HIERARCHICAL MULTISCALE LBP FOR FACE AND PALMPRINT RECOGNITION

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ABSTRACT

Local binary pattern (LBP), fast and simple for implementation, has shown its superiority in face and palmprint recognition. To extract representative features, "uniform" LBP was proposed and its effectiveness has been validated. However, all "non-uniform" patterns are clustered into one pattern, so a lot of useful information is lost. In this study, the authors propose to build a hierarchical multiscale LBP histogram for an image. The useful information of "non-uniform" patterns at large scale is dug out from its counterpart of small scale. The main advantage of the proposed scheme is that it can fully utilize LBP information while it does not need any training step, which may be sensitive to training samples. Experiments on one public face database and one palmprint database show the effectiveness of the proposed method.

Index Terms**—** LBP, multiscale, face recognition, palmprint recognition

1. INTRODUCTION

Biometrics refers to the study of methods for recognizing humans based on one or more physical or behavioral traits [1]. As a complementary or supplementary method to traditional person authentication, biometrics gets more and more popular. Among different biometric traits, face and palmprint recognition receive great amount of attention in the past decade. They can get high recognition rate and are user friendly.

How to extract discriminant information from an image is one of the key components for biometrics system. There are many different algorithms proposed in the past, such as principal component analysis (PCA) [2], Gabor phase encoding [3], and local binary pattern (LBP) [4-9] for feature extraction. Among them, LBP based method has shown its superiority in face [4-7] and palmprint [8-9] recognition. LBP was originally proposed as a texture descriptor. It owns many advantages, such as it is simple to implement and fast to compute [10].

It has been validated that "uniform" patterns play an important role in texture classification [10]. "Uniform" patterns also showed its superiority in face and palmprint recognition [4-5, 8-9]. Incorporating "uniform" idea, many patterns, which are not "uniform" patterns, are clustered into one "non-uniform" pattern. By this way, many discriminant but "non-uniform" patterns fail to provide useful features. And, the percentage of "non-uniform" patterns increases as the radius increases, so much information is lost. Recently, some works were proposed to address this issue. Many "non-uniform" patterns are isolated from the "non-uniform" cluster [6-7]. However, such methods are learning based algorithms, which require some training samples to discover useful "non-uniform" patterns. Thus, the recognition performance may be related with the training samples.

In this paper, we propose a hierarchical multiscale LBP algorithm for face and palmprint recognition. The LBPs for biggest radius is firstly extracted. Then, for those "non-uniform" patterns, the counterpart LBPs of smaller radius is extracted. Among the new LBPs, those "non-uniform" patterns is further proceeded to extract "uniform" patterns in even smaller radius. The procedure is iterated until the smallest radius is proceeded. The proposed scheme could fully utilize the information of "non-uniform" LBPs of bigger radius. Furthermore, this hierarchical scheme is totally training free which are not sensitive to the training samples.

The rest of the paper is organized as follows. Section 2 reviews the LBP. Section 3 presents the proposed hierarchical multiscale LBP method. Sections 4 shows experimental results on one face database and one palmprint database. Section 5 gives the conclusion and future work.

2. BRIEF REVIEW OF LBP

LBP [10] is a gray-scale texture operator that characterizes the local spatial structure of the image texture. Given a central pixel in the image, a pattern code is computed by comparing it with its neighbours:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{1}$$

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

where g_c is the gray value of the central pixel, g_p is the value of its neighbors, P is the total number of involved neighbors and R is the radius of the neighborhood. Suppose the coordinate of g_c is (0, 0), then the coordinates of g_p are (R*cos(2$\pi p/P$),R*sin(2$\pi p/P$)). Fig. 1 gives examples of circularly symmetric neighbor sets for different configurations of (P,R). The gray values of neighbours that are not in the center of grids can be estimated by interpolation.

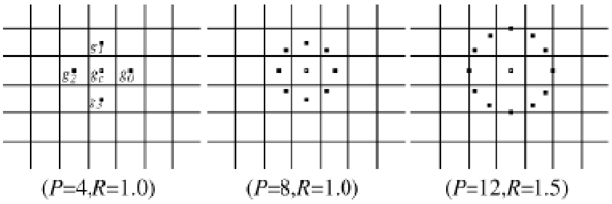


Figure 1: Circularly symmetric neighbour sets for different (P, R).

Suppose the texture image is of size $N\times M$. After identifying the LBP pattern of each pixel (i, j), a histogram is built to represent the whole texture image:

$$H(k)=\sum_{i=1}^{N}\sum_{j=1}^{M} f(LBP_{P,R}(i,j),k), k\in[0,K] \tag{3}$$

$$f(x,y)=\begin{cases}1, x=y\\ 0, otherwise\end{cases} \tag{4}$$

where K is the maximal LBP pattern value. The U value of an LBP pattern is defined as the number of spatial transitions (bitwise 0/1 changes) in that pattern

$$U(LBP_{P,R})=\left|s(g_{P-1}-g_c)-s(g_0-g_c)\right|+\sum_{p=1}^{P-1}\left|s(g_P-g_c)-s(g_{p-1}-g_c)\right| \tag{5}$$

For example, the LBP pattern 00000000 has a U value of 0 and 01000000 has a U value of 2. The uniform LBP patterns refer to the patterns which have limited transition or discontinuities ($U\leq 2$) in the circular binary presentation [10]. It was verified that only those "uniform" patterns are fundamental patterns of local image texture [10]. In practice, the mapping from $LBP_{P,R}$ to $LBP_{P,R}^{u2}$ (superscript "$u2$" means that the uniform patterns have a U value of at most 2), which has P*(P-1)+3 distinct output values, is implemented with a lookup table of 2^P elements.

The dissimilarity of sample and model histograms is a test of goodness-of-fit, which could be measured with a nonparametric statistic test. In this study, the dissimilarity between a test sample S and a class model T is measured by the chi-square distance:

$$D(S,T)=\sum_{n=1}^{N}\frac{(S_n-T_n)^2}{S_n+T_n} \tag{6}$$

where N is the number of bins, S_n and T_n are the values of the sample and model images at the n^{th} bin.

3. HIERARCHICAL MULTISCALE LBP

The performance of single LBP operator is limited. Multiscale or multiresolution could represent more image feature under different settings. Traditionally, LBP features of different scale are extracted first, and then the histograms are concatenated into a long feature. Joint distribution could contain more information, but it suffers from huge feature dimension.

As shown in Section 2, (2^P -P*(P-1)-2) "non-uniform" patterns are clustered into one "non-uniform" pattern. By applying this scheme, much information is lost. And, as the radius increases, the percentage of "non-uniform" pattern increases. For example, Table I shows the percentage of "non-uniform" patterns in palmprint images.

Table I. Percentage (%) of "non-uniform" patterns in PolyU palmprint database [13].

	R=1	R=2	R=3
P=8	15.82	23.68	29.86

As shown in Table I, around one third information is wasted by using previous method. To extract more useful feature from the image, some works were proposed to dig out information from these "non-uniform" patterns [6-7]. However, such methods require a training step to learn which patterns are useful. The recognition accuracy may be dependent on the training samples.

Fig. 2 shows an example. The pattern of a bigger radius is "non-uniform", but its counterpart in a smaller radius is "uniform". Thus, it is possible to classify the "non-uniform" patterns according to their counterpart of smaller radius.

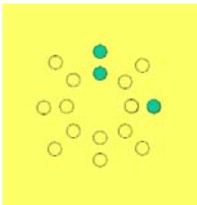


Figure 2: Binary Patterns of different radius of a local region. Solid circles represent 1 while hollow circles mean 0.

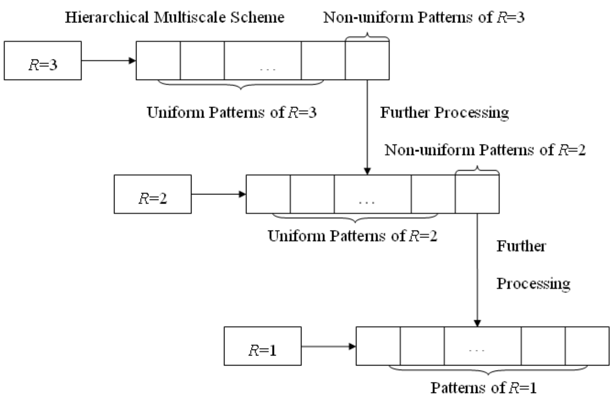


Figure 3: An example of the proposed hierarchical multiscale LBP scheme.

Here, we propose to build a mutliscale LBP histogram from big radius to small radius. First, LBP map of the biggest radius for each pixel is built. The pixels are divided by two groups through the type of patterns, “uniform” and “non-uniform”. A sub histogram is built for those “uniform” patterns. Those pixels, whose pattern is “non-uniform”, are further processed to extract their LBP patterns by smaller radius. The process stops for pixels whose new patterns are “uniform”, and the remaining pixels are continued to extract LBP patterns by smaller radius until the smallest radius.

Fig. 3 shows an example of the proposed hierarchical multiscale LBP scheme. The LBP histogram for R=3 is first built. For those “non-uniform” patterns by R=3 operator, a new histogram is built by R=2 operator. Then, the “non-uniform” patterns of R=2 are further proceeded to build a histogram by R=1 operator. Finally, three histograms are concatenated into one multiscale histogram.

There are mainly two differences compared with traditional multiscale LBP. Suppose the number of scale is S, the dimension of the proposed scheme is smaller than traditionally scheme by S-1. Second, sum of frequencies of the proposed histogram is 1/S of traditional one.

4. EXPERIMENTAL RESULTS

In this section, we verify the performance of the proposed method on a palmprint database, PolyU database [13] and a face database, AR database [12]. The proposed method is compared with PCA [2], which is one of the most well known methods in face and palmprint recognition, one of state-of-the-art subspace learning methods, DICA [11], single scale LBP and traditional mutliscale LBP. The simple nearest neighborhood classifier is used for all the methods. The code of the proposed method can be downloaded at http://www4.comp.polyu.edu.hk/~cslzhang/code.htm.

4.1. Palmprint Database

The palmprint database used in this study (PolyU Version 1.0) [13] was collected from 100 hands at two times. For every hand, it provides 3 samples for each session. The palmprints from each hand are treated as palmprints from different people. The size of the original images is 384*284. After preprocessing [3], the central part of the image (size is 128*128), is cropped for feature extraction and matching. Fig. 4 shows some samples of one palm after preprocessing.

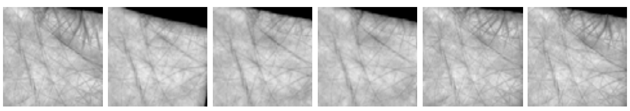


Figure 4: Some samples of one palm after preprocessing.

For LBP based methods, rather than getting one histogram for the whole image, the palmprint image is divided into many non-overlapping windows, as suggested by [4]. The dissimilarity of two images is the sum of dissimilarity of all the windows. Here, the image is divided into 8*4 windows to get a good balance between feature size and recognition accuracy.

Table II. Recognition accuracy (%) of different methods.

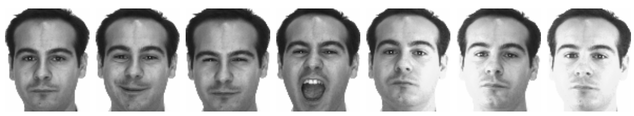
Method	Recognition Accuracy
PCA	88
DICA	99.33
Single scale LBP (R=2, P=8)	94.67
Traditional multiscale LBP (R={2,3,4}, P=8)	98.67
Proposed multiscale LBP (R={2,3,4}, P=8)	99.67

In the experiment, we selected the samples from the first session for training, and the samples from the second session for testing. Thus, the total number of training samples and test images are both 300. Table II shows the recognition accuracy of different methods.

From Table II, several findings could be found. First, multiscale LBP is an effective method, no less than 4% improvement could be gotten by multiscale scheme. Second, as more information could be extracted, the proposed method could get better result than traditionally multiscale method. Finally, the proposed method could get better result than learning based methods, PCA and DICA.

4.2. Face Database

In the AR database [12], the images of 120 individuals (65 men and 55 women) were taken in two different sessions and each session contains 13 images. The facial portion of each image is manually cropped and then normalized to a size of 100*80 (For PCA and DICA, the image is further reduced to 50*40 to speed up feature extraction.). The images from the first session with (a) neutral expression, (b) smile, (c) anger, (d) scream, (e) left light on, (f) right light on, and (g) both side light on, were selected for testing. Thus, we totally have 840 images from 120 individuals. Fig. 5 shows some samples of one subject.



(a) (b) (c) (d) (e) (f) (g)

Figure 5: Some samples of one subject.

Here, the image is divided into 5*3 windows to get a good balance between feature size and recognition accuracy. Two experiments were implemented. In the first experiment, the four sample images per person with (a) neural expression, (b) smile, (c) anger and (d) scream, in the first session were used for training, and the other three images for testing. The second experiment exchanges the training and testing sets. Table III lists the recognition accuracy for different methods on two experiments.

Table III. Recognition accuracy (%) of different methods.

Method	Accuracy (1st Experiment)	Accuracy (2nd Experiment)
PCA	68.89	79.79
DICA	99.72	95.83
Single scale LBP (R=2, P=8)	87.5	81.46
Traditional multiscale LBP (R={2,3,4}, P=8)	97.78	94.79
Proposed multiscale LBP (R={2,3,4}, P=8)	98.89	96.67

Similar findings as Table II could be found from Table III, such as both multiscale schemes could significantly improve the recognition accuracy and the proposed multiscale scheme is better than traditional one.

The proposed scheme could not get better result than DICA in the first experiment, but, it can get around 1% improvement in the second experiment. This is mainly because DICA is a training based method in feature extraction, thus it requires many training samples to learn representative features. It can get good results when the training sample is enough, however, it may fail to get good enough features when fewer training samples are provided. This is why DICA get around 4% drop from 4 training samples per subject to 3 samples per subject. As a training free method in feature extraction, the proposed method is more robust to the variation of training sample. As shown in Table III, it only gets around 2% drop from the first experiment to the second experiment. It is a very good property in many applications, as getting enough training samples is not a trivial issue.

However, there is one disadvantage of the proposed scheme. The feature dimension of multiscale LBP is a little higher. For example, in AR database, the feature sizes of the proposed scheme and traditional multiscale are 2,625 ((3*59-2)*5*3) and 2,655 (3*59*5*3), respectively. It is much larger than PCA (418 for the first experiment and 100 for the second experiment) and DICA (96 for the first experiment and 72 for the second experiment) [11]. Fortunately, 2,622 is not a big issue for current PC.

5. CONCLUSION

In this paper, to fully extract useful feature from an image, a hierarchical mutliscale LBP is proposed. It could dig out useful information from those “non-uniform” patterns. The main advantage of the proposed method could maintain the training free property during feature extraction, which is very important for some applications. Its effectiveness is shown in one palmprint and one face database. Compared with traditionally multiscale LBP, the proposed method could get more than 1% improvement. It could also get better result than those training based methods, when the training samples are not enough.

The feature size of multiscale LBP is a little high. How to reduce the feature size but get good performance in recognition will be our future work.

6. ACKNOWLEDGEMENT

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