A Gait Sequence Analysis for IP Camera Using a Modified LBP

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Abstract

This work proposes a method that is a modified form of the local binary pattern technique by changing the sorting method for the local binary pattern according to the blend direction to develop a new method, which is termed the Modified Local Binary Pattern (MLBP). After synchronizing and calibrating the gait sequence images, a cycle of images from the gait sequence is captured to form a gait energy image. The MLBP is then applied to the gait energy image to derive different blend direction images and to calculate the ability to recognize each blend direction image for feature selection. To allow classification, the Euclidean distance and nearest neighbor approaches are used. In the experiments that are carried out on the gait database, this approach achieves the best recognition rate, even when the appearance of the objects changes. Because the complexity is low, it is suitable for implementation in embedded systems and supports many Internet Protocol (IP) camera applications.

Keywords: Local binary pattern, Gait energy image, Internet protocol camera

1 Introduction

Gait recognition is an emerging biometric technology that identifies individuals from their walking style. The advantage of gait recognition in comparison to other biometrics is that it does not require the attention or cooperation of the observed subject so gait recognition can be used in situations where other biometrics might not be perceivable. Generally speaking, there are three steps to gait recognition: moving object tracking, gait feature extraction and classification. Many studies [1-4] focus on the second step. In general, the gait recognition methods can be roughly classified into two major categories. The first is the model-based method explicitly models the human body or motion and the gait features are extracted by tracking the human body frame by frame. A human body model, which uses 14 rigid body parts to represent the human body, is used in [5]. This method uses a tracking algorithm to extract the kinematic features, such as the rotation angles of the legs and hips. Bouchrika and Nixon [6] used elliptic Fourier descriptors to model the motion templates for gait sequences as a parametric form. A motion analysis is used to obtain the positions of the feature points. The positions of these feature points represent the gait features. Generally, the feature extraction methods rely on precise 2-D or 3-D model generation techniques to give a more accurate recognition result so the computational complexity of the model-based methods is relatively high [7].

The second method is the appearance-based method, which uses a sequence of silhouettes to express the gait information image [8]. One of the most common methods uses the Gait Energy Image (GEI) [1]. This represents the gait by using a single gray scale image, which is obtained by averaging the silhouettes that are extracted over a complete gait cycle. This method provides a simple approach to get the complete gait information. Another similar representation of GEI is a Motion Silhouette Image (MSI), wherein the value of the intensity of a pixel is computed as a function of the motion of that pixel in the temporal dimension over all silhouettes for a gait cycle. Both GEI and MSI use one image to describe a human moving in one gait cycle, so computation is easy and the method is mostly immune to noise in the silhouette's extraction. In [9], a width vector mean method is used. This produces a group of width vectors by projecting the silhouettes onto the vertical axis and then averages the width vector over one gait cycle as the gait features. Sun et al. [10] proposed an extension of the frieze pattern method to mitigate the effects of changes in appearance on the silhouette. This method uses a double-leg support on the floor image as the key frame and then subtracts all silhouettes that have the key frame to obtain a signature as the gait feature. Finally, a dynamic time warp is used as the classifier because there may be

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different number of images in each gait cycle. Because the frieze pattern method projects silhouettes onto the vertical or horizontal axis, much structural information about the gait can be lost and the difference between each object is reduced. This study uses GEI as the key feature. Although there is a wealth of information on GEI, the process for the extraction of useful features from GEI is worthy of development [2-3].

Human movement is a progressive action so when the images are stacked into GEI, the result is an image with a blend of characteristics. Therefore, this study uses a new appearance-based method to extract these features. The new method is an extension of a local binary pattern. A new sorting method, a Modified Local Binary Pattern (MLBP), is proposed, and the pattern is changed according to the direction of the blend. The experimental results for the proposed method demonstrate that its effectiveness.

2 Related Works

In order to extract human silhouettes from video, the approach that was proposed by Guo et al. [11] is used for background subtraction. After background subtraction, the silhouettes are normalized and calibrated to eliminate the different heights and centroids that result from different camera perspectives and silhouette scales. A sequence of human silhouettes of the same height and centroid is then obtained. After preprocessing, one cycle is located within the gait sequence and GEI is used to describe the human gait. The MLBP method is then applied to the GEI to extract more characteristic features from the GEI. The resolution of the image is poor so Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are used to achieve better recognition results.

2.1 Gait Period Estimation

Human walking is a cycle of actions that is repeated at a stable frequency. This characteristic allows the gait to be split from different cycles so that it can be used for recognition. Therefore, the new feature extraction method that is proposed in this paper focuses on gait images for one cycle. One gait cycle spans the period from when the heel of one foot strikes the ground to the time at which the same one contacts the ground again. It is determined by observing the changes in the number of pixels in the lower silhouette [12]. When both feet strike the ground, the number of pixels is the greatest and when only one foot strikes the ground, the number of pixels is the smallest. Therefore, the images for one gait cycle include the images for three consecutive strikes of feet on the ground.

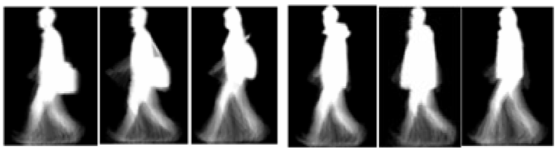
2.2 Human Gait Representation Using a GEI

When the gait period is estimated, the GEI is computed from the calibrated and normalized silhouettes using the (1):

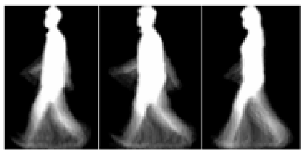
$$G(x,y)=\frac{1}{N}\sum_{t=1}^{N}I(x,y,t) \quad \textbf{(1)}$$

where $G(x,y)$ denotes the intensity of the GEI intensity at location (x,y), N is the period of the gait and $I(x,y,t)$ is the normalized and calibrated silhouette at time t.

A GEI gives a simple method to describe the gait features [1] that simultaneously shows both static and dynamic information. The pixels with the highest values (white color) in a GEI correspond to the body parts that move only a little during a walking cycle, such as the torso and the head. The pixels that have intensities that are between the highest and lowest values (grey color) correspond to the body parts that move constantly, such as the arms and the legs. Examples of GEI's are shown in Figure 1. Bobick and Davis [13] proposed a Motion Energy Image (MEI) and Motion History Image (MHI) to describe human movement. Both the MEI and the MHI are vector images that represent characteristics of human movement in each pixel. A comparison of a GEI with a MSI and a MHI shows that a GEI better describes human movement characteristics.



(a) The bag case (b) The coat case



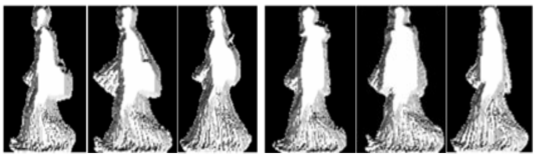
(c) The normal case

Figure 1. GEI examples: the three columns indicate three different subjects, and the three rows indicate three cases

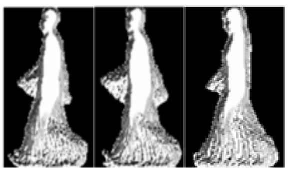
Although a GEI contains much useful information, such as static and dynamic features, it also has several drawbacks: (1) Because GEI compresses one cycle of images into one image, the information in a GEI is compacted. (2) When the number of image frames in one gait cycle is different, there are different values in a GEI. For example, if one position is repeated 3 times in one gait cycle over 30 image frames, the value of the GEI is 25.5. If one position is repeated 3 times in one gait cycle over only 27 image frames, the value of the GEI is 28. Therefore, the direct use of GEI results in some discrepancies. Because of these problems, this study proposes the use of a new MLBP to extract more meaningful features from the GEI.

2.3 LBP

The pattern for the traditional local binary pattern was proposed by Matti et al. [14], and it was widely used in many pattern recognition studies for facial recognition and textural recognition [14-15]. The local binary pattern is an operator that describes the surroundings of a pixel by generating a bit-code from the binary derivatives of a pixel. It considers the 3×3 pixel area surrounding a pixel and generates a binary 1 if the value of a neighboring pixel is greater than that of the central pixel; otherwise it generates a binary 0. Every binary value is then connected in a clockwise or counter-clockwise direction, using one neighbor as the starting point. This generates an 8-bit binary code, which is the final value of the pattern. There are no hard rules, as long as a consistent direction is maintained. Figure 2 shows a GEI after using a local binary pattern to process every pixel. The method operator considers the relationship between itself and the neighbors, so the structural information is retained after processing. The method cannot effectively represent the image features because it lacks a meaningful sorting method, so a new sorting method is proposed to address this problem.



(a) The bag case (b) The coat case



(c) The normal case

Figure 2. The LBP examples: the three columns indicate three different subjects, and the three rows indicate three cases

2.4 Subspace Learning Using PCA+LDA

Although this study proposes a method that has useful identification features, problems arise when it directly recognizes the gait using MLBP images. Because the dimensions of the MLBP are high, the method requires greater computational time the recognition rate is affected. This is commonly known as the *curse of dimensionality*. When reducing the dimensions in processing, the images are projected into the LDA space, rather than simply calculating the Euclidean distance between images. LDA maximizes the differences between frames from different subjects and minimizes the distances between frames from the same subject under different conditions. However, using LDA directly can cause singularity problems so the PCA + LDA method is used [16]. A singular may arise because the feature vector size may be larger than the training set.

Assume there are C individuals from one class (X^1, X^2, …, X^C) and for each individual, X^C, there are m stance-frames under various conditions from the samples for that class, X_m^C. The within-class scatter matrix is:

$$W_X = \sum_{c=1}^{c}\sum_{m=1}^{M}(X_m^C - \overline{X}^C)(X_m^C - \overline{X}^C)^T \tag{2}$$

The between-class scatter matrix for the between-class is:

$$B_X = \sum_{c=1}^{c}(\overline{X}^C - \overline{X})(\overline{X}^C - \overline{X})^T \tag{3}$$

where $\overline{X}^C$ denotes the mean vector of class c and $\overline{X}$ denotes the mean vector of all samples. LDA uses these parameters to determine a transformation matrix, W, which increases the distance between different classes and decreases the distance between the same classes, as follows:

$$z_m^c = W^T X_m^c \tag{4}$$

In order to obtain the appropriate transformation, W, it is necessary to determine a balance between the between-class scatters and the within-class scatters. The maximum F is then determined as follows:

$$F = \frac{tr(\sum B_z)}{tr(\sum W_z)} \tag{5}$$

The mean vector for class c is determined as follows:

$$\overline{X}^C = \frac{1}{M}\sum_{m=1}^{M} X_m^c \tag{6}$$

The mean vector for all samples is obtained as follows:

$$\overline{X} = \frac{1}{CM}\sum_{c=1}^{C}\sum_{m=1}^{M} X_m^c \tag{7}$$

The mean vector for class c after transformation by W is calculated as follows:

$$\overline{Z}^c = W^T \overline{X}^c \tag{8}$$

The mean vector for all samples after transformation by W is determined as follows:

$$\overline{Z} = W^T \overline{X} \tag{9}$$

The within-class scatter after transformation by W is:

$$W_x = W^T \sum W_X W \tag{10}$$

The between-class scatter after transformation by W is as follows:

$$B_Z = W^T \sum B_X W \tag{11}$$

If W_Z and B_Z are respectively replaced by $W^T W_X$ and $W^T B_X W$, the result is:

$$F = \frac{tr(W^T B_z W)}{tr(W^T W_X W)} \tag{12}$$

Equation (12) is the Fisher criterion function. The optimal discriminating space, W_{opt}, for classification is simply computed as:

$$W_{opt} = \arg\max \frac{tr(W^T B_X W)}{tr(W^T W_X W)} \tag{13}$$

Specifically, $W_{opt} = \{W_1, W_2, ..., W_m\}$ is the set of generalized eigenvectors of B_X and W_X that correspond to the m largest eigenvalues $(\lambda_1, \lambda_2, ..., \lambda_m)$. The relationship between B_X, W_X, W_i, and eigenvalue λ_i is:

$$B_X W_i = \lambda_i W_X, i = 1, 2, ..., m \tag{14}$$

However, the rank of W_X is no more than N–C, where N is the total number of subjects in the training set and C is the number of individuals. If the dimension of W_X, which is determined by the size of the feature vector, is less than the number of samples, N–C, then W_X is not singular. However, the feature vector is obtained from the row-scanned image and its size is the product of the height and the width of the image. This size, which is of the order of 10,000, is much greater than N–C, which is of the order of 100. Therefore, W_X is singular for most training set sizes. For training sets that are larger than the number of pixels in the image, W_X is not singular.

One solution is to project the within-class and the between-class scatter matrices into a lower dimension space, i.e., which reduces the feature vector size and renders W_X nonsingular. The PCA is used to reduce the dimension as follows:

$$W'_{opt} = W_{PCA} W_{LDA} \tag{15}$$

where

$$W_{PCA} = \arg\max |W^T S_T W| \tag{16}$$

$$W_{LDA} = \arg\max \frac{|W^T W_{PCA}^T S_B W_{PCA} W|}{|W^T W_{PCA}^T S_W W_{PCA} W|} \tag{17}$$

W_{PCA} must have a value that is no more than the greatest N–C principal components, to ensure that the corresponding W_X is nonsingular.

3 Proposed Methodology

3.1 Gait Recognition Using MLBP

The main task in gait recognition is the extraction of the appropriate and salient features that effectively capture the gait characteristics. Human walking is a progressive movement, so extracting the progressive information is critical. This work uses a Modified Local Binary Pattern (MLBP) for GEI to extract many meaningful features. A traditional local binary pattern connects each neighbor in a clockwise or counter-clockwise direction to generation an 8-bit binary code. However, it lacks a meaningful sorting method for the physical properties so this study proposes a new sorting method that gives greater physical significance to the binary code.

The MLBP firstly compares the surrounding neighbors with the middle pixel, similarly to the original local binary pattern. By dividing the neighbors into three blocks, a high bit block, a middle bit block and a low bit block, it then uses three graphics to represent each block (a horizontal stripe, a diagonal stripe and a vertical stripe). Therefore, eight sorting methods are defined for these three blocks, as shown in Figure 3. 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 (18) are used to find the final value:

$$\mathrm{top}(x) = \begin{cases} 224, \text{if } x = 3 \\ 192, \text{if } x = 2 \\ 128, \text{if } x = 1 \\ 0, \text{ otherwise} \end{cases} \tag{18}$$

where top(x) is the final value and x is the number of 1's in this block. The diagonal stripe block corresponds to the middle two bits of the 8-bit binary code (2^4, 2^3) and (19) is used to find the final value:

$$\mathrm{median}(x) = \begin{cases} 24, \text{if } x = 3 \\ 16, \text{if } x = 2 \\ 0, \text{otherwise} \end{cases} \tag{19}$$

where median(x) is the final value and x is the number of 1's 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:

$$\mathrm{bottom}(x) = \begin{cases} 7, \text{if } x = 3 \\ 3, \text{if } x = 2 \\ 1, \text{if } x = 1 \\ 0, \text{otherwise} \end{cases} \tag{20}$$

where bottom(x) is the final value and x is the number of 1's in this block. Finally, (21) is used to obtain the final value of MLBP:

$$D_v = \text{top}(i) + \text{median}(j) + \text{bottom}(k) \quad \textbf{(21)}$$

where D_v is the final value of MLBP.

The sorting names correspond to the sorting method, as shown in Figure 3. The eight sorting methods are: the left-up (LU) sorting method, the up (UP) sorting method, the right-up (RU) sorting method, the left (LE) sorting method, the right (RI) sorting method, the left-down (LD) sorting method, the down (DO) sorting method and the right-down (RD) sorting method.

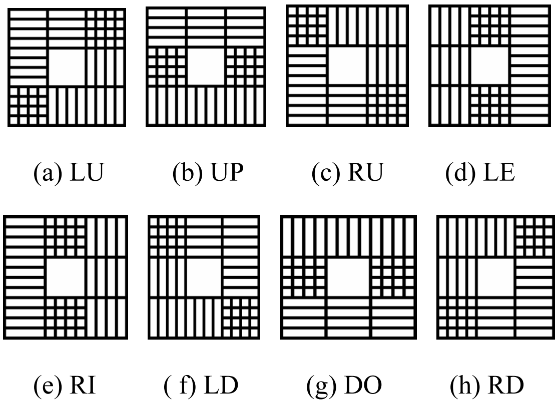


Figure 3. The sorting methods of MLBP

Figure 4(a) shows the original 3×3 pixels and Figure 4(f) shows the result when the surrounding pixels are compared with the middle pixel. Figures. 4(b)-(h), 4(o) and 4(j) show the different MLBP results for the eight sorting methods. The largest value of MLBP is obtained by using the LE sorting method (Figure 3(d)). Because the original 3×3 pixels can be seen as a blend, with values increasing from right to left, the LE sorting method (Figure 3(d)) extracts the features where the blend value increases from right to left. Similarly, the LU sorting method (Figure 3(a)) extracts the features where the blend value increases from lower-right to upper-left. The UP sorting method (Figure 3(b)) extracts the features where the blend value increases from bottom to top. The RU sorting method (Figure 3(c)) extracts the features where the blend value increases from lower-left to upper-right. The RI sorting method (Figure 3(e)) extracts the features where the blend value increases from left to right. The LD sorting method (Figure 3(f)) extracts the features where the blend value increases from upper-right to lower-left. The DO sorting method (Figure 3(g)) extracts the features where the blend value increases from top to bottom. The RD sorting method (Figure 3(h)) extracts the features where the blend value increases from upper-left to lower-right. Using these different sorting methods, the features are extracted from different blend directions.

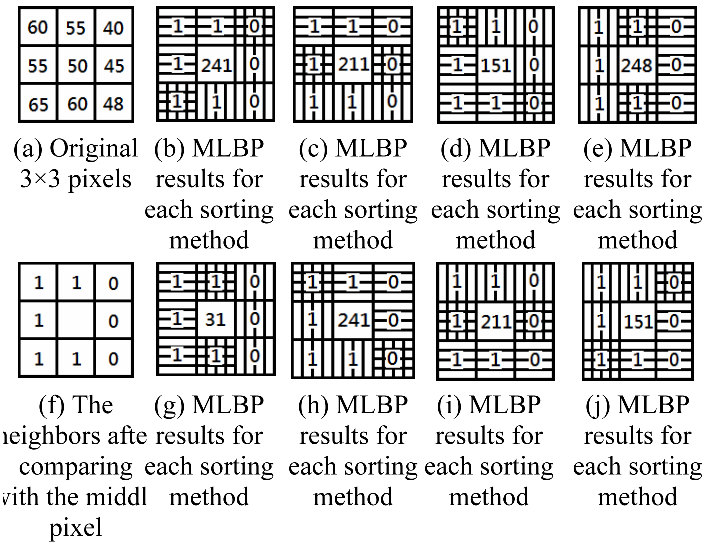


Figure 4. For example of MLBP

3.2 Feature Selection

Although there are eight images for the blend features after using MLBP, these blend features must be combined to allow better recognition. It is necessary to determine which blend features are suitable for recognition and then to associate these useful features. The blend features that increase the distance between different objects and decrease the distance between objects that are the same must be identified, similarly to the concept of the LDA. The distance between the average images for each individual and the average image for all of the individuals is calculated as the between-class distance and the distance between the average images for each individual and the images for each individual is calculated as the within-class distance. The between-class distance represents the distance between different individuals. This distance must be as large as possible. The within-class distance represents the distance between the same individuals. This distance must be as small as possible. The recognition ability is calculated by dividing the between-class distance by the within-class distance. This value should be as large as possible. The following equation is used to calculate the between-class distance:

$$BC_d = \sum abs\,|\,A_v g_d(i, j) - Img_d^{obj_n}(i, j)\,| \quad \textbf{(22)}$$

where d denotes the direction of the blend feature, obj is the individual number, n is the stance of the individual, BC_d is the between-class distance in direction d of the blend feature and $A_v g_d(i, j)$ is the pixel that is located at (i, j) in direction d of the blend feature average image after PCA+LDA processing. $Img_d^{obj_n}(i, j)$ denotes the pixel that is located at (i, j) in direction d of the blend feature with obj individuals of n stance image, after PCA + LDA processing. Equation (23) calculates the within-class distance:

$$WC_d = \sum abs \mid A_v g_d^{obj}(i,j) - Img_d^{obj_n}(i,j) \mid \quad \textbf{(23)}$$

where WC_d denotes the within-class distance in direction d of the blend feature and $A_v g_d^{obj}(i,j)$ denotes the pixel that is located at (i, j) in direction d of the blend feature of *obj* individuals' average image after PCA + LDA processing. The following equation is used to calculate the recognition ability:

$$\text{Recognition ability} = BC_d / WC_d \quad \textbf{(24)}$$

The recognition ability, obtained from (24), for different directions of the blend features is shown in Figure 5. In Figure 5, the vertical axis is the recognition ability and the horizontal axis shows the different directions of the blend features. This study uses the four best recognition ability directions for the blend features (DO, UP, RD and LD) as the features and use the following equation to combine these features as the similarity distance:

$$S = \sum D_{dir}, dir = \text{DO, UP, RD, LD} \quad \textbf{(25)}$$

where S denotes the similarity distance, *dir* is the selected direction for the blend feature and D_{dir} is the similarity distance in direction *dir*. The similarity distance is calculated as the Euclidean distance and the data that is transformed by PCA and LDA is used for the calculation. Finally, the nearest neighbor classifier method is used to identify the objects.

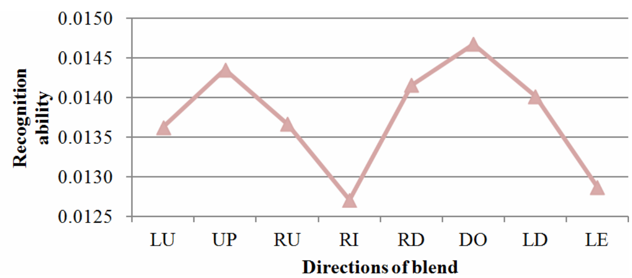


Figure 5. The recognition ability of eight directions of the blend feature

4 Experimental Results

The aim is to prove the robustness of the proposed method and the feature selection method. To verify the proposed method, a number of experiments are performed using the public database (CASIA-B) [17]. There are 124 individuals and the gait data is captured using eleven views in increments of 18°. There are three variations in this database: the view angle, the clothing and the carrying conditions. The sequences that were collected at the 90° view (i.e. front parallel) with normal, clothing, and carrying conditions were used for the experiments, which are the same conditions as those that were used in [2-4].

For each individual there are ten gait sequences, which consist of six normal gait sequences, where the individual does not wear a bulky coat or carry a bag, two sequences carrying a bag and two sequences wearing a coat. The first four of the six normal gait sequences were used as the gallery set (CASIAsetA) and the rest of the normal gait sequences (CASIAsetA2) were used as the probe. The two gait sequences carrying a bag were used as the probe (CASIAsetB) and the two gait sequences wearing a coat were used as the probe (CASIAsetC).

4.1 Recognition Using MLBP

The proposed method was compared with the original GEI method [1] and other improved GEI methods, SEI [2], AEI [3], and M_G^j [4] and the recognition results are shown in Table 1. Table 1 shows that when the probe set (CASIAsetA2) is tested with the gallery set, all four methods have a good recognition rate. However, when there are different covariate conditions, the recognition rates for all four methods decrease. This method produces stable recognition rates for different conditions. For the gait sequences wearing a coat, this study's method outperforms other methods and the CS-LBP can compete with other methods under carrying-bag gait sequences. The average recognition rate of 82% demonstrates that the proposed MLBP method for gait recognition produces better recognition results than all other methods, as shown in Table 1. For all of these methods, including the proposed method, the recognition rate is increased when the changes in the appearance of the gait features are reduced.

The dimension reduction methods that are provided with CDA and PCA + LDA are similar to those for the proposed approach. The nearest neighbor classifier is used for the proposed classification procedure, similarly to the other approaches.

Table 1. Performance with the CASIA-B database

Methods	[1]	[2]	[3]	[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	60%	78%	74%	74%	82%

4.2 Feature Selection

In Section III, (22) is used to calculate the recognition ability for different directions of the blend features. The four best features are then selected for gait recognition, according to the estimated recognition ability. It is necessary to determine the effect of selecting different numbers of features for gait recognition. Equation (22) is used to estimate the recognition ability for different directions of the blend features and then all eight directions are sorted according to the estimated recognition ability, from high to low. The direction with the highest recognition ability for the blend features is selected first as the gait features. The second highest one, the third highest one, and all the way to all eight of them are selected. The actual recognition rate using these selections is shown in Figure 6, where the horizontal axis is the number of directions selected and the vertical axis is the recognition rate. It is seen that the recognition rate is the highest when the top four highest recognition abilities are chosen. In this study, the four directions with the highest recognition ability are chosen as the gait features.

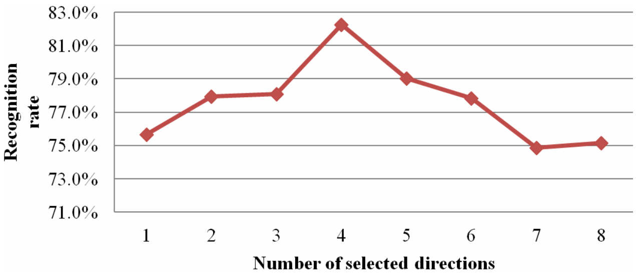


Figure 6. The recognition rate of different numbers of selected directions

5 Conclusion

A new method, called MLBP, which is an extension of the local binary pattern, is used to describe gait features. It is applied to a GEI to extract more meaningful gait features. The public database is used to evaluate the proposed method. The experimental results show that the proposed method achieves a high recognition rate, even when there are changes in appearance. The average recognition rate for this method is 82% for different walking conditions, which is a better rate that those that have been demonstrated by recent studies.

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