Circle-Block Local Binary Patterns for Face Recognition

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Abstract. In this paper a new texture operator based on Local Binary Patterns (LBP) was proposed for face recognition called Circle-Block Local Binary Patterns (CB-LBP). The mean gray values of a circle block pixels are calculated to achieve macroscopic feature extraction. Our method was compared with the LBP-based patterns tested on Extended Yale B face image databases. Experimental results show the effectiveness of the proposed method.

Introduction

Local binary patterns (LBP), proposed by Ojala et al. in 2002 [1], has been successfully applied to facial expression analysis [2] and face recognition [3] owning to its computational simplicity and high efficiency [4]. By comparing the gray value of the central pixel to its neighborhood, LBP operator labels each result as 0 (less than) or 1 (greater than or equal to) [5]. Gray-scale invariant, rotation invariant and uniform LBP were introduced in succession by the same author [6]. Since then, many extensions and modifications have been made to improve the performance of the original LBP [7]-[11]. In multi-block LBP (MBLBP) [12][13], multi-scale mean filters are applied to capture robust macroscopic information.

The objective of this research is to improve the multi-block LBP operator using a novel circle-block local texture patterns computing the average pixel value of each center and each neighbor. The rest of the papers is organized as follows: In Section 2, we briefly review the original LBP multiresolution feature extraction. In Section 3 the details of the proposed Circle-Block LBP method are presented. We evaluate the effectiveness with extensive experiment on Extended Yale B face image database in Section 4. Finally, a conclusion is drawn in Section 5.

Local binary patterns (LBP)

A multiresolution approach is proposed by Ojala et al. [6] encoding a circularly symmetric set of pixels in a local neighborhood. It can be described by the new following formula:

$$LBP_{P,R} = \sum_{p=1}^{P} s(g_p - g_c)2^{p-1}, s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

where P is the size of the neighbor set of pixels, R is the radius of the local region, g_c represents the gray value of the center pixel and $g_p (p = 1, 2, ..., P)$ denotes those of the neighbors. Suppose the coordinate of g_c is (0, 0), then the coordinates of g_p is $(R\cos(\frac{2\pi p}{P}), R\sin(\frac{2\pi p}{P}))$ .The grey values of neighbor pixels that are not in the center of image grids are approximately calculated by bilinear interpolation.

Circle-Block Local Binary Patterns

Extract CB-LBP features

Inspired by [12], we choose a circle round block area around each local center and every neighbor. The mean value of the circles is set as the comparator while the value of local center circle as an extra feature to be compared. Given the number of neighbors P in a local patch, we treat each p-thneighbor pixel as a micro center g_p and determine its P sub-neighbor pixels g_p^i on a circle of radius R_c. The

sub-neighbor pixels of both the local center g_c and its micro center g_p in the neighborhood are taken into computation. The Circle-Block LBP (CB-LBP) operator is defined as follows:

$$CB-LBP_{P,R} = s(g_c^m - g_M)2^P + \sum_{p=1}^{P} s(g_p^m - g_M)2^{p-1},$$

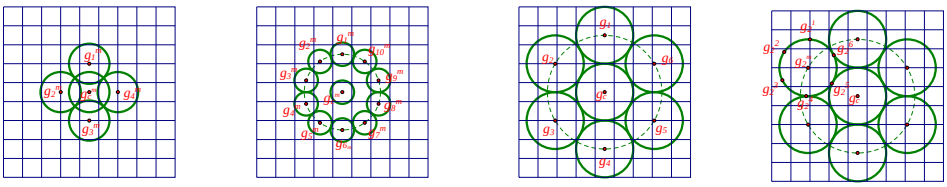
$$g_c^m = \frac{1}{P+1}(g_c + \sum_{i=1}^{P} g_c^i),\ g_p^m = \frac{1}{P+1}(g_p + \sum_{i=1}^{P} g_p^i)$$

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

where g_p^i and g_p^m are the value of each pixel and the mean value in the p-th neighbor circle. g_c^i and g_c^m represent the value of each pixel and the mean value in the center circle and g_M is the total mean value including all the calculated pixel values. Enlightened by [8] and [12], we take g_M as the comparator to encode image robustly and g_c^m as a feature to emphasize the importance of the local center.

Radius R_c and neighbors n

The radius of the neighbor circle R_c should be adjusted according to the number of neighbors n and radius R. It is easy to prove that when R_c satisfies the equation $R_c = R\sin\frac{180°}{n}$, all of the neighbor circles are perfectly tangent to their two nearby circles.



(a) P=4 (b) P=10 (c) P=6 (d) P=6

Figure 1.Different neighborhood size in Circle-Block LBP.

There are different ways to choose the number of neighbors n as illustrated in Figure 1. In Figure 1(a) there are significant overlaps and the center resulting in unavoidable redundant information. In Figure 1(b) many blanks remain which fails to capture enough useful information. In Figure 1(c) R_c is equal to $R/2$. All the neighboring circles are tangent to the center circle if and only if P=6 where the feature dimension becomes 2^6=64, as is demonstrated in Figure 1(d). But 64 bins are not enough to form an descriptive histogram. So we choose 7-8 as the neighborhood size in our experiment.

Comparison between encoded images

L1 distance is adopted to measure the similarity of different face images. As is shown in Figure 2, two images of the same subject are depicted in the picture (a) (f), then encoded with LBP operator in (b)(g) and with CB-LBP with different radius in the picture (c)-(e) and (h)-(j). For LBP encoded images, the edges of light in (b) are more apparent than those in (g), while for CB-LBP encoded images the lighting variation between two subjects is much smaller. Details in eyes, nose and mouths are illustrated clearer in CB-LBP. It is easy to notice that as the radius R increases, the edges and angles of the senses become much more remarkable.

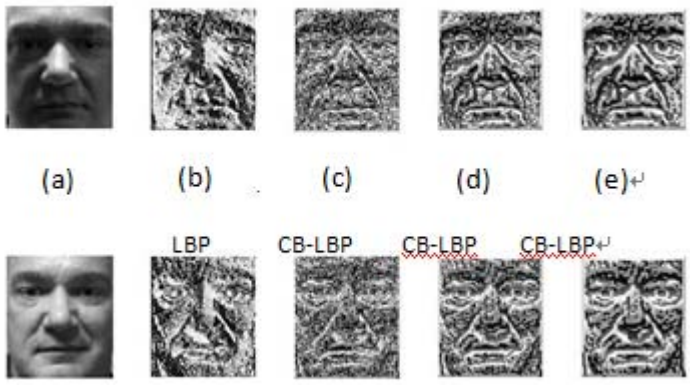


Figure 2. Comparison between two images and the encoding results using LBP and CB-LBP operators.

Experiment

Parameter description

In the following experiments, the optimal parameters of the compared algorithms are listed as follows. For all the LBP-based features, the neighbor size is 8 and the sub-block size is 7×7, while for CB-LBP the neighbor size keeps 7. Each block is with a 59-D histogram. The parameters of three patch based LBP (TPLBP) descriptors are r = 2, S =8, and w = 3. For the LTP features, the threshold for coding is 0.02. For LPQ, the local window size is 3 in all experiments.

Experiment on Extended Yale B database

There are 38 human subjects under 9 poses and 64 illumination conditions in the extended Yale B face image database. 60 frontal-face images of each subject are used in this experiment and each is resized to 96×84 and 48×42 pixels. We randomly choose K samples from each subject as a class for training and the remaining for test. Here, K varies from 4 to 24 with an interval of 4. For each K, we perform 10 runs of tests for each tested method and compute the average recognition rate as the result. Additionally, the standard NN classifier is employed for classification. Figure 3 shows the average recognition rate curve versus the variation of training sample size of 96×84 images after 10 runs.

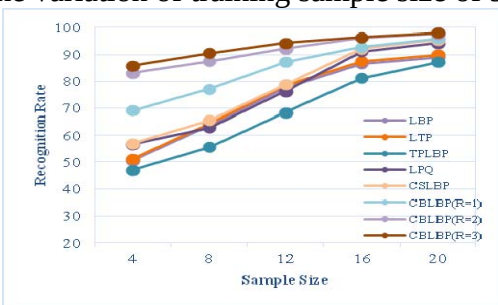


Figure 3. Average recognition rate curve versus the variation of training sample size using 96×84 images tested on Extended Yale B database.

From Figure 3, although TPLBP is not robust for face recognition especially under such difficult lighting conditions. LBP and LTP descriptors achieve better results for their general adaptability. CSLBP and LPQ descriptors slightly outperform the above two when the sample number K is large enough to sustain a stable extraction. However, these four descriptors are still not satisfying especially when the sample number K is small, since they all capture the local structural information by measuring point-to-point differences in a local region. CBLBP consistently achieves the best results especially because it covers a wide range of local pixels to gain a more robust recognition ability than the point-to-point methods above. R=3 is the best radius configuration, for the recognition result achieves best and smoothly along with the change of sample size.

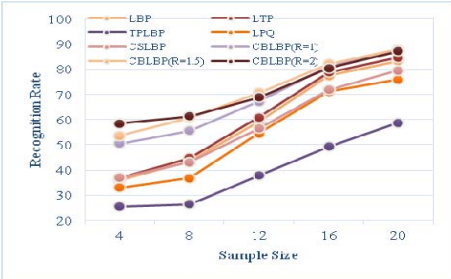


Figure 4. Maximum recognition rate curve versus the variation of training sample size using 48×42 images on Extended Yale B database.

Figure 4 gives a demonstration of recognition results on 48×42 images without modifying any other parameters. As the quality of images decreases, still CBLBP performs relatively well especially on a small sample size. The robustness of each algorithm meets a challenge thus the curves are not smooth. It should be noted that the curve of R=1.5 runs ahead of other radius on the specific image size partly compared with R=3 in the former experiment because of the compression of images. The performances of other descriptors are heavily influenced when the sample size is not large enough to extract adequate features.

Conclusion

In this paper, we develop a novel image feature extraction method called Circle-Block Local Binary Patterns for face recognition. The local structural information is exploited by measuring the local pixel difference between the average pixel values within a circle of a central pixel and those of its neighbor circles. CB-LBP exceeds the traditional LBP-based methods on its ability to adapt expression and illumination changes and its resistance to noise. Different block sizes and shapes will be combined together appropriately to achieve better results in the future studies.

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