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ORIGINAL PAPER

Selective local texture features based face recognition with single sample per class

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Abstract Local appearance-based methods have been successfully applied to face recognition and achieved state-of-the-art performance. In this paper we propose a local selective feature extraction approach based on Gabor filters and the Local Binary Pattern (LBP) approach to face recognition. A Gabor filter extracts the textural features from the face image and generates the binary face template using those features. The binary face template acts like a mask to extract the local texture information of the face image using a Local Binary Pattern technique. This selective local texture feature approach uses the histogram-based matching for face recognition. This method reduces the computation time considerably. This method also reduces the number of Local Binary Patterns into half compared to the existing LBP method. This proposed approach reduces the computation time for the FERET dataset by 45%. Experiments on well-known face databases such as FERET, Yale, Indian Faces and ORL show that this approach obtains consistent and promising results in the scenario of one training sample per person with significant facial variation.

Keywords Face recognition · Local Binary Pattern · Gabor filter · Binary face template · Expression invariant face recognition · Single Sample Problem

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1 Introduction

In recent years, face recognition has received much attention in many areas such as entertainment, information security, law enforcement, and surveillance [36]. Most of the face-recognition methods such as eigenfaces [26], Fisher faces [4] and Laplacian faces [9], nearest feature line-based subspace analysis, neural networks [14, 25], elastic bunch graph matching [30] and kernel methods [33] were initially developed with face images collected under relatively well controlled conditions, and in practice they have difficulty in dealing with the range of variation of the appearance that commonly occurs in unconstrained natural images due to illumination, pose, facial expression, ageing and partial occlusions. Another most challenging problem for face recognition is the so-called Single Sample Problem (SSP), where the training process uses a single sample per subject. In some specific scenarios, such as law enforcement, passport or identification card verification etc., only one image per person is available for training. Some face-recognition algorithms [5, 6, 18, 24, 25] were proposed to solve the one-sample problem in various process modes. Face-recognition methods are generally divided into two categories: holistic matching methods and local matching methods.

The holistic matching approaches use the whole face region as input to the face-recognition system. The principle of holistic methods is to build a subspace using Principal Component Analysis (PCA) [26], Linear Discriminant Analysis (LDA) [4, 7, 31] or Independent Component Analysis (ICA) [3]. The face images are then projected and compared in a low-dimensional subspace to avoid the curse of dimensionality. Wang and Tang [27] have unified PCA, LDA and Bayesian methods into the same framework and present a method to find the optimal configuration for LDA. In order to handle the nonlinearity in face feature space, nonlinear kernel techniques such as kernel PCA [23], kernel LDA [18] etc. are also introduced.

Compared with holistic methods, local methods are more suitable for handling the one-sample problem due to the following observations: Firstly, in local methods, the low-dimensional local feature vectors represent the original face rather than one single full high-dimensional vector. Thus the "curse of dimensionality" is alleviated from the beginning. Secondly, local methods offer more flexibility to recognize a face based on its parts; thus the common and class-specific features are easily identified. Thirdly, different facial features improve the classifiers diversity, which is helpful for face identification. The local matching approaches have shown some promising results in face recognition [1, 2, 8, 12, 13, 15–17]. These methods first extract several facial features and then make a comparison on the basis of local statistics for recognition. The comparison of local approaches with global approaches shows that the local system outperformed the global system with 60% [10]. There exist several local appearance-based methods for extracting the most useful features from face images to address face recognition.

The Local Binary Pattern (LBP) method [19] was originally proposed as an image texture descriptor [20], but it also applied on face-recognition application [1]. Face recognition using the LBP method [2] provides very good results, both in terms of speed and discrimination performance. More recent work on LBP [28], the Heat Kernel Local Binary Pattern (HKLBP) descriptor, extracts multiscale Heat Kernel Structural Information (HKSI) matrices to capture the intrinsic structural information of the face appearance. Then, the Local Binary Pattern analysis on HKSI matrices provides the HKLBP descriptor for the representation of the face. The feature extraction with LBP is a straightforward (real-time) process. Due to this reason LBP has a positive influence on the processing speed and integration of the method in a new environment. One more benefit of LBP is that it is less sensitive to variations of the illumination of the image. It is also less sensitive to rotation and scaling variations.

A Gabor features-based [16] face representation has attained more attention in computer vision, image processing, pattern recognition, and so on. Wenchao et al. [29] present a Local Gabor-based Binary Pattern Histogram Sequence (LGBPHS) [29] for face representation by combining the Gabor and LBP descriptors. This approach much improves LBP's robustness to illumination changes. The Gabor phase [35] was also used to improve the recognition rate and a typical method [34] of this class is the histogram of Gabor phase patterns (HGPP), which captures the global Gabor phase and local Gabor phase variation.

Gabor filters can exploit salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristics. Due to its great success in face recognition, this paper addresses Gabor features to represent the face in the form of a binary face template. In this paper we propose a selective local texture features-based face representation for face recognition with a single sample per class.

The rest of the paper is organized as follows. Section 2 gives a brief introduction on LBP and the Gabor filter. Section 3 presents the selective local texture features-based face descriptors that are proposed. Experimental results are given in Sect. 4, which compares the performances of the LBP method with the selective local LBP method on the expression, accessories and slightly view-point variant faces of the Yale, ORL and FERET databases. Section 5 concludes the paper.

2 Outline of LBP and Gabor filter

In this section, we provide a brief review of the Local Binary Pattern and the Gabor filter.

2.1 Local Binary Pattern

Ojala et al. [19] introduced the Local Binary Pattern operator in 1996 as a means of summarizing the local grey-level structure. The operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3×3 neighborhoods, giving 8-bit codes based on the eight pixels around the central one.

Formally, the LBP operator takes the form

$$\mathrm{LBP}(x_c, y_c) = \sum_{n=0}^{7} 2^n s(i_n - i_c)$$

where in this case n runs over the eight neighbors of the central pixel c, i_c and i_n are the grey-level values at c and n, and $s(u)$ is 1 if $u \geq 0$ and 0 otherwise. Figure 1 illustrates the LBP encoding process.

To be able to deal with textures at different scales, the LBP operator was later extended to use circular neighborhoods of different sizes. Ahonen et al. [1] introduced a LBP-based method for face recognition [2] that divides the face into a regular grid of cells and finds histograms for the uniform LBPs within each cell. Finally, the cell-level histograms concatenation produces a global descriptor vector.

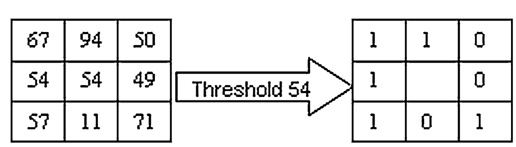

Fig. 1 Illustration of the LBP operator

2.2 Gabor filter

A Gabor filter works as a band pass filter for the local spatial frequency distribution, achieving an optimal resolution in both the spatial and the frequency domain. The 2D Gabor filter $\psi_{f,\theta}(x, y)$ is represented as a complex sinusoidal signal modulated by a Gaussian kernel function as follows:

$$\varphi_{f,\theta}(x, y) = \exp\left[-\frac{1}{2}\left\{\frac{x^2\theta_n}{\sigma^2 x} + \frac{y^2\theta_n}{\sigma_y^2}\right\}\right]\exp\left(2\prod f x\theta_n\right)$$

$$\begin{bmatrix} x\theta_n \\ y\theta_n \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix}$$

σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y dimensions; f is the central frequency of the sinusoidal plane wave and θ the orientation. The rotation of the x–y plane by an angle θ_n will result in a Gabor filter at the orientation θ_n. The angle θ_n is defined by

$$\theta_n = \frac{\pi}{p}(n-1)$$

for $n = 1, 2, \ldots, p$ and $p \in N$, where p denotes the number of orientations. The design of the Gabor filters is accomplished by tuning the filter with a specific band of spatial frequency and orientation by appropriately choosing σ_x and σ_y, the radial frequency, f, and the orientation of the filter, θ_n.

3 Proposed approach

This section describes the proposed selective local texture feature extraction based on the Gabor binary face template.

3.1 Gabor filter-based binary face template creation

In this case, first we make the Gabor representation of a face image. The convolution process of a face image with the Gabor filter provides the Gabor representation of that face. Let $I(x, y)$ be the intensity at the coordinate (x, y) in a grey-scale face image; its convolution with the Gabor filter $\psi_{f,\theta}(x, y)$ is defined as

$$\mathrm{g}_{\mathrm{f},\theta}(X, Y) = \mathrm{I}(X, Y) \otimes \Psi_{\mathrm{f},\theta}(X, Y)$$

where $\otimes$ denotes the convolution operator. The response to each Gabor kernel filter representation is a complex function with real part $\Re\{g_{f,\theta}(\mathrm{x,y})\}$ and an imaginary part $\Im\{g_{f,\theta}(x, y)\}$. The magnitude response is expressed as

$$\|g_{f,\theta}(X, Y)\| = \sqrt{\mathrm{R}^2\{\mathrm{g}_{\mathrm{f},\theta}(x, y)\} + \mathrm{F}^2\{\mathrm{g}_{\mathrm{f},\theta}(x, y)\}}$$

We generate the binary face template (BFT) from the real part of the complex information of the Gabor representation as

$$\mathrm{BFT}(X, Y) = 1 \quad \text{if } \Re\{\mathrm{g}_{\mathrm{f},\theta}(X, Y)\} > 0$$

$$\mathrm{BFT}(X, Y) = 0 \quad \text{if } \Re\{\mathrm{g}_{\mathrm{f},\theta}(X, Y)\} \le 0$$

3.2 Selective Local Binary Pattern

Normally the Local Binary Pattern approach generates the LBP for each pixel of the face image to describe that face. But in this approach it is enough to generate LBP for selective pixels of the face image to represent that face. Figure 2 shows the response of the Gabor filter on the image of the face and its corresponding binary face template image.

The response of the Gabor filter for a face image provides the local image features efficiently. On the basis of those local image features, we generate the binary face template. The binary face template clearly describes the region which has more information on the variation of the local texture, which is a feature robust against facial variations. Only for that reason we in our proposed approach use Gabor filters before LBP as an efficient feature selection process for face recognition.

This approach generates the Local Binary Pattern only for the pixel in the $I(x, y)$, which has the value of one in the corresponding $\mathrm{BFT}(x, y)$. Due to this, we reduce the number of pattern generations.

The Gabor filter-based selected region of a face gives more unique information about that face. Hence there is no variation in the performance due to the missing pixels. So we probably get a good matching score with less computation overhead. Similar to LBP the feature extraction with this approach is also a straightforward (real-time) process. So there is no need for training.

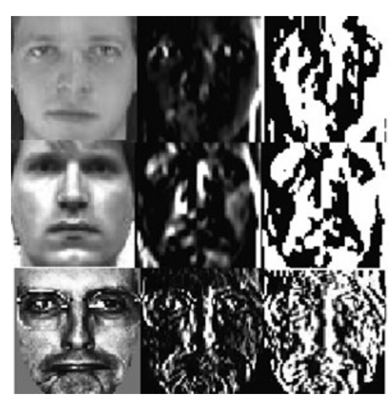

Fig. 2 The *first column* shows sample faces from the ORL, Yale and FERET datasets. The *second column* shows the response of the Gabor filter. The Gabor filter features-based generated binary face templates are shown in the *third column*

Fig. 3 Some cropped faces used in this experiment

Table 1 Experimental Databases

Face Dataset	No. of testing persons	No. of testing images	Primary variations in the testing dataset
Yale	15	150	Expression, Illumination Accessories
ORL	40	252	Expression, View- point
FERET	1 196	1 195	Expression
Indian Faces	60	600	Expression, Pose Variation

Fig. 4 Given test image of size (64×64)

4 Experimental results

This section evaluates the recognition performance of LBP and the selective local feature extraction based on a Gabor filter and LBP on the Single Sample Problem.

We test the proposed approach for face recognition using the Yale [32], ORL [21], Indian Faces [11] and FERET Databases [22].

All images in Yale and ORL are cropped to the size of 64×64 from the middle of the location of the eye. In the training section we are using one frontal image for each subject.

In the Indian Face database images of 60 persons with 10 sample images with different orientations and views are available. The resolution of the images we used in the algorithm is 128×128 for computational purpose.

We test the recognition performance of the proposed feature selection approach with the FERET database [22] according to the standard FERET evaluation protocol, which has exactly defined the gallery and probe sets. In the case of the FERET dataset the images are registered using eye coordinates and cropped with an elliptical mask to exclude the non-face area from the image. After this, we do a grey-level histogram equalization over the non-masked area. In our experiments, we strictly test the methods based on the standard gallery (1 196 images of 1 196 subjects) and expression probe set fb (1 195 images).

Figure 3 shows some sample images for each dataset. The first row shows faces from the Yale database. The second row shows faces from the ORL database. The third row shows faces from the FERET dataset. The fourth row shows the faces from the Indian Face dataset.

The number of distinct subjects and the number of testing images in the respective databases are shown in Table 1.

The Gabor filter used for our approach has single frequency (0.2) and single orientation (90^{θ}) with a window size of 5×5 as its parameters. For an efficient representation of the face, first the image is divided into k^2 regions. In this experiment we divide a face image of the size 64×64 into $8^2 = 64$ regions. For every region a histogram with all possible labels is constructed. This means that every bin in a histogram represents a pattern and contains the number of appearances of it in the region. The feature vector is then constructed by concatenating the regional histograms to one big histogram. For every region all non-uniform patterns (more than two transitions) are labeled with one single label. This means that every regional histogram consists of $P\ (P-1)+3$ bins, where $P=8$. We have $P\ (P-1)$ bins for the patterns with two transitions, two bins for the patterns with zero transitions and one bin for all non-uniform patterns. The total feature vector for an image contains $k^2 \times (P(P-1)+3)$ bins. So, for an image divided into 64 regions and eight sampling points on the circles, the feature vector has a size of 3776 bins. The LBP code cannot be calculated for the pixels in the area with a distance R from the edges of the image. For an $N \times M$ image the feature vector is constructed by calculating the LBP code for every pixel (x_c, y_c) with $x_c \in \{R+1, \dots, N-R\}$ and $y_c \in \{R+1, \dots, M-R\}$.

The number of patterns and computation time reduction for the single face in Fig. 4 is shown in Table 2. From the above result we can find that in the traditional LBP method the pattern generation is done for all the pixels numbering 3 844. The proposed Gabor feature-based selection approach reduces those 3 844 pixels for the face shown in

Table 2 Computation time and number of Local Binary Patterns reduction by selective local texture features for the face in Fig. 4

	LBP	Selective local texture features
Number of Local Binary Patterns	3 844	1 873
Computation time (Seconds)	2.3910	1.953

Table 3 Overall computation time in seconds for the Yale, ORL, FRET and Indian Face datasets in the training process

	LBP	Selective Local texture features
Yale (15 subjects)	43.2650	13.9060
ORL (40 subjects)	92.6250	28.9220
FERET (1 196 subjects)	8 072.4	5 352.6
Indian Faces (60 subjects)	144.36	85.624

Table 4 Overall reduction of the patterns on LBP operation

	LBP	Selective local texture features	Rate of reduction
Yale	57 660	30 093	52.1904%
ORL	153 760	80 127	52.1117%
FERET	18 987 696	9 492 399	49.9924%
Indian faces	952 560	495 002	51.97%

Fig. 4 to 1 873. So this approach makes an enormous reduction in computation process and time possible. For example the LBP generations for some faces are reduced up to 1 664, 1 687, 1 715 pixels and so on. This face-recognition system is performed with an Intel Pentium(R) D 2.40 GHz CPU and 512 MB RAM with Matlab7.0.

Table 3 summarizes the overall computation time for the Yale (15 subjects), ORL (40 subjects), FERET (1 196 subjects) and Indian Face Dataset (60 subjects), and Table 4 shows the overall pattern reduction for the training process.

Table 5 summarizes the respective performances of the above described methods based on the expression variant faces with single training image. Table 6 shows the recognition rate obtained whilst using normal/view-point variant faces for the recognition. Table 7 shows the results obtained whilst using faces with accessories for testing.

Table 8 summarizes the recognition rate for the illumination variant faces for testing. Table 9 shows the dataset-based recognition rate. In Fig. 5, we plot the cumulative match curves of LBP and the proposed approach on the FERET fb probe set.

Table 5 Results obtained for expression invariant face recognition with a single sample

	LBP	Selective local texture features
Yale	92%	94.6666%
ORL	82.5396%	82.5396%
FERET	92.9707%	92.7196%
Indian faces	85.41666%	86.25%

Table 6 Results obtained for normal and view-point and pose invariant face recognition with single sample per class

	LBP	Selective local texture features
Yale	100%	100%
ORL	86.7724%	85.1851%
Indian faces	78.7115%	78.1512%

Table 7 Results obtained whilst using faces with accessories for recognition with single sample per class

Methods	Yale
LBP	80%
Selective local texture features	86.6666%

Table 8 Results obtained for illumination variant faces with single sample per class

Methods	Yale
LBP	93.333%
Selective local texture features	90%

Table 9 Face recognition results based on different databases

	LBP	Selective local texture features
Yale	91%	93%
ORL	85.3175%	84.5238 %
FERET	92.9824%	92.7819%
Indian faces	81.2395%	81.4070%

The results clearly show that the method based on the selective local texture feature reduces the number of Local Binary Pattern into half compared to the existing LBP method. Due to this reduction the proposed method reduces the computation time considerably without being harmful to the recognition accuracy (90%). The reduction of 45% of computation time for the FERET dataset training is very considerable.

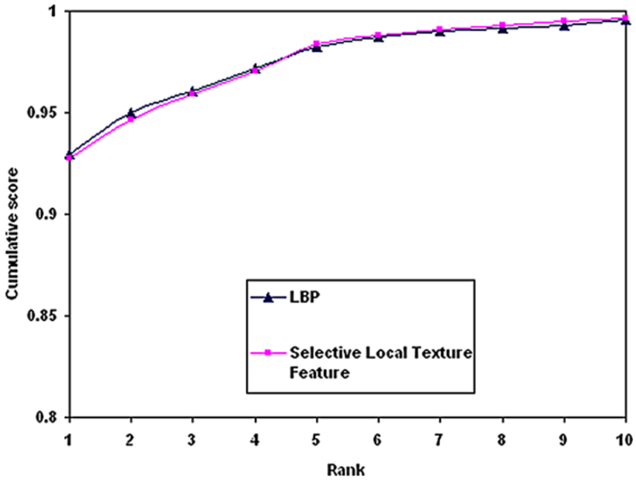

Fig. 5 Cumulative match curves for the FERET *fb* probe set

In terms of the recognition rate, the proposed method outperforms LBP with an increase of accuracy of 2.6666% for the Yale (Expression) and 0.83334% for the Indian Face dataset. The recognition accuracy is almost intact for the FERET and ORL datasets.

In the case of a normal face with a slight view-point variation, the recognition rate is similar to LBP in the Yale dataset but slightly down in the ORL and Indian Face datasets due to perspective and view-point variations, which needs some more features to represent the face than the selective features. This approach outperforms LBP with 6.6667% for accessories (Yale) invariant face recognition. Due to the nature of the Gabor filter, the LBP-based face recognition performs well for the illumination variant faces.

5 Conclusion

In this paper, we have proposed an approach of local selective texture feature-based face recognition using Gabor filter and LBP techniques. First we extracted the facial features using the Gabor filter. Then we encode these features into a binary form to generate a binary face template. The binary face template acts like a mask to extract the local texture information of the face image using a Local Binary Pattern technique. Compared with the conventional LBP method, this kind of feature selection approach reduces the number of Local Binary Patterns to describe the face. The experimental result reveals that the proposed feature selection approach reduces the computation time considerably, without affecting the recognition performance. Furthermore, for training we are using only one image per person which makes it useful for practical face-recognition applications.

This paper has also evaluated the performances of the LBP and the selective local texture feature methods in terms of normal, changes in view-point, accessories and facial expressions of the faces of the Yale, ORL, Indian Face and FERET datasets. The results clearly showed that the selective local feature-based face representation attains a good result for the expression and accessories invariant face recognition. In future, we can combine this local selective feature-based approach with pose invariant face-recognition approaches to improve the recognition performance with less computation time for the Single Sample Problem.

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