation can be used to find the final value:

$$\mathrm{top(x)} = \begin{cases} 224, & \text{if } \mathrm{x} = 3 \\ 192, & \text{if } \mathrm{x} = 2 \\ 128, & \text{if } \mathrm{x} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where top(x) is the final value, and x is the number of 1 in this block. The diagonal stripe block corresponds to the middle two bits of the 8-bit binary code (2^4, 2^3), and the following equation can be used to find the final value:

$$\mathrm{median(x)} = \begin{cases} 24, & \text{if } \mathrm{x} = 3 \\ 16, & \text{if } \mathrm{x} = 2 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where median(x) is the final value, and x is the number of 1 in this block. The vertical stripe block corresponds to the least significant three bits of the 8-bit binary code (2^2, 2^1, 2^0), and the following equation can be used to find the final value:

$$\mathrm{bottom(x)} = \begin{cases} 7, & \text{if } \mathrm{x} = 3 \\ 3, & \text{if } \mathrm{x} = 2 \\ 1, & \text{if } \mathrm{x} = 1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where bottom(x) is the final value, and x is the number of 1 in this block. Finally, the following equation is to obtain the final value of CS-LBP:

$$Dv = \mathrm{top(i)} + \mathrm{median(j)} + \mathrm{bottom(k)} \tag{5}$$

where Dv is the final value of CS-LBP. The sorting names are named to correspond the sorting method as shown in Fig. 2. The 8 sorting methods are: left-up (LU) sorting method, up (UP) sorting method, right-up (RU) sorting method, left (LE) sorting method, right (RI) sorting method, left-down (LD) sorting method, down (DO) sorting method, and right-down (RD) sorting method.

B. Feature Selection

Although there are eight images of the blend features after using CS-LBP, the critical issue is how to combine these blend features for better recognition. It has to find the blend features that can increase the distance between different objects and decrease the distance between same objects, just like the LDA concepts. The distance between the average images of each individual and average image of the total individuals is calculated as between-class distance, and the distance between the average images of each individual and images of each individual is calculated as the within-class distance. The between-class distance represents the distance of different individuals and the distance should be as large as possible, and the within-class distance represents the distance of the same individuals and the distance should be as small as possible. The recognition ability, proposed here, represents the between-class distance divided by the within-class distance, and the value should be as large as possible. The following equation is used to calculate the between-class distance:

$$BC_d = \sum \mathrm{abs}\left| Avg_d(i,j) - Img_d^{obj_n}(i,j) \right| \tag{6}$$

where d is the direction of the blend feature, obj the individual number, n the stance of the individual, BC_d the between-class distance of direction d of the blend feature, and $Avg_d(i,j)$ the pixel located at (i,j) of direction d of the blend feature average image. $Img_d^{obj_n}(i,j)$ is the pixel located at (i, j) of direction d of the blend feature with numbers of obj individuals of n stance image. The following equation is to calculate the within-class distance:

$$WC_d = \sum \mathrm{abs}\left| Avg_d^{obj}(i,j) - Img_d^{obj_n}(i,j) \right| \tag{7}$$

where WC_d is the within-class distance of direction d of the blend feature, and $Avg_d^{obj}(i,j)$ is the pixel located at (i, j) of direction d of the blend feature of numbers of obj individuals average image. The following equation is used to calculate the Recognition Ability (RA):

$$RA_d = BC_d / WC_d \tag{8}$$

The recognition ability, obtained from (8), of different directions of the blend features is shown in Fig. 3. In Fig. 3, the vertical axis is the recognition ability and the horizontal axis is different directions of the blend features. In this work, we select top four recognition ability directions of the blend features (DO, UP, RD, and LD) as our features, and use the following equation to fuse these features as the similarity distance:

$$S = \sum D_{dir}\,, dir = \mathrm{DO, UP, RD, LD} \tag{9}$$

where S is the similarity distance, dir the selected direction of the blend feature, and D_{dir} the similarity distance at direction dir.

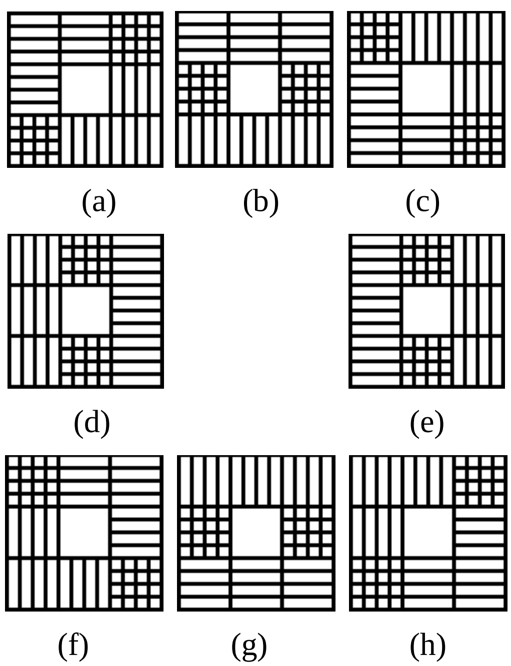


Fig. 2. The sorting methods of CS-LBP: (a) left-up (LU) sorting method, (b) up (UP) sorting method, (c) right-up (RU) sorting method, (d) left (LE) sorting method, (e) right (RI) sorting method, (f) left-down (LD) sorting method, (g) down (DO) sorting method, (h) right-down (RD) sorting method.

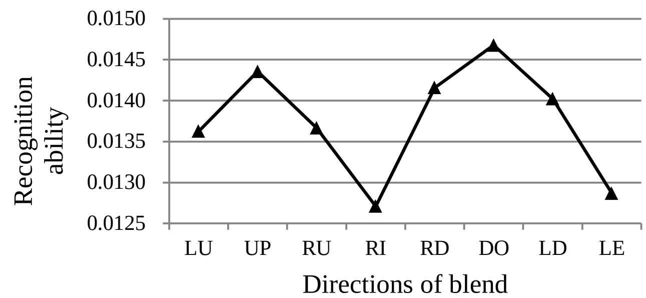


Fig. 3. The recognition ability of eight directions of the blend feature.

IV. EXPERIMENTAL RESULT

In the experiment, we would like to prove the robust of the proposed method and feature selection method. To verify our proposed method, this work has performed a number of experiments on the CASIA-B database [12]. There are 124 individuals and three variations in this database, namely view angle, clothing, and carrying conditions changes. For each individual there are ten gait sequences consisting of six normal gait sequences where the individual does not wear a bulky coat or carry a bag, two carrying-bag sequences and two wearing-coat sequences. The first four of the six normal gait sequences were used as the gallery set, and the rest of the normal gait sequences were used as the probe. The two carrying-bag gait sequences were used as the probe, and the two wearing-coat gait sequences were used as the probe.

A. Recognition with CS-LBP

We compared the proposed method with the original GEI method [1] and other improved GEI methods [2]-[4], and the recognition results are shown in Table 1. It shows from Table 1 that when the probe set is tested with the gallery set, all four methods yield pretty good recognition rates. However, with different covariate conditions, the recognition rates of all four methods are degraded. Nevertheless, our method can maintain stable recognition rates under different conditions. In the case of wearing-coat gait sequences, our CS-LBP outperforms the rest methods, and the CS-LBP can compete with other methods under carrying-bag gait sequences. The average recognition results, 82%, indicate that our CS-LBP method for gait recognition produces the best recognition results compared to all other methods as shown in Table 1.

TABLE 1. Performance with the CASIA-B database.

Methods	GEI + PCA + LDA [1]	SEIS + LDA [2]	AEI + PCA + LDA [3]	M_G^j + CDA [4]	This work
Normal	99%	99%	89%	100%	99%
Bag-carrying	44%	64%	75%	78%	75%
Coat-wearing	37%	72%	57%	44.0%	73%
Average recognition rate	60%	78%	74%	74%	82%

B. Feature Selection

In Section III, we proposed equation (8) to calculate and estimate the recognition ability for different directions of the blend features, and select the top four features for gait recognition according to the estimated recognition ability. Here we would like to evaluate different numbers of selecting features for gait recognition. After using equation (8) to estimate the recognition ability of different directions of the blend features, all eight directions are sorted according to the estimated recognition ability from high to low, and the direction with the highest recognition ability of the blend features is selected first as the gait features. Then, the second highest one, the third highest one, and all the way to all eight of them are selected. The actual recognition rate based on the selections is shown in Fig. 4. It shows that the recognition rate is the highest when the top four highest recognition abilities are chosen. The actual recognition rates are then compared with the recognition ability calculated by equation (8). Fig. 5 shows the comparison results, where the black line is the actual recognition rate and the block dotted line is the calculated recognition ability. The corresponding values are shown in Table 2. From Tables 2, the recognition ability, calculated by equation (8), closely matches the actual recognition rate for the top six features, and there are only two misses on the lowest two features. According to Table 2, the recognition ability difference between the last two features is only 0.002 (0.0129 and 0.0127) and the difference of the actual recognition rate between these two features is only 1.1% (57.4% and 58.5%). Therefore, our proposed approach is really robust.

TABLE 2. The values of the recognition rate and recognition ability.

Direction of blend feature	Recognition rate	Recognition ability
LU	63.2%	0.0136
UP	71.9%	0.0144
RU	65.9%	0.0137
RI	58.5%	0.0127
RD	70.6%	0.0142
DO	75.7%	0.0147
LD	69.1%	0.0140
LE	57.4%	0.0129

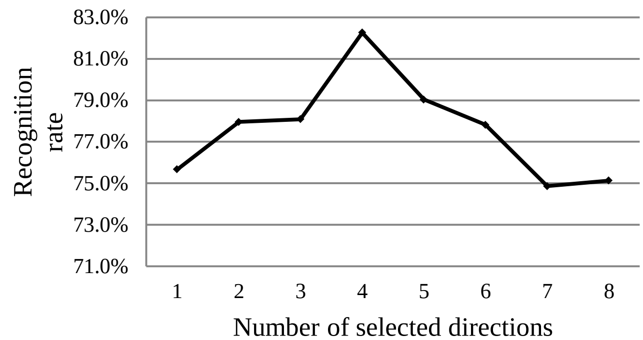


Fig. 4. The recognition rate of different number of selected directions.

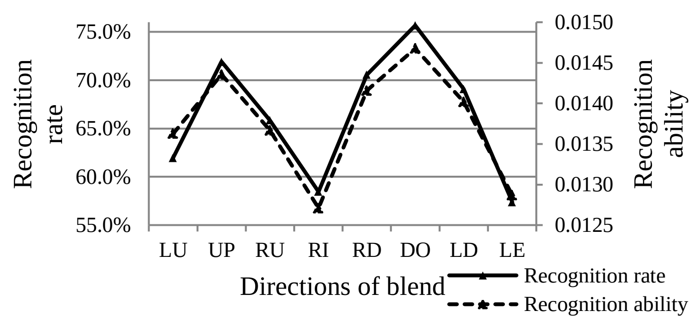


Fig. 5. Comparisons of the recognition rate and the recognition ability.

V. Conclusion

In this work, we propose a new method, Conditional-Sorting Local Binary Pattern (CS-LBP), which is extending from the local binary pattern to describe the gait feature. It is applied on Gait Energy Image (GEI) to extract more meaningful gait features. The CASIA-B database is used to evaluate the proposed method. The experiment results show that the proposed method can achieve better performance under appearance changes. Compared to recent literatures, the recognition rate of our method can achieve average recognition rate of 82% under different walking conditions.

Acknowledgement

This research is partially supported by National Science Council of Taiwan, ROC, under grant number: 101-2221-E-032-066-

References

[1] J. Han and B. Bhanu, “Individual recognition using gait energy image,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 2, pp. 316-322, February 2006.

[2] X. Huang and N. V. Boulgouris, “Gait recognition with shifted energy image and structural feature extraction,” *IEEE Transactions on Image Processing*, vol. 21, no. 4, pp. 2256-2268, April 2012.

[3] E. Zhang, Y. Zhao, and W. Xiong, “Active energy image plus 2DLPP for gait recognition,” *Signal Processing*, vol. 90, no. 7, pp. 2295-2302, July 2010.

[4] K. Bashir, T. Xiang, and S. Gong, “Gait recognition without subject cooperation,” *Pattern Recognition Letters*, vol. 31, no. 13, pp. 2052-2060, June 2010.

[5] L. Wang, H. Ning, T. Tan, and W. Hu, “Fusion of static and dynamic body biometrics for gait recognition,” *IEEE Transaction on Circuits and Systems for Video Technology*, vol. 14, no. 2, pp. 149-158, February 2004.

[6] I. Bouchrika and M. S. Nixon, “Model-based feature extraction for gait analysis and recognition,” *Proceedings of Mirage: Computer Vision/Computer Graphics Collaboration Techniques*, pp. 150-160, May 2007.

[7] L. Wang, T. Tan, H. Ning, and W. Hu, “Silhouette analysis-based gait recognition for human identification,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, pp. 1505-1518, December 2003.

[8] D. Xu, S. Yan, D. Tao, L. Zhang, X. Li, and H. Zhang, “Human gait recognition with matrix representation,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 16, no. 7, pp. 896-903, July 2006.

[9] T. H. W. Lam and R. S. T. Lee, “A new representation for human gait recognition: motion silhouettes image (MSI),” *International Conference on Biometrics*, pp. 612–618, 2006.

[10] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 7, pp. 971-987, Jul. 2002.

[11] Z. Guo, L. Zhang, and D. Zhang, “A completed modeling of local binary pattern operator for texture classification,” *IEEE Transactions on Image Processing*, vol. 19, no. 6, pp. 1657-1663, June 2010.

[12] S. Yu, D. Tan, and T. Tan, “A framework for evaluating the effect of view angle, clothing and carrying condition on gait recognition,” *Interenational Conference on Pattern Recognition*, vol. 4, pp.441-444, August 2006.