Local Gabor Binary Pattern Histogram Sequence (LGBPHS): A Novel Non-Statistical Model for Face Representation and Recognition

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Abstract

For years, researchers in face recognition area have been representing and recognizing faces based on subspace discriminant analysis or statistical learning. Nevertheless, these approaches are always suffering from the generalizability problem. This paper proposes a novel non-statistics based face representation approach, Local Gabor Binary Pattern Histogram Sequence (LGBPHS), in which training procedure is unnecessary to construct the face model, so that the generalizability problem is naturally avoided. In this approach, a face image is modeled as a "histogram sequence" by concatenating the histograms of all the local regions of all the local Gabor magnitude binary pattern maps. For recognition, histogram intersection is used to measure the similarity of different LGBPHSes and the nearest neighborhood is exploited for final classification. Additionally, we have further proposed to assign different weights for each histogram piece when measuring two LGBPHSes. Our experimental results on AR and FERET face database show the validity of the proposed approach especially for partially occluded face images, and more impressively, we have achieved the best result on FERET face database.

1. Introduction

Face recognition, as one of the most representative applications of image analysis and understanding, has received significant attention in both the wide range of security applications [1] and research fields [2]. Although many commercial systems have emerged, it is still an active and challenging topic, due to the fact that the appearance of the same face looks dramatically different in uncontrolled environments with rich variations of pose, expression, illumination and occlusion etc. Many systematic evaluations, such as FERET [3] and FRVT2002 [1], have experimentally verified this point. Therefore, many on-going researches are aiming at improve the face recognition systems' robustness to these variations. Apparently, face representation invariant to these variations is one of the key points.

Many representation approaches have been proposed in the previous work, nevertheless most of them are based on statistical learning, such as subspace discriminant analysis [4], SVM [5], or AdaBoost [6], which inherently suffer from the generalizability problem due to the unpredictable distribution of the real-world "testing" face images, which might differ dramatically from that of the "training" samples. For example, for subspace approaches, in order to extract the most discriminating representation for final classification, a training set is required to compute the discriminant subspace. However, the discriminant subspace is greatly dependent on the training set. So, in case that the testing images are captured under different environment from those of the training ones, the so-called discriminant subspace would be actually inapplicable to those probe faces. Though, generalizability problem has been theoretically discussed in SVM through the Vapnik-Chervonenkis (VC) theory and Structural Risk Minimization (SRM) principle [7], in most real-world face recognition applications, generalizability problem remains a huge bottleneck for most face recognition systems.

Unlike the mainstream approaches based on statistical learning, we devote to develop a novel non-statistics based face representation approach, Local Gabor Binary Pattern Histogram Sequence (LGBPHS), which is not only robust to the variations of imaging condition but also with much discriminating power. Briefly speaking, LGBPHS is actually a representation approach based on multi-resolution spatial histogram [8] combining local intensity distribution with the spatial information, therefore, it is robust to noise and local

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image transformations due to variations of lighting, occlusion and pose. Additionally, instead of directly using the intensity to compute the spatial histogram, multi-scale and multi-orientation Gabor filters are used for the decomposition of a face image, followed by the local binary patterns (LBP) [9][10] operator. The combination of Gabor and LBP further enhances the representation power of the spatial histogram greatly. Note that, to construct the LGBPHS model, one does not need a training stage necessarily, which has naturally avoided the generalizability problem.

For recognition, histogram intersection is used to measure the similarity of different LGBPHSes and the nearest neighborhood is exploited for final classification. Additionally, considering the fact that different local regions in face image are with different contribution to classification, we have further proposed to set different weights for each histogram piece when matching two LGBPHS. Our experimental results on the FERET face database show the validity of the proposed approach, and additionally we have achieved the best result on FERET face database.

The remaining part of the paper is organized as follows: Section 2 describes the computation of the proposed LGBPHS face representation in detail, as well as some analysis on its robustness to variations of imaging condition. How to recognize faces based on LGBPHS are presented in Section 3, followed by the experimental part with rich comparisons with other approaches. Some brief conclusions are drawn in the last section with some discussion on future work.

2. Face Representation Based on LGBPHS

The overall framework of the proposed representation approached based on Local Gabor Binary Pattern Histogram Sequence is illustrated in Fig.1. In this approach, a face image is modeled as a "histogram sequence" by the following procedure: (1) An input face image is normalized and transformed to obtain multiple Gabor Magnitude Pictures (GMPs) in frequency domain by applying multi-scale and multi-orientation Gabor filters; (2) Each GMP is converted to Local Gabor Binary Pattern (LGBP) map; (3) Each *LGBP Map* is further divided into non-overlapping rectangle regions with specific size, and histogram is computed for each region; (4) The LGBP histograms of all the *LGBP Maps* are concatenated to form the final histogram sequence as the model of the face. The following sub-sections will describe the procedure in detail.

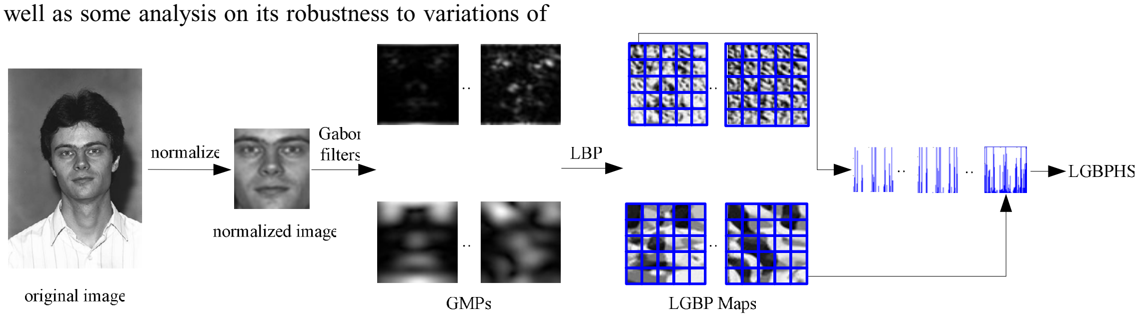


Figure 1. The framework of the proposed LGBPHS face representation approach.

2.1. Gabor Magnitude Picture

Considering the advantages of the Gabor filters in face recognition [11], we exploit the multi-resolution and multi-orientation Gabor filters to de-composite the input face images for sequential feature extraction. The Gabor filters we used are defined as follows [12]

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

where μ and ν define the orientation and scale of the Gabor filters, $z=(x,y)$, $\|\cdot\|$ denotes the norm operator, and the wave vector $k_{\mu,\nu}=k_\nu e^{i\phi_\mu}$, where $k_\nu=k_{\max}/\lambda^\nu$ and $\phi_\mu=\pi\mu/8$. λ is the spacing factor between filters in the frequency domain.

The Gabor representation of a face image is derived by convolving the face image with the Gabor filters. Let $f(x,y)$ be the face image, its convolution with a Gabor filter $\psi_{\mu,\nu}(z)$ is defined as follows

$$G_{\psi f}(x,y,\mu,\nu)=f(x,y)*\psi_{\mu,\nu}(z) \tag{2}$$

where $*$ denotes the convolution operator. Five scales $\nu\in\{0,\cdots,4\}$ and eight orientations $\mu\in\{0,\cdots,7\}$ Gabor filters are used. Convolving the image with each of the 40 Gabor filters can then generate the Gabor features. Note that, because the phase information of the transform is time-varying, generally, only its magnitude is explored. Thus, for each Gabor filter, one magnitude value will be computed at each pixel position, which will totally result in 40 Gabor Magnitude Pictures (GMPs).

2.2. Local Gabor Binary Pattern (LGBP)

The magnitude values of the Gabor transform change very slowly with displacement [13], so they can be further encoded. In order to enhance the information in the GMPs, we encode the magnitude values with LBP operator. The original LBP operator [9] labels the pixels of an image by thresholding the 3×3 -neighborhood of each pixel $f_p\left(p=0,1,\ldots,7\right)$ with the center value f_c and considering the result as a binary number [10]

$$S\left(f_p-f_c\right)=\begin{cases}1, & f_p\ge f_c\\ 0, & f_p<f_c\end{cases} \tag{3}$$

Then, by assigning a binomial factor 2^p for each $S\left(f_p-f_c\right)$, the LBP pattern at the pixel is achieved as

$$LBP=\sum_{p=0}^{7}S\left(f_p-f_c\right)2^p \tag{4}$$

which characterizes the spatial structure of the local image texture. The operator *LGBP* denotes the LBP operates on GMP. We denote the transform result at position (x,y) of (μ,ν)-GMP as $G_{\text{lgbp}}(x,y,\mu,\nu)$, which composes the (μ,ν)-*LGBP Map*.

2.3. LGBP Histogram Sequence

Face recognition under varying imaging conditions such as illumination and expression is a very difficult problem. Usually, the variations will appear more on some specific regions in face image. Therefore, we exploit local feature histogram to summarize the region property of the LGBP patterns by the following procedure: Firstly, each *LGBP Map* is spatially divided into multiple non-overlapping regions. Then, histogram is extracted from each region. Finally, all the histograms estimated from the regions of all the *LGBP Maps* are concatenated into a single histogram sequence to represent the given face image. The above process is formulated as follows:

The histogram $\mathbf{h}$ of an image $f(x,y)$ with gray levels in the range $[0,L-1]$ could be defined as

$$\mathbf{h}_i=\sum_{x,y}I\{f(x,y)=i\},i=0,1,\ldots,L-1 \tag{5}$$

where i is the i-th gray level, $\mathbf{h}_i$ is the number of pixels in the image with gray level i and

$$I\{A\}=\begin{cases}1, & A \text{ is true}\\ 0, & A \text{ is false}\end{cases} \tag{6}$$

Assume each *LGBP Map* is divided into m regions $R_0,R_1,\ldots,R_{m-1}$. The histogram of r-th region of the specific *LGBP Map* (from (μ,ν)-GMP) is computed by

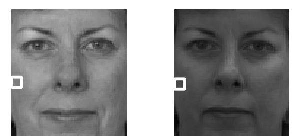
$$\mathrm{H}_{\mu,\nu,r}=\left(\mathbf{h}_{\mu,\nu,\mathrm{r},0},\mathbf{h}_{\mu,\nu,\mathrm{r},1},\cdots,\mathbf{h}_{\mu,\nu,\mathrm{r},\mathrm{L}-1}\right) \tag{7}$$

where

$$\mathbf{h}_{\mu,\nu,\mathrm{r,i}}=\sum_{(x,y)\in\mathrm{R}_r}I\{G_{\text{lgbp}}(x,y,\mu,\nu)=i\} \tag{8}$$

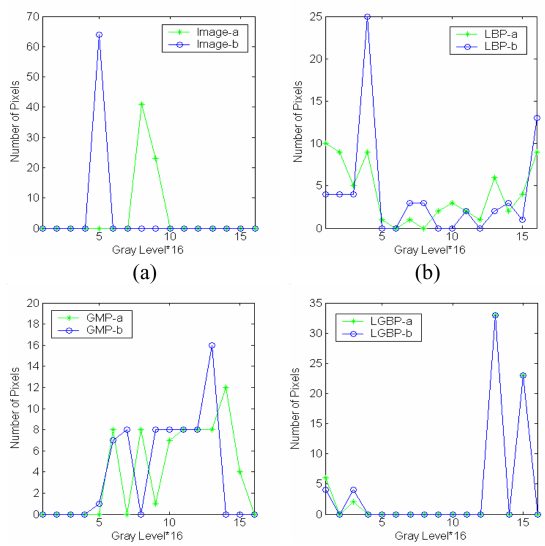
Finally, all the histogram pieces computed from the regions of all the 40 *LGBP Maps* are concatenated to a histogram sequence, $\Re$, as the final face representation $\Re=(\mathrm{H}_{0,0,0},\cdots,\mathrm{H}_{0,0,m-1},\mathrm{H}_{0,1,0},\cdots,\mathrm{H}_{0,1,m-1},\cdots,\mathrm{H}_{7,4,m-1})$.

2.4. Robustness Analysis of the LGBPHS



(a) (b)

Figure 2. Two face images from the same subject.



(a) (b) (c) (d)

Figure 3. Robustness of the different histograms to images with lighting variation.

Evidently, a good face representation should robust to image variations. In order to investigate the robustness of the proposed approach, we compare the histograms of four representations extracted from two images of the same person with different lighting. The four representations are respectively the original image intensity, LBP of the image, Gabor magnitude of the

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image, and the proposed LGBP of the image. We divide the image into regions of the same window size 8×8 pixel array. A white region as shown in Fig. 2 is selected to extract different histograms, and the results are shown in Fig. 3. One can see clearly that the histograms of the proposed LGBP are the most similar. This implies that face representation of LGBP is robust to the lighting variation.

3. Face Recognition Based on LGBPHS

We present two approaches to measuring the similarity between two LGBPHSes: the direct LGBPHS measurement and the weighted LGBPHS measurement.

3.1. Direct LGBPHS Matching

Many similarity measurement approaches have been presented for histogram matching [14]. We use the histogram intersection $\Psi(\mathrm{H}^1, \mathrm{H}^2)$ as the similarity measurement of two histograms [15]

$$\Psi(\mathrm{H}^1, \mathrm{H}^2) = \sum_{i=1}^{L} \min(\mathbf{h}_i^1, \mathbf{h}_i^2) \tag{9}$$

where $\mathbf{h}^1$ and $\mathbf{h}^2$ are two histograms, and L is the number of bins in the histogram. The intuitive motivation for this measurement is the calculation of the common part of two histograms. Using this measurement, the similarity of two face images based on the LGBPHS face representation is computed by

$$S(\Re_1, \Re_2) = \sum_{\mu=0}^{7}\sum_{\nu=0}^{4}\sum_{r=0}^{m-1} \Psi(\mathrm{H}^1_{\mu,\nu,r}, \mathrm{H}^2_{\mu,\nu,r}) \tag{10}$$

where

$$\Re_1 = (\mathrm{H}^1_{0,0,0}, \mathrm{H}^1_{0,0,1}, \cdots, \mathrm{H}^1_{0,0,m-1}, \mathrm{H}^1_{0,1,0}, \cdots, \mathrm{H}^1_{0,1,m-1}, \mathrm{H}^1_{0,2,0}, \cdots, \mathrm{H}^1_{7,4,m-1})$$

and

$$\Re_2 = (\mathrm{H}^2_{0,0,0}, \mathrm{H}^2_{0,0,1}, \cdots, \mathrm{H}^2_{0,0,m-1}, \mathrm{H}^2_{0,1,0}, \cdots, \mathrm{H}^2_{0,1,m-1}, \mathrm{H}^2_{0,2,0}, \cdots, \mathrm{H}^2_{7,4,m-1})$$

.

Given the histogram sequence, the computation of Equ. 10 is very efficient, since there is no float multiplication operator in the procedure. In addition, from the computation procedure of both the LGBPHS and the similarity measurement, it is clear that no statistical or learning stage is involved, which has naturally obviated the inherited generalizability problem based on the statistical learning approaches.

3.2. Weighted LGBPHS Matching

Previous work has shown that different facial areas are of different importance for recognition. Therefore, it is easy to understand that the histogram pieces extracted from different regions take different discriminative information. Naturally, different weights can be set to different histogram pieces when matching two LGBPHSes. Thus, Equ. 10 can be rewritten as

$$S'(\Re_1, \Re_2) = \sum_{\mu=0}^{7}\sum_{\nu=0}^{4}\sum_{r=0}^{m-1} W_{\mu,\nu,r} \Psi(\mathrm{H}^1_{\mu,\nu,r}, \mathrm{H}^2_{\mu,\nu,r}) \tag{11}$$

where $W_{\mu,\nu,r}$ is the weight for the r-th region of the (μ,ν) *-LGBP Map*. Setting appropriate weights for different histogram pieces is of great importance for the final performance of the face recognition system. We further present an approach to learning suitable weights based on Fisher separation criterion [16] as follows.

For a C class problem, let the similarities of different samples of the same person compose the intrapersonal similarity class, and those of samples from different persons compose the extrapersonal similarity class as in [17].

For the r-th region of the (μ,ν) *-LGBP Map*, the mean and the variance of the intrapersonal similarities can be computed by

$$m_{\mathrm{I}(\mu,\nu,r)} = \frac{1}{C}\sum_{i=1}^{C} \frac{2}{N_i(N_i-1)} \sum_{k=2}^{N_i}\sum_{j=1}^{k-1} \Psi\left(\mathrm{H}^{(i,j)}_{\mu,\nu,r}, \mathrm{H}^{(i,k)}_{\mu,\nu,r}\right) \tag{12}$$

$$S^2_{\mathrm{I}(\mu,\nu,r)} = \sum_{i=1}^{C}\sum_{k=2}^{N_i}\sum_{j=1}^{k-1} \left(\Psi\left(\mathrm{H}^{(i,j)}_{\mu,\nu,r}, \mathrm{H}^{(i,k)}_{\mu,\nu,r}\right) - m_{\mathrm{I}(\mu,\nu,r)}\right)^2 \tag{13}$$

where $\mathrm{H}^{(i,j)}_{\mu,\nu,r}$ denotes the histogram extracted from the j-th sample of the i-th class, and N_i is the sample number of the i-th class in the training set.

Similarly, the mean and the variance of the extrapersonal similarities can be computed by

$$m_{\mathrm{E}(\mu,\nu,r)} = \frac{2}{C(C-1)} \sum_{i=1}^{C-1}\sum_{j=i+1}^{C} \frac{1}{N_i N_j} \sum_{k=1}^{N_i}\sum_{l=1}^{N_j} \Psi\left(\mathrm{H}^{(i,k)}_{\mu,\nu,r}, \mathrm{H}^{(j,l)}_{\mu,\nu,r}\right) \tag{14}$$

$$S^2_{\mathrm{E}(\mu,\nu,r)} = \sum_{i=1}^{C-1}\sum_{j=i+1}^{C}\sum_{k=1}^{N_i}\sum_{l=1}^{N_j} \left(\Psi\left(\mathrm{H}^{(i,k)}_{\mu,\nu,r}, \mathrm{H}^{(j,l)}_{\mu,\nu,r}\right) - m_{\mathrm{E}(\mu,\nu,r)}\right)^2 \tag{15}$$

Finally, $W_{\mu,\nu,r}$ is set by the following formulation

$$W_{\mu,\nu,r} = \frac{\left(m_{I(\mu,\nu,r)} - m_{E(\mu,\nu,r)}\right)^2}{S^2_{I(\mu,\nu,r)} + S^2_{E(\mu,\nu,r)}} \tag{16}$$

4. Experimental Evaluations

We use two publicly available face databases for the evaluations of the proposed approach. One is the AR face database consisting of over 3200 color images of the frontal view faces of 126 subjects [18]. The other is the FERET face database [3].

In the proposed approach, the window size of the local region will affect the performance of the recognition. In order to keep more spatial information, in our experiments we empirically choose a smaller window size of 4 by 8 pixels when the face image is normalized to 80 by 88 pixels in our experiments.

4.1. Experiments on Partially Occluded Faces

It is a difficult problem for face recognition when the face image is partially occluded. Typical method deal with this problem exploits local patch-based models [19][20], in which face images are divided into different patches. And a voting space is used to find the best match. A voting technique, however, can easily misclassify a test image because it does not take into account how good a local match is. In [21] a probabilistic approach is proposed to compensate for partially occluded faces, but in the approach the test subject must have been trained.

To evaluate the performance of the proposed approach on partially occluded faces, we do experiments on the AR-face database and compare with the results of [21]. Because the occluded parts in the face image are random usually, we treat all the regions equally with the same weight. We test our approach on the classical wearing occlusions, i.e., the sun glasses and the scarf occlusions. 50 subjects are randomly selected from the AR-face database as in [21]. The neutral expression images of the first session are used to form the gallery, and all the partially occluded images of the first session and the second session are used as the probes. The performance comparisons of our approach with that in [21] are shown in Table 1.

From Table 1, one can see that our approach outperforms that in [21], especially for the mouth occlusion case. Additionally, the observation that our method achieves better results for mouth occlusion than eye occlusion is more consistent with human intuitions.

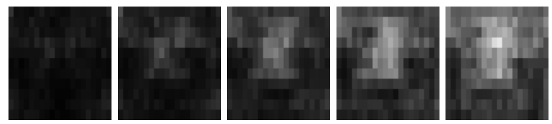
Table 1. The recognition rates on the AR face database.

Methods	Session-1		Session-2	
	sun glasses	scarf	sun glasses	scarf
Direct LGBPHS	0.80	0.98	0.62	0.96
Results of [21]	0.80	0.82	0.54	0.48

4.2. Discriminant Capacity of Different Regions

For the proposed weighted LGBPHS matching, each weight, $W_{\mu,\nu,r}$, corresponding to the *r*-th region of the (μ,ν)-th LGBP map, is computed according to Equ. 16 using the 1002 frontal images in the FERET training set. In order to see the distribution of the weights, we visualize the weights as an image by stretching them to gray values of the range $[0,255]$, as shown in Fig. 4. Note that, in the figure, a darker intensity indicates a smaller $W_{\mu,\nu,r}$, on the contrary a higher intensity means a bigger $W_{\mu,\nu,r}$. Since the weight distributions of the different orientations in the same scale are similar, only the mean weights of different orientations in each scale are shown in Fig. 4.

The weights shown in Fig. 4 are well consistent with our intuitions in that the eye-nose region contributes more to face distinguishing. In addition, it also suggests information with larger scales is relatively more discriminant than that with smaller scales.



(a) $\nu=0$ (b) $\nu=1$ (c) $\nu=2$ (d) $\nu=3$ (e) $\nu=4$

Figure 4. Weights of different local regions for five scales learned from the FERET training set.

4.3. Experiments on Robustness to Image Variation

To test the robustness of the approach against different facial expressions, lighting and aging, we evaluate the proposed method on all the four FERET probe sets and compare it with Fisherface [4], the best result in FERET'97 [3], and the latest published results in [10]. Note that the result in [10] is one of the state-of-the-art results on FERET (at least to our knowledge).

The rank-1 recognition rates of different methods on the FERET probe sets are shown in Table 2. Evidently, on all the four probe sets, the performance of the proposed weighted LGBPHS is better than the best results reported in [10] and the FERET'97 test [3], especially for the *fc* probe set. These observations have impressively illustrated the robustness and high discriminating capacity of the proposed LGBPHS-based face representation and recognition, considering the fact that the images in *fb* set are with expression variation, *fc* probe set contains images with lighting variation, and *Dup.I* and *Dup.II* include aging images.

Table 2. The rank-1 recognition rates of different algorithms on the FERET probe sets.

Methods	fb	fc	Dup.I	Dup.II
Fisherface	0.94	0.73	0.55	0.31
Best Results of [3]	0.96	0.82	0.59	0.52
Results of [10]	0.97	0.79	0.66	0.64
Direct LGBPHS	0.94	0.97	0.68	0.53
Weighted LGBPHS	0.98	0.97	0.74	0.71

5. Conclusion and Discussion

This paper proposes a novel face representation, LGBPHS, which is impressively insensitive to appearance variations due to lighting, expression, and aging. Moreover, the modeling procedure of LGBPHS does not involve in any learning process, that is, it is non-statistical learning based. Therefore, the inherited generalizability problem is naturally avoided in this representation approach. The effectiveness of the LGBPHS comes from several aspects including the multi-resolution and multi-orientation Gabor decomposition, the Local Binary Pattern, and the local spatial histogram modeling. LGBPHS actually consists of many pieces of histogram corresponding to different face components at different scale and orientation.

Experimental evaluations of the proposed approach on the AR and the FERET face database have evidently illustrated the effectiveness and robustness of LGBPHS to the general variations of lighting, expression, and occlusion. Especially on the FERET face database, we have achieved the best results.

Future efforts will be focused on how to match more effectively and efficiently two LGBPHSes, especially for pose and occlusion variations. At the same time, we will further investigate the discriminant capacity of the spatial histogram-based object representation approach for object other than faces.

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