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LOCAL GABOR BINARY PATTERNS BASED ON MUTUAL INFORMATION FOR FACE RECOGNITION

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Appropriate representation is one of the keys to the success of face recognition technologies. In this paper, we present a novel face representation approach based on a reduced set of local histograms based on Local Gabor Binary Patterns (LGBP). In the proposed method, a face image is first represented by the local Gabor binary patterns (LGBP) histograms which are extracted from the LGBP images. Then, the local LGBP histograms with high separability and low relevance are selected to obtain a dimension-reduced face descriptor. Extensive experimental results demonstrate that the proposed method not only greatly reduces the dimensionality of face representation, but also outperforms the state-of-the-art approaches for face recognition, such as Fisherfaces, and Gabor Fisher Classification (GFC).

Keywords: Local binary patterns (LBP); Gabor wavelets; mutual information; Fisher linear discriminant; local Gabor binary patterns (LGBP).

1. Introduction

Face recognition has been one of the most challenging and active research topics in computer vision for several decades due to its scientific values and wide potential applications. Much progress has been made in the last decade.[1,2] However, the general problem of face recognition remains unsolved, since most of the systems to date can only successfully recognize faces when images are obtained under constrained conditions. Their performance will degrade abruptly when face images are captured under varying lighting conditions, poses, expressions, ages and so on.

In earlier works, geometric feature-based methods[3–7] have been widely investigated. Feature-based methods use properties and relations (e.g. distances and angles) between facial features, such as eyes, mouth, nose, and chin to perform recognition. One of the most successful systems is elastic bunch graph matching (EBGM) system,[6] which is robust to illumination change, translation, distortion, rotation, and scaling. Although the feature-based representation methods are insensitive to variations in illumination and pose, precise alignment and facial feature extraction process, however, are critical for their performance.

Later, appearance-based methods have been introduced which use low dimensional representations of objects to perform recognition.[8–15] Eigenfaces[8] and Fisherfaces[12] have demonstrated the power of appearance-based methods both in ease of implementation and in recognition accuracy. Their performance, however, will be degraded when the distribution of the test images is different from that of the training images.

One of the main difficulties for face recognition arises from large within-class variations (due to illumination, facial expression, aging) and rather small between-class variations (due to similarity of individual appearances) in human face images. These variations include the local variations (e.g. wrinkles appearing at the mouth corner) and the global variations (e.g. lighting can change the whole variation of face image). Therefore, robust face representation against facial variations is critical for a practical face recognition system.

Recently, local binary patterns (LBP) operator has been successfully used for face detection[16] and recognition.[17] Face representation with LBP encodes both the local and global information by a concatenated LBP histogram. Facial feature extracted by the LBP operator is robust to illumination variations because the LBP features are invariant to the monotonic gray-scale changes. The authors reported the state-of-the-art results on the FERET face database. However, under the condition of varying lighting and aging, its performance is still not satisfactory.

Since multiresolution histograms could improve the performance of object classification,[18] meanwhile, Gabor based face representation is robust to illumination variations[6] and efficient to describe local image features.[19] We have proposed combining Gabor wavelets with LBP operator to represent face image to obtain robust feature against facial variations. The combining operator is termed as local Gabor binary patterns (LGBP)[20] operator. In this method, firstly, we obtain the multiresolution images by convolving the face image with multi-scale and multi-orientation Gabor filters. Secondly, LBP operator is conducted on the multiresolution images to obtain the LGBP images. Thirdly, local histograms are extracted from the LGBP images and all the local LGBP histograms are concatenated into one histogram to represent the given face image. Experimental results have demonstrated that the performance of face recognition with LGBP is superior to both of LBP-based approach[17] and Gabor-based approach.[19]

However, face representation with LGBP is high dimensional due to the multiple Gabor transformations of LGBP operator. Thus further dimensionality reduction is necessary after obtaining the LGBP histograms. There are two major categories of methods of dimensionality reduction, feature selection and feature transform. *Feature selection* methods keep only useful features and discard others. *Feature transform* methods construct new features out of the original ones.

In this paper, we propose to use the mutual information between the features as a criterion for dimensionality reduction to select the effective discriminant feature. Meanwhile, the separability of features is determined by Fisher linear discriminant between the class labels and the features. The approach considers the separability of each local LGBP histogram and the relevance between the local LGBP histograms. By selecting the local LGBP histograms with high separability and low relevance, this approach not only can reduce the dimensionality of face representation with LGBP, but also can bring impressive performance improvement for face recognition.

The rest of this paper is organized as follows. Section 2 presents the face representation and recognition with LGBP. Section 3 introduces how to select the effective discriminant features based on Fisher linear discriminant and mutual information. Section 4 reports on the experimental results. Finally, Sec. 5 concludes the paper.

2. Local Gabor Binary Patterns for Face Representation and Recognition

In this section, we first briefly introduce Gabor wavelets for face representation and LBP operator. Then, we describe the local Gabor binary patterns (LGBP) operator. In the last two subsections, we give face representation and recognition using LGBP.

2.1. *Gabor wavelets for face representation*

The 2D Gabor wavelets can be defined as follows[21]:

$$\psi_{\nu,\mu}(z) = \frac{\|k_{\nu,\mu}\|^2}{\sigma^2} e^{(-\|k_{\nu,\mu}\|\|z\|2\sigma^2)} \left[e^{ik_{\nu,\mu^2}} - e^{-\sigma^2/2}\right], \tag{1}$$

where ν and μ define the scale and orientation of the Gabor wavelets, $z = (x, y)$, $\|\cdot\|$ denotes the norm operator, and the wave vector $k_{\nu,\mu} = k_\nu e^{i\phi_\mu}$, where $k_\nu = k_{\max}/\lambda^\nu$ and ϕ_μ is the orientation parameter, λ is the spacing factor between wavelets in the frequency domain.

The Gabor transformation of a face image can be obtained by convolving the face image with the Gabor wavelets. Let $f(x, y)$ be the intensity of a face image, the convolution of $f(x, y)$ with a Gabor wavelet $\psi_{\nu,\mu}(x, y)$ can be defined as:

$$\mathrm{O}_{\nu,\mu}(x, y) = f(x, y) * \psi_{\nu,\mu}(x, y), \tag{2}$$

where $*$ denotes the convolution operator. The magnitudes of the convolution slowly vary across the whole face image. This property implies that face representation using the magnitudes of Gabor transformation is insensitive to local variations in face image. Thus, only the magnitudes are considered in this study. To obtain multi-resolution Gabor features, five different scales $\nu \in \{0, 1, \ldots, 4\}$ and eight orientations $\phi_\mu = \pi\mu/8$, $\mu = 0, 1, \ldots, 7$ Gabor filters are used, as in.[19,22–24]

2.2. *Local binary patterns*

The original LBP operator, first proposed by Ojala *et al.*[25] is a powerful means of texture descriptor.[26] The basic version of the LBP operator labels the pixels of an image by thresholding the neighborhood of each pixel with the center value and considering the result as a binary string.

Figure 1 shows an example of the convolution results, i.e. the 40 Gabor "images" of the magnitudes.

Formally, as shown in Fig. 2(a), let the eight neighbors of the center pixel located at (x_c, y_c) be (x_p, y_p), $p = 0, 1, \ldots, 7$. The LBP pattern at (x_c, y_c) is calculated as:

$$LBP(x_c, y_c) = \sum_{p=0}^{7} S(f(x_p, y_p) - f(x_c, y_c))2^p, \tag{3}$$

where

$$S(A) = \begin{cases} 1, & A \geq 0 \\ 0, & A < 0 \end{cases}.$$

Intuitively, the pth bit stands for the order relationship between the center pixel and its pth neighbor. The LBP approach codifies the occurrence of some micro-patterns, such as spot, edge, corner, etc. Figure 3 shows the LBP image of an example face image.

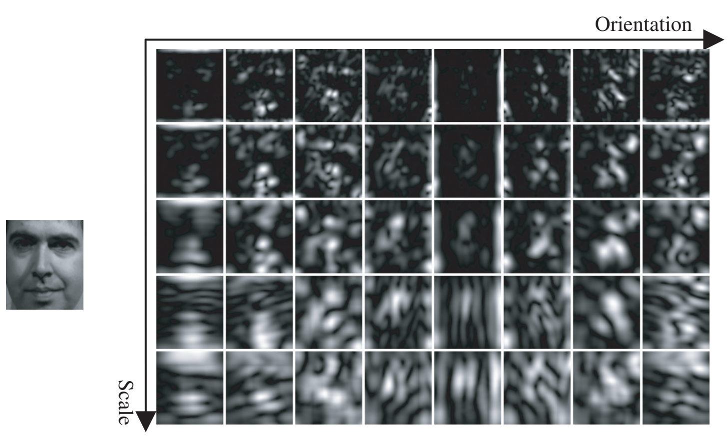


Fig. 1. Gabor representation of a sample image.

0	1	2
7		3
6	5	4

(a) The position order of p.

2^0	2^1	2^2
2^7		2^3
2^6	2^5	2^4

(b) The corresponding weight.

Fig. 2. LBP operator.

(a) A face image. (b) The LBP image.

Fig. 3. The LBP image of a sample image.

2.3. *Local Gabor binary patterns*

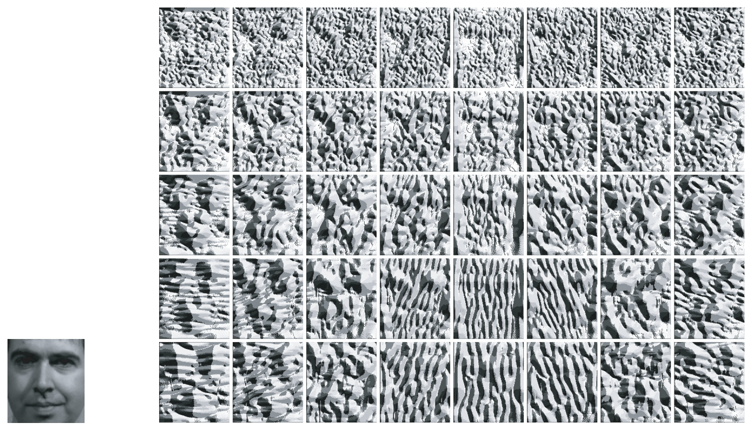
A signal can be decomposed into different frequency sub-bands by applying Gabor transformation. Thus the signals which can not be classified in a certain scale will be distinguished in some other frequencies. Meanwhile, the fine local features of the signal can be extracted by Gabor transformations. In addition, Gabor filter can smooth the noise in signal to some degree. It is a reasonable way to combine Gabor and LBP to improve the performance of LBP for face representation.

Given a face image, its features are first extracted by convolving the image with multiple Gabor filters at different scales and orientations. Then, LBP operator is exploited to encode the micro-patterns of the Gabor features. The combining of Gabor and LBP operator is called Local Gabor Binary Pattern (LGBP) operator. Formally, the LGBP operator is defined as:

$$LGBP_{\nu,\mu}(x_c, y_c) = \sum_{p=0}^{7} S(\mathrm{O}_{\nu,\mu}(x_p, y_p) - \mathrm{O}_{\nu,\mu}(x_c, y_c))2^p, \tag{4}$$

where $\psi_{\nu,\mu}$ is the Gabor filter, ν and μ are the scale and orientation parameter respectively, as explained in Eq. (1).

Thus, by enumerating the 40 Gabor filters (5 scales and 8 orientations), 40 LGBP images can be obtained. Figure 4 shows the visualization of the LGBP images of an input face image.



(a) A face image. (b) The visualization of LGBP images.

Fig. 4. LGBP images of a sample image.

2.4. *Face representation with LGBP*

Histogram is used to collect up the occurrences of different patterns in LGBP image. To avoid the loss of spatial information in face representation by histogram, we divide the LGBP image into non-overlapping multi-regions and extract histogram from each sub-region. All the histograms are concatenated into a single histogram to represent the given face image. Assume each LGBP image is divided into n regions, and $\mathrm{H}_{\nu,\mu,r}$ denotes the histogram of (ν,μ,r)th region. Then, the final face representation by LGBP can be denoted as $\mathrm{H} = (\mathrm{H}_{0,0,0},\ldots,\mathrm{H}_{0,0,n-1},\mathrm{H}_{0,1,0},\ldots,\mathrm{H}_{0,1,n-1},\ldots,\mathrm{H}_{4,7,n-1})$. Figure 5 shows the face representation with LGBP.

2.5. *Face recognition with LGBP*

This section presents how LGBP representation is applied to face recognition. Histogram interaction is used to measure the similarity of different histograms. The

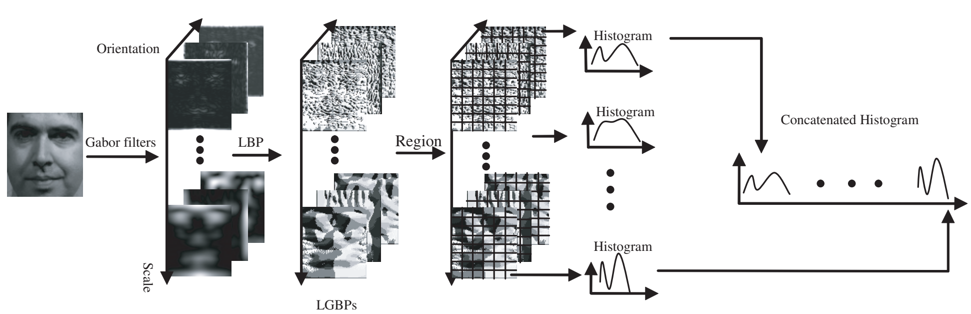


Fig. 5. Face representation with LGBP.

advantage of histogram intersection is that features occurred in one of the histograms are neglected. So the influence of the variation in different images of the same subject can be reduced further.

The intersection measurement of two histograms[27] can be defined as:

$$\mathrm{I}(\mathbf{h}^1, \mathbf{h}^2) = \sum_{i=0}^{L-1} \min(\mathbf{h}_\mathrm{i}^1, \mathbf{h}_\mathrm{i}^2), \tag{5}$$

where $\mathbf{h}^1$ and $\mathbf{h}^2$ denote histogram and L is the number of histogram bins. Using this measurement, the similarity of two face images represented by LGBP is:

$$\mathrm{S}(\mathrm{H}^1, \mathrm{H}^2) = \sum_{\nu=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{R-1} \mathrm{I}\big(\mathrm{H}_{\nu,\mu,r}^1, \mathrm{H}_{\nu,\mu,r}^2\big), \tag{6}$$

where H^1 and H^2 denote two LGBP histograms.

3. An Effective Discriminant Feature Selection

As has mentioned above, though LGBP achieves very impressive recognition rate for face recognition, its representation concatenating a great number of local histograms is relatively too high dimensional from the point of view of both storage and classifier designing. Therefore, in this section, we further propose method of feature selection based on mutual information to reduce the dimensionality of LGBP-based face representation.

3.1. *Separability analysis based on fisher linear discriminant*

Previous works show that some facial areas contain more discriminative information than others in terms of distinguishing between subjects.[2] To take advantage of these cues, a weight can be set to each area based on its contribution to classification. In this case, the similarity of two face images represented by weighted LGBP can be defined as:

$$\mathrm{S}'(\mathrm{H}^1, \mathrm{H}^2) = \sum_{\nu=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{R-1} \mathrm{W}_{\nu,\mu,r}\big(\mathrm{I}\big(\mathrm{H}_{\nu,\mu,r}^1, \mathrm{H}_{\nu,\mu,r}^2\big)\big), \tag{7}$$

where H^1 and H^2 denote two LGBP histograms, $\mathrm{W}_{\nu,\mu,r}$ denotes the weight of the (ν, μ, r)th region.

In this study, the weight of each region is learned by Fisher linear discriminant[28] which can achieve the purpose of high separability between different patterns. It is generally believed that the similarities of different images from the same subject are higher than those of from the different subjects. Based on this intuition, we define two distinct and mutually exclusive classes: Ω_b representing the similarities of inter-class (corresponding to the similarity between two local region LGBP histograms extracted from two images of different subjects) and Ω_w representing the similarities of intra-class (corresponding to the similarity between two local region LGBP histograms extracted from two images of one subject).

The similarities mean $m_{w,(\nu,\mu,r)}$ and variance $S^2_{w,(\nu,\mu,r)}$ of intra-class Ω_w can be defined as:

$$m_{w,(\nu,\mu,r)} = \frac{1}{N_w} \sum \mathrm{I}\big(\mathrm{H}^i_{\nu,\mu,r}, \mathrm{H}^j_{\nu,\mu,r}\big), \tag{8}$$

$$S^2_{w,(\nu,\mu,r)} = \frac{1}{N_w} \sum \left(\mathrm{I}\big(\mathrm{H}^i_{\nu,\mu,r}, \mathrm{H}^j_{\nu,\mu,r}\big) - m_{w,(\nu,\mu,r)}\right)^2, \tag{9}$$

where $\mathrm{H}^i_{\nu,\mu,r}$ and $\mathrm{H}^j_{\nu,\mu,r}$ denote the (ν, μ, r)th local region histograms from two images of the same subject, N_w is the number of sample in intra-class.

The similarities mean $m_{b,(\nu,\mu,r)}$ and variance $S^2_{b,(\nu,\mu,r)}$ of inter-class can be defined as:

$$m_{b,(\nu,\mu,r)} = \frac{1}{N_b} \sum \mathrm{I}\big(\mathrm{H}^i_{\nu,\mu,r}, \mathrm{H}^j_{\nu,\mu,r}\big), \tag{10}$$

$$S^2_{b,(\nu,\mu,r)} = \frac{1}{N_b} \sum \left(\mathrm{I}\big(\mathrm{H}^i_{\nu,\mu,r}, \mathrm{H}^j_{\nu,\mu,r}\big) - m_{b,(\nu,\mu,r)}\right)^2, \tag{11}$$

where $\mathrm{H}^i_{\nu,\mu,r}$ and $\mathrm{H}^j_{\nu,\mu,r}$ denote the (ν, μ, r)th local region histograms from two images of the different subjects, N_b is the number of samples in inter-class. The region with higher separability should have higher difference of $m_{b,(\nu,\mu,r)}$ and $m_{w,(\nu,\mu,r)}$ and lower sum of $S^2_{w,(\nu,\mu,r)}$ and $S^2_{b,(\nu,\mu,r)}$. Therefore, the weight of each region can be set by Fisher linear discriminant:

$$\mathrm{W}_{\nu,\mu,r} = \frac{(m_{w,(\nu,\mu,r)} - m_{b,(\nu,\mu,r)})^2}{S^2_{w,(\nu,\mu,r)} + S^2_{b,(\nu,\mu,r)}}. \tag{12}$$

The higher value of $\mathrm{W}_{\nu,\mu,r}$ represents the greater class separability of the region. The method is represented as F_LGBP.

3.2. *Feature selection based on mutual information*

The multi-scale and multi-orientation Gabor transformations lead to high dimensional face representation using LGBP. Moreover, the relevance between the local LGBP histograms also disturbs the performance. To reduce computational burden and improve the performance, effective components for classification should be selected from local LGBP histograms using the feature selection methods.

Since mutual information does not need to assume the distribution of the data and overcomes many limitations of feature selection approaches, it has been used widely in feature selection. However, face recognition is a multi-class classification problem and each class has only a few samples. The lack of samples in high dimensional space leads to the difficulty in estimating the sample probability density. But when the multi-class classifier transforms to within-class and between-class (two classes), as described in Sec. 3.1, the density of samples will enhance, and the estimation of probability density will be more accurate. Therefore, we define the importance of feature by considering the separability of regions learned from Fisher linear discriminant criterion and the mutual information among regions to select important regions for classification.

We first briefly introduce the definition of mutual information. An ensemble X is a triple $(x, \mathrm{A}_X, \mathrm{P}_X)$, where the outcome x is the value of a random variable, which takes on one of a set of possible values, $\mathrm{A}_X = \{a_1, a_2, \ldots, a_i, \ldots, a_I\}$, having probabilities $\mathrm{P}_X = \{p_1, p_2, \ldots, p_I\}$. The Shannon information content of a random variable x is defined to be $h(x) = -\log_2 P(x)$. The entropy of an ensemble X is defined to be the average Shannon information content of a random x[30]:

$$H(X) = \sum_{x \in \mathrm{A}_X} -P(x) \log P(x). \tag{13}$$

The conditional entropy of X given Y is the average, over y, of the conditional entropy of X given y:

$$\begin{aligned} H(X|Y) &= \sum_{y \in \mathrm{A}_Y} P(y) \left[\sum_{x \in \mathrm{A}} -P(x|y) \log P(x|y) \right] \\ &= \sum_{xy \in \mathrm{A}_X \mathrm{A}_Y} -P(x, y) \log P(x|y) \end{aligned}. \tag{14}$$

The mutual information between X and Y is defined as:

$$I(X; Y) = H(X) - H(X|Y). \tag{15}$$

Since evaluating mutual information between two scalar variables is feasible through histograms, local LGBP histogram extracted from a region is used to denote its probability. Let f_i denote the histogram extracted from a region of an LGBP image and F is a feature set. We define the relevance of different regions as:

$$rel(f_m, f_n) = \frac{I(f_m; f_n)}{\max(I(f_k; f_l))}, \quad \text{for all } k \neq l. \tag{16}$$

Though the histogram-based mutual information estimation works with two or even three variables, it fails in higher dimensions due to the lack of data in high-dimensional spaces for histogram-based estimation. Considering the limitation, we use the maximum relevance of the feature and all the other features in the feature set instead of calculating the mutual information of multiple variables. The relevance between $f_m \notin F_s$ and F_s can be defined as:

$$rel(f_m, F_s) = \max(rel(f_m, f_k)), \quad \text{for } \forall f_k \in F. \tag{17}$$

Considering the weight W_m and the relevance between features, we define the effectiveness of discriminant feature as:

$$\mathrm{W}_m^*(f_m) = \mathrm{W}_m \times (1 - rel(f_m, F_s)), \tag{18}$$

and denote it as FM_LGBP.

Thus, the similarity of two face images can be calculated as:

$$\mathrm{S}'(\mathrm{H}^1, \mathrm{H}^2) = \sum_{\nu=0}^{4} \sum_{\mu=0}^{7} \sum_{r=0}^{\mathrm{n}-1} \mathrm{W}^*_{\nu,\mu,r} \left(\mathrm{I}\left(\mathrm{H}^1_{\nu,\mu,r}, \mathrm{H}^2_{\nu,\mu,r} \right) \right). \tag{19}$$

The flow chart of the proposed algorithm is shown in Fig. 6.

Input
(1) training set $S = \{(s_1, \nu_1), K, (s_N, \nu_N)\}$
(2) feature space $F = \{f_1, K, f_M\}$
(3) M^* dimensions of selected feature subset F^*
(4) ε: a small constant
Initialize: the selected feature subset $F^* \Leftarrow \{\ \}$
Set the undetermined feature set $F' \Leftarrow F$
for each feature $f_m \in F'$ do
Set $F' \Leftarrow F' - \{f_m\}\ if\ \mathrm{W}_{\mu,\nu,r} < \varepsilon$
End for
for i = 1 to M^* do
Find feature $f_1 \in F'$, $f_1 = \mathrm{argmax}\{\mathrm{W}^*(f_m)|f_m \in F'\}$
Set $F^* \Leftarrow F^*\mathrm{Y}\{f_1\}$ and $F' \Leftarrow F' - \{f_1\}$
Update $\mathrm{W}^*(f_m)$; if $\mathrm{W}^*(f_m) < \varepsilon$, set $F' \Leftarrow F' - \{f_m\}$
End for
Output: the selected feature subsect: F^*; F^* and W^*

Fig. 6. The flow chart of the effective feature selection algorithm.

4. Experiments

4.1. *The effectiveness of the proposed approach*

To verify the effectiveness of the proposed approach, we first test the variation of the recognition rates under the condition of the number of the selected local LGBP histograms with W^* from high to low. The experiment is conducted on the FERET face database.

The FERET face database[29] contains training set, gallery and probe sets. The training set which is used to train the model for face representation contains 1002 frontal images of 429 subjects. The gallery contains the set of the known individuals which consist of 1196 subjects with one image per subject. The probe set contains the unknown individuals, and it is used to test the face recognition algorithm. The **FB** (facial expression) probe set contains 1195 probe images taken on the same day and under the same illumination conditions as the corresponding gallery images. The **fc** probe set contains 194 images taken on the same day as the corresponding gallery images, but with a different camera and lighting condition. The duplicate I and duplicate II probe sets contain 722 and 234 duplicate (aging) frontal images in the FERET face database for the gallery images. Figure 7 shows some example images of the FERET face database.

In our experiments, a face image is geometrically and photometricaly normalized as an image patch of 80×88 pixels. In order to keep more spatial information, we choose a smaller region with the size of 4×8 pixels. Therefore, there are 220 regions in each LGBP image and 8800 regions for face representation by LGBP.

(a) Gallery image

(b) **FB** (c) **fc** (d) Dup.I (e) Dup.II

Fig. 7. Example images in the FERET face database.

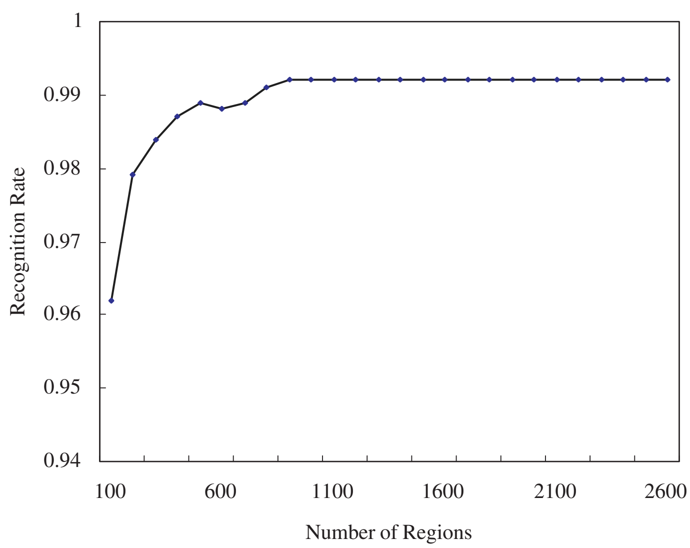


Fig. 8. The recognition rate with the variation of the feature dimension on **FB** set.

For classification, a nearest-neighbor classifier is used. The recognition result on **FB** set is shown in Fig. 8.

From Fig. 8, we can see that the recognition rate increases with the number of the selected regions (the number of the local LGBP histograms) increasing. Using fewer local LGBP histograms which have higher W^*, we could achieve good performance for recognition.

4.2. *Experiments on the FERET face database*

To validate the proposed approach, we conduct experiments on the FERET face database using the standard FERET evaluation protocol.[29] We compare the performance of the proposed approach with Fisherfaces,[12] Gabor-Fisher Classifier (GFC),[19] as well as the best results of FERET97,[29] the best results of LBP.[17] For Fisherfaces, GFC, and the proposed approach, they are all trained on the FERET training set. The experimental results are given in Table 1.

From Table 1, it can be seen that the proposed FM_LGBP method outperforms all the other approaches on all the probe sets. For instance, under different lighting conditions (fc set), FM_LGBP has achieved the best performance with recognition rate of 98% against 79%, 82%, 84% and 73% for LBP, best of FERET97, GFC, and Fisherfaces, respectively.

Additionally, the LGBP-based approach also performed better than the others on recognizing duplicate faces (when the face images are taken later in time). Moreover, the dimension of face representation with FM_LGBP is only about 6% of F_LGBP, while the recognition rates of FM_LGBP are all higher than those of F_LGBP. Especially on duplicate I and duplicate II, the recognition rates improve 5% and 9% respectively.

4.3. *Experiments on the CAS-PEAL face database*

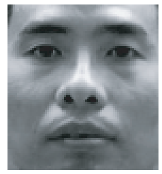
To further verify the effectiveness of the proposed approach, we conduct the experiment on the CAS-PEAL face database. The CAS-PEAL face database[31] contains 1040 subjects and the protocol of CAS-PEAL face database is the same as to the FERET face database. The training set involves 1200 images of 300 subjects. The gallery contains 1040 subjects with one image per subject. The experiment is conducted on the expression set, which includes different facial expressions and consists of 1570 images of 377 subjects. Figure 9 shows the example images in the CAS-PEAL face database. The experimental results are shown in Table 2.

From the results of Table 2, it can be seen that FM_LGBP also outperforms all the other methods. The result of F_LGBP is higher than that of LGBP. So, we can see that not only the separability analysis based on Fisher linear discriminant is

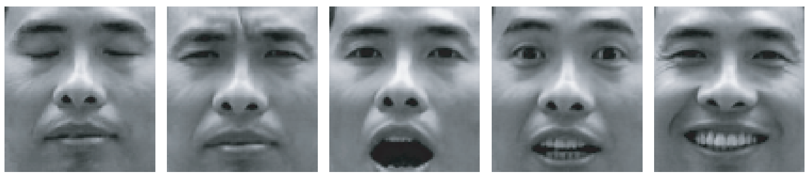
Table 1. The recognition rates of different methods on the FERET face database.

Methods	**FB**	**fc**	Duplicate I	Duplicate II
Fisherfaces	0.94	0.73	0.55	0.31
GFC	0.95	0.84	0.67	0.61
FERET97[29]*	0.96	0.82	0.59	0.52
LBP[17]*	0.97	0.79	0.66	0.64
LGBP	0.94	0.97	0.68	0.53
F_LGBP	0.98	0.97	0.74	0.71
FM_LGBP	0.99	0.98	0.79	0.80

Note: *denotes the results are cited directly from the original paper.



(a) gallery image.



(b) Expression images.

Fig. 9. Example images of the CAS-PEAL face database.

Table 2. The recognition rates of different methods on the CAS-PEAL face database.

Methods	Expression
Fisherfaces	0.803
GFC	0.942
LGBP	0.946
F_LGBP	0.948
FM_LGBP	0.952

effective for classification, but the feature selection based on the relevance and the separability analysis also improve the performance.

5. Conclusion

In this paper, we proposed a novel face recognition approach using the effective LGBP representation. A face image is first described by a concatenated LGBP histogram. Then, the local LGBP histograms with high separability and low relevance between local LGBP histograms are selected. The method not only significantly reduces the dimension of face representation using LGBP histogram, but also improves the performance of face recognition. Since the proposed approach encodes global information as well as local information of a face, it is robust to variation of expression, illumination, and aging. Experiments on the standard FERET face database and the CAS-PEAL face database show the effectiveness of the proposed approach.

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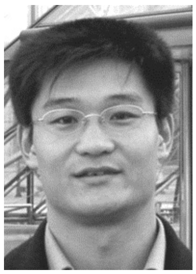

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