Multi-radius centralized binary pattern histogram projection for face recognition

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The existing local binary pattern (LBP) operators have several disadvantages such as rather long histograms, lower discrimination, and sensitivity to noise. Aiming at these problems, we propose the centralized binary pattern (CBP) operator. CBP operator can significantly reduce the histograms' dimensionality, offer stronger discrimination, and decrease the white noise's influence on face images. Moreover, for increasing the recognition accuracy and speed, we use multi-radius CBP histogram as face representation and project it onto locality preserving projection (LPP) space to obtain lower dimensional features. Experiments on FERET and CAS-PEAL databases demonstrate that the proposed method is superior to other modern approaches not only in recognition accuracy but also in recognition speed.

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In recent years, many approaches have been developed for face recognition, including Gabor wavelet[1,2], principal component analysis (PCA)[3], linear discriminant analysis (LDA)[4], manifold[5], and local binary pattern (LBP)[6]. Gabor wavelet-based approaches have the drawback of expensive computation and thus are not appropriate to construct the fast and efficient face recognition system. The approaches based on PCA and LDA preserve the global structure of image space, while manifold-based methods preserve the local structure of image space. However, local structure is more important than global structure in real-world applications. LBP-based approaches are arousing researchers' high attention due to the advantages of simple computation, robustness to illumination variation, and discriminative ability.

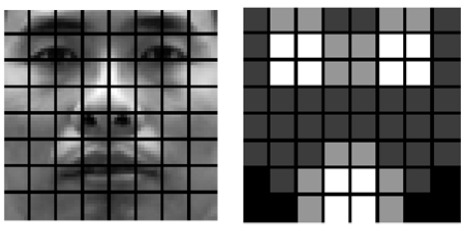
Nevertheless, the existing LBP operators have several unsatisfactory aspects. Firstly, they produce rather long histograms, which slow down the recognition speed especially on large-scale face database. Secondly, under some certain circumstances, they miss the local structure as they do not consider the effect of the center pixel. Thirdly, the binary data produced by them are sensitive to noise. Therefore, we propose the centralized binary pattern (CBP) operator which overcomes the above shortcomings of existing LBP operators. In detail, CBP operator decreases the histograms' length largely by comparing pairs of neighbors in the operator. Because of taking the center pixel into consideration and giving it the largest weight, CBP operator's discrimination is improved. CBP operator is insensitive to noise owing to its modified sign function. Furthermore, in order to improve the recognition accuracy, we use multi-radius CBP histogram (MCBPH) as face representation. Out of consideration for recognition speed, we do not choose Chi square statistic[6], as used by existing LBP-based method, but project MCBPH onto locality preserving projection (LPP)[5] space and finish the classification in this low-dimensional space. In this way, the proposed method's recognition rate is improved further due to LPP's powerful discrimination. The approach of multi-radius CBP histogram projection (MCBPHP) has many advantages such as significant dimensionality reduction, more powerful discrimination, insensitivity to noise, and high recognition speed. Experiments on two well-known large-scale face databases show that the proposed method outperforms the existing LBP-based method not only in recognition rate but also in recognition speed.

The conventional LBP operator[7] is shown as

$$\mathrm{LBP}(M,R)=\sum_{m=0}^{M-1}s(g_m-g_\mathrm{c})2^m, \tag{1}$$

in which R is the radius, $s(x)=\begin{cases}1, x\geq 0\\ 0, x<0\end{cases}$, g_c represents the center pixel, and g_m (m=0,$\cdots$, $M-1$) are the neighbors of g_c. The image pixels are first labeled by thresholding the difference between g_c and g_m using the sign function $s(x)$. The concatenation of the neighboring labels is then used as a unique descriptor for each pattern.

The patterns are uniform if the transitions between "0" and "1" are less than or equal to two. The histogram of the uniform patterns in the whole image is used as the feature vector. For efficient face representation, the extracted feature should also retain spatial information.



(a) (b)

Fig. 1. (a) A face image divided into 8×8 small regions, (b) weight set for different regions. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0, and white 4.0.

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So the face image is divided into k small regions B_1, B_2,$\cdots$, B_k, as shown in Fig. 1.

As expected, a larger region size induces a decreased recognition rate because of the loss of spatial information. Hence the number of regions, k, cannot be too small. Let n be the histogram bins of binary patterns, then the final feature vector's length would be $n \times k$. Indeed, using a feature vector of such a length slows down the recognition speed, especially for very large face databases. Based on the fact, we apply a dimensionality reduction to the binary patterns. As shown in Fig. 2, the pairs of neighbors are compared only if their connecting lines pass through the center pixel g_c. It should be noted that the benefit of CBP (in Fig. 2) over conventional LBP is not only due to the dimensionality reduction, but also to the fact that it captures better the gradient information than conventional LBP.

In addition, conventional LBP features miss the local structure in some certain situation. For the instance of LBP(8,1), we can only obtain 256 of all the 512 patterns by using Eq. (1). The reason is that the center pixel g_c is set to 0 all through. The center point, in most cases, provides more information than its neighborhood, so we should consider its effect and give it the largest weight.

Furthermore, conventional LBP has a serious problem, i.e., the binary data obtained from Eq. (1) are sensitive to noise. Hence in application, the noise existing in images limits seriously the texture extraction effect of LBP operator. The reason is that LBP operator considers the correlation between pixel points and the correlation is mutual, i.e., if $s(g_a - g_b) = 0$, then $s(g_b - g_a) = 1$. Therefore, in order to decrease the white noise's effect on images, we modify the sign function $s(x)$ to be

$$s(x) = \begin{cases} 1, & |x| \geq C \\ 0, & |x| < C \end{cases}, \tag{2}$$

where C is a threshold constant.

Thus we propose a CBP operator which can be expressed as

$$\mathrm{CBP}(M,R) = \sum_{m=0}^{(M/2)-1} s(g_m - g_{m+(M/2)})2^m + s(g_c - \frac{1}{M+1}(\sum_{m=0}^{M-1} g_m + g_c))2^{M/2}, \tag{3}$$

in which the sign function $s(x)$ is just as Eq. (2). From Eq. (3) we can see that CBP operator considers the center pixel and gives it the largest weight. This strengthens the effect of the center pixel and is beneficial for the discrimination of CBP. In addition, the dimensionality of histogram produced by CBP operator would be quite smaller than the one by conventional LBP. Taking (M=8, R=2) for example, using Eq. (1), the conventional LBP histogram's dimensionality is 256, even for uniform LBP the value can be 59, while the value is 32 for CBP. The larger M is, the more significant the superiority of CBP on dimensionality is. Furthermore, unlike conventional LBP which compares neighbors with the center pixel, CBP captures better gradient information through comparing pairs of neighbors. In this way, the discrimination of CBP is improved very much. Moreover, the extracted CBP features from images are less sensitive to white noise due to the modified sign function. In a word, compared with conventional LBP, CBP has several superiorities, e.g., significant dimensionality reduction, more powerful discrimination, and less sensitivity to white noise.

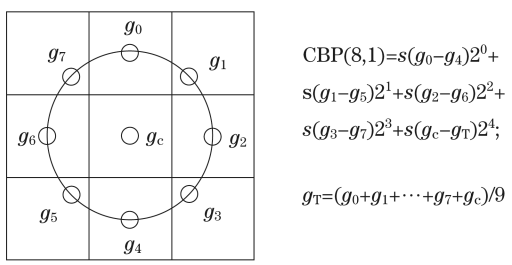

Fig. 2. CBP(8,1) operator.

The multi-resolution representation has been applied to texture classification and the results demonstrate that its accuracy is better than that of the single-radius LBP method[7]. In order to improve the face recognition rate, we developed the multi-radius CBP, which could be obtained by varying the radius R and combining the information provided by multiple CBP operators. In detail, the face image is firstly partitioned into k small regions (as shown in Fig. 1). In each region, multi-radius CBP histograms are extracted and summed up as a regional feature which can be stated formally as

$$H_j = \sum_{i=1}^{t} \mathrm{CBPH}(M, R_i), \; j = 1, \cdots, k, \tag{4}$$

where H_j is the jth regional feature, R_i is the ith value of the t varying radii, and CBPH(M, R_i) denotes the histogram produced by CBP(M, R_i) operator. It should be noted that the multi-radius CBP histograms all have the same length due to the same M, so they can be summed up. In this way, the obtained feature not only has lower dimensionality than the one obtained by concatenating multi-radius CBP histograms, but also preserves the histograms' information. Finally, all the regional features are concatenated into a feature vector $\mathrm{H_f}$ as the face representation. Essentially $\mathrm{H_f}$ is the multi-radius CBP histogram of the face image.

In recognition, the conventional LBP-based methods use the weighted Chi square statistic (χ^2)[6] as the dissimilarity measure which is expressed by

$$\chi^2_\omega(D,G) = \sum_{i,j} \omega(j) \frac{(D(i,j) - G(i,j))^2}{D(i,j) + G(i,j)}, \quad i = 1, 2, \cdots, n, \; j = 1, 2, \cdots, k, \tag{5}$$

where D and G are two histograms to be compared, indices i and j refer to ith bin in histogram corresponding to the jth region, and $\omega(j)$ is the weight for region j. During χ^2 computation, it is possible that $D(i,j)+G(i,j)$ =0, so the summation only includes the nonzero bins. In a specific algorithm, this step needs a judgemental statement. Under the assumption that there would be k small regions in each image and n bins in each histogram, it is necessary to do the judgemental statement $n \times k$ times, which undoubtedly increases the weight of computation.

```
for ii=1 to p do
    D=H_test(ii)
    for jj=1 to g do
        G=H_train(jj)
        temp=0
        for i=1 to n do
            for j=1 to k do
                if D(i,j)+G(i,j) equals to zero then
                    go to the fourth for–loop
                end
                temp=temp+w(j)* (D(i,j)–G(i,j))^2/(D(i,j)+G(i,j))
            end
        end
        X(jj, ii)=temp
    end
end
result=X(jj, ii), ii=1 to p, jj=1 to g
```

Fig. 3. Procedure of Chi square statistic dissimilarity measure.

The algorithm shown in Fig. 3 provides the pseudo code for the procedure of Chi square statistic dissimilarity measure, in which H_test(ii) and H_train(jj) are respectively the histograms for iith testing sample and jjth training sample, p is the number of testing samples, g is the number of training samples, "temp" is a temporary variable, n is the number of bins in each histogram, k is the number of small regions in each image, D and G are two histograms to be compared, $w(j)$ is the weight for region j, and $X(jj, ii)$ is the result.

From the algorithm, we can see that calculating one testing sample's result needs $g \times n \times k$ cycles which also involve doing the judgemental statement. Hence the computation of χ^2 is very expensive, especially on large-scale face databases. In order to improve the recognition speed, we must avoid computing expensively. In this letter, we project H_{f}, the multi-radius CBP histogram of face image, onto LPP space and obtain the final feature which can be called MCBPHP. When a new sample is to be tested, it is only necessary to compare the sample's MCBPHP with all the training samples' MCBPHP. The recognition process is carried out in the lower dimensional space so that its speed is much higher than the recognition using χ^2. Moreover, the proposed method's recognition rate is improved further due to LPP's powerful discrimination.

We compared the performance of MCBPHP method with uniform LBP-based method and Gabor wavelet-based approach on two well-known large-scale face databases: FERET database[8,9] and CAS-PEAL database[10].

In order to test the proposed method's tolerance to noise, we added relatively weak Gaussian noise to the selected images. At first, all the selected images were cropped and resized to 64×64 pixels, with 256 gray levels per pixel. No further preprocessing was performed in our algorithm. Each face image was divided into 8×8 small regions as shown in Fig. 1(a). In the uniform LBP-based method, we selected the uniform LBP(8,2) operator. Then the uniform LBP histograms were extracted from each region and concatenated into a feature vector as face representation. In the recognition stage of uniform LBP-based method, the weighted Chi square statistic was used as dissimilarity measure whose results were fed to a nearest-neighbor classifier. The weight sets for weighted dissimilarity measure are illustrated in Fig. 1(b). While in MCBPHP method, we chose CBP(8,1), CBP(8,2), and CBP(8,3) operators to extract multi-radius CBP histograms from each region and summed them up as a regional feature. All the regional features, after being weighted as shown in Fig. 1(b), were concatenated into a feature vector which was essentially the face image's multi-radius CBP histogram. Then this histogram was projected onto LPP space to obtain the final feature MCBPHP. In the recognition stage, the testing sample's MCBPHP was compared with all the training samples' MCBPHP. The compared results were fed to the nearest-neighbor classifier. In the Gabor wavelet-based approach, we chose the same Gabor wavelets as in Ref.[11] and used the nearest-neighbor classifier. With Matlab 7.1 software, this experiment was carried out on a computer of Pentium IV 2.8 GHz with 512 M memory.

We selected 8850 images from the FERET database. The number of classes was 885. In each class, 10 samples were divided randomly into 10 groups. A 10-fold cross-validation test scheme was adopted, i.e., in each class, one group was as the testing set, the other 9 groups were as the training set in every recognition time. Hence, for each class, there were 10 results whose average value was the final result. Table 1 shows the experimental results on the FERET database.

It is observed that MCBPHP method is superior to uniform LBP-based method and Gabor wavelet-based approach in both recognition accuracy and recognition speed. This phenomenon demonstrates that MCBPHP excels uniform LBP and Gabor wavelet in facial feature extraction. There are several reasons. 1) By comparing pairs of pixels in the neighborhood, CBP captures better gradient information than uniform LBP. 2) CBP operator's discrimination is also enhanced owing to considering the center pixel and giving it the largest weight. 3) CBP operator is insensitive to noise because of its modified sign function. 4) The application of multi-radius CBP histogram contributes to recognition accuracy. 5) LPP has the powerful discrimination. From the point of recognition speed, we can see that in MCBPHP method the dimensionality of multi-radius CBP histogram is reduced from 2048(=32×64) to 298 after being projected onto LPP space. The recognition process is performed in this low-dimensional space so that its speed is very high. While in the uniform LBP-based method, the recognition is much slower due to the complicated χ^2 computation in the space of 3776(=59×64) dimensionalities. Moreover, the dimensionality of Gabor feature is much higher than that of MCBPHP feature. So the computation of Gabor wavelet-based approach is more expensive. On large-scale face databases, face recognition (e.g., facial identity authentication) would give prominence to our

Table 1. Comparison of Different Methods on FERET Database

Method	Recognition Accuracy (%)	Time of Recognizing One Sample (s)
Gabor Wavelet	90.19	986.354
Uniform LBP	94.65	191.683
MCBPHP	96.72	0.258

Table 2. Comparison of Different Methods on CAS-PEAL Database

Method	Recognition Accuracy (%)	Time of Recognizing One Sample (s)
Gabor Wavelet	89.37	897.192
Uniform LBP	92.15	172.972
MCBPHP	95.83	0.231

proposed approach.

We selected 8050 images from the CAS-PEAL database. The number of classes was 402. A 10-fold cross-validation test scheme was adopted. The experimental results are shown in Table 2.

From Table 2, we can see also that the MCBPHP method outperforms uniform LBP-based method and Gabor wavelet-based approach not only in recognition accuracy but also in recognition speed. The superiorities of our proposed method originate in CBP on one hand, and the multi-radius CBP histogram projection on the other hand.

In conclusion, we describe a novel approach to face recognition. Aiming at the existing LBP's disadvantages, we propose the CBP operator. Moreover, in order to improve the recognition accuracy and speed, we use multi-radius CBP histogram as face representation and project it onto LPP space. Compared with existing LBP-based methods, our proposed method has many superiorities such as significant dimensionality reduction, powerful discrimination, insensitivity to noise, and high recognition speed.

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