ISSN: 2319-8753

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 9, September 2013

Palmprint Recognition by using Modified LOCAL BINARY PATTERN

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Abstract: In This paper presents a efficient texture based recognition on multi scale local binary pattern (LBP) texture features .It's a simple and fast for implementation, To extract useful representative features, "uniform" LBP was proposed and its effectiveness has been evaluated. However, all "non-uniform" patterns are grouped into one pattern, so a lot of useful information is lost. In this study, propose to build a modified multiscale LBP histogram for a palmprint image. The palmprint image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a image descriptor. The useful information of "non-uniform" patterns at large scale is dug out from its counterpart of small scale; the performance of the proposed method is that it can be fully utilize LBP features. Other applications and several extensions are also discussed.

Key words:-Facial image representation, local binary pattern, multiscale, component based face recognition, texture features, face misalignment

I. INTRODUCTION

Securing property and data is a very important topic. An effective way to perform the security is the use of biometric characteristics that is unique to each individual. THE Palmprint has its own advantages over other biometrics for people identification and verification related applications, fortunately, all human palmprints are different to each other in their configurations and hence offer high distinctiveness, unlike other biometrics, [1]. Furthermore, lot of palmprint recognition techniques like principle line detection and interest points to be there in biometrics, It has been validated uniform pattern play a important role in Texture based classification .They can get high recognition rate and are user friendly.

How to extract discriminate 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], local ternary pattern(LTP) and local binary pattern (LBP) [4-9] for feature extraction. Among them, LBP based method has shown its superiority in face recognition. LBP was originally proposed as a texture descriptor. It owns many advantages, such as it is simple to implement and fast to compute.

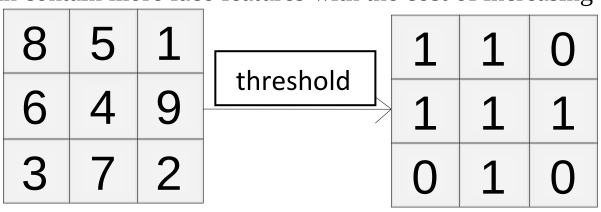
"Uniform" patterns are showed its superiority in face recognition [4-5, 8-9]. Incorporating "uniform" idea, many patterns, which are not "uniform" patterns, are clustered into one "non-uniform" pattern. By this way, many discriminate but "non-uniform" patterns fail to provide useful features. And, the 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 modified multiscale LBP algorithm for 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 modified 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 modified multiscale LBP method, Section 4 gives the conclusion and future work.

II. INEAR BINARY PATTERN

The original LBP operator labels the pixels of an image by thresholding a 3 × 3 neighborhood of each pixel with the center value and considering the results as a binary operator. Converting the binary code into a decimal one. Figure 1 gives an illustration for the basic LBP Based on the operator, each pixel of an image is labeled with an LBP code. The 256-bin histogram of the labels contains the density of each label and can be used as a texture descriptor of the considered region. The procedure of extracting LBP features for facial LBP approach can obtain the relationship among the original LBP operator [10]. The LBP code of the center pixel in the neighborhood is obtained by pixels of a facial image in a larger scale, which can contain more face features with the cost of increasing data redundancy,



Binary pattern: 11010101

Fig.1.Fundamental LBP operator

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 neighbors:

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

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

where gc is the gray value of the central pixel, gp 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 gc is (0, 0), then the coordinates of gp are (R*cos(2πp/P),R*sin(2πp/P)). Fig. 1 gives examples of circularly symmetric neighbor sets for different configurations of (P,R). The gray values of neighbors that are not in the center of grids can be estimated by interpolation.

ISSN: 2319-8753

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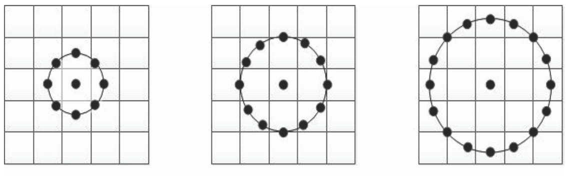

(P=8, R=1.0) (P=12, R=2.0) (P=16, R=3.0)

Figure 2: Circularly symmetric neighbor sets for different (P, R).

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

$$H(k)=\sum_{i=1}^{N}\sum_{j=1}^{M} f(LBP_{P,R}(i,j),k), k \in [0,k] ----------(2)$$

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

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

$$U(LBP_{P,R}) = \left| s\langle g_{p-1} - g_c \rangle - s\langle g_0 - g_c \rangle \right| +$$

$$\sum_{p=1}^{p-1} \left| s\langle g_p - g_c \rangle - s\langle g_{p-1} - g_c \rangle \right| -----------(3)$$

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≤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 ,PR LBP to 2 , u PRL BP (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 2P 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:

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

where N is the number of bins,

Sn are the values of the sample,

Tn are model images at the n th bin.

III. MODIFIED MULTISCLE LBP

The performance of ordinary LBP operator is limited. Multiscale or multiresolution could initiated more amount of image feature under different settings. Traditionally, LBP features of various scale are extracted first, and then the histograms are concatenated into one long feature. Joint distribution could contain lot of information, but it affected from huge feature dimension

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

Table I. Percentage (%) of "non-uniform" patterns in PolyU palmprint database [10].

	R=1	R=2	R=3
P=8	16.82	22.68	28.86

As shown in Table I, around huge amount of 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 more training step to learn which patterns are useful and which is not. The recognition accuracy may be dependent on the training samples.

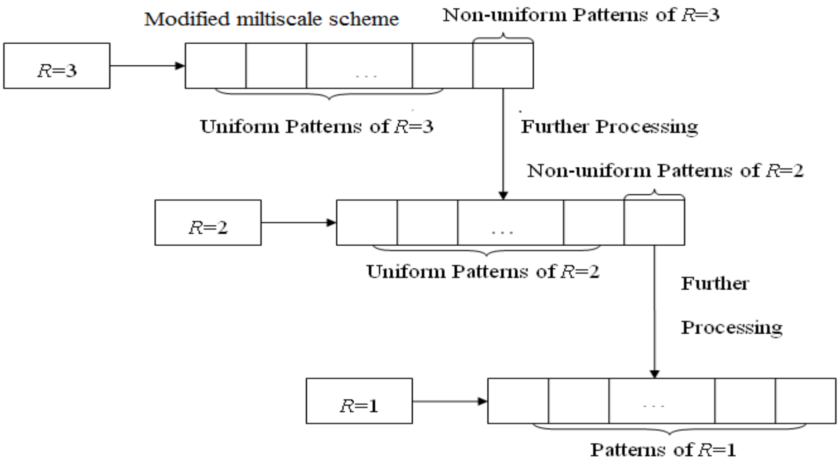

Figure 3: An example of the proposed hierarchical multiscale LBP scheme

Now we propose to build a histogram for biggest radius scale to smaller radius in the multiscale LBP,LBP first map for 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 Modified 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 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.

IV. EXPERIMENTAL RESULTS

In this section, we verify the performance of the proposed method on a palmprint database, PolyU database [12] , The

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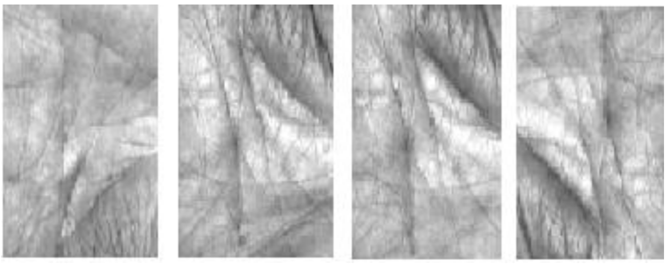
proposed method is compared with PCA [2], which is one of the most well known methods in face and palmprint recognition, one of the subspace learning method. single scale LBP and traditional mutliscale LBP. The simple nearest neighborhood classifier is used for all the methods.

A. 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-Some of palmprint images after preprocessing of that images



PolyU01-1 PolyU01-2 PolyU02-1 PolyU02-2

Figure 4: Some samples of palms after preprocessing

Table II:- Recognition rate for MMLBP

S.No	Training samples	Testing samples	Future measure	Recognition rate
1	1	9	90.4773	90
2	2	8	97.6387	97.5000
3	3	7	97.3211	97.1429
4	4	6	98.4522	98.3333
5	5	5	98.1664	99

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 III shows the recognition accuracy of different methods. The performance of different methods are evaluated at given below.

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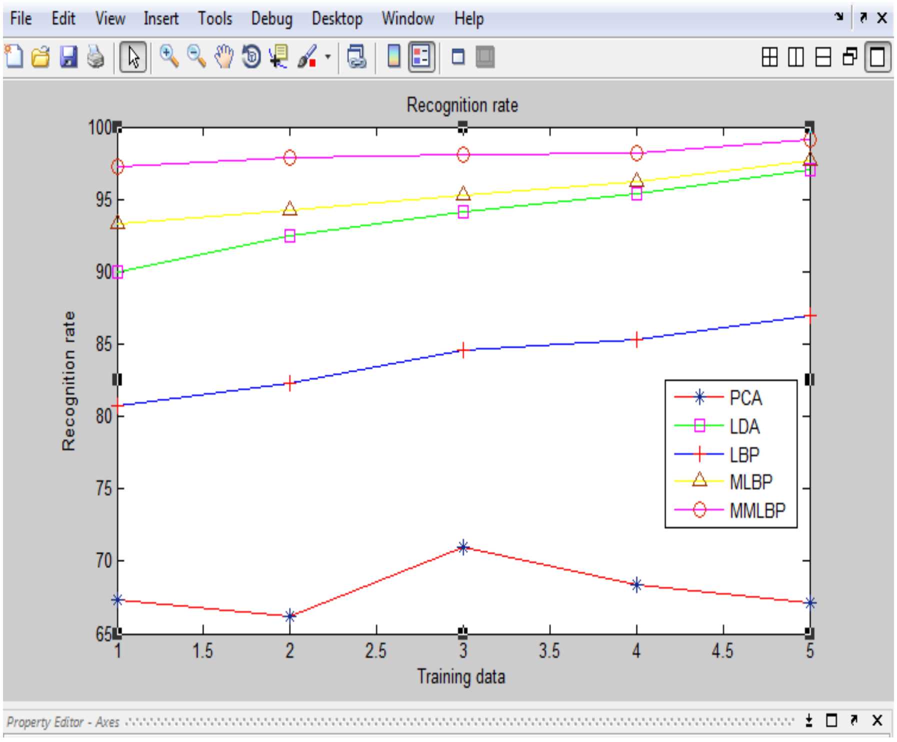

Figure 5: Recognition Different Methods at some Training Samples.

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

Method	Accuracy Rate (@ Experiment)
PCA	68.89
LDA	99.72
Single scale LBP (*R*=2, *P*=8)	87.5
Traditional multiscale LBP (*R*={2,3,4}, *P*=8)	97.78
Proposed multiscale LBP (*R*={2,3,4}, *P*=8)	98.89

From Table III, 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 LDA

V. CONCLUTION

In this paper, to fully extract useful feature from an image, a Modified 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. 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.

ACKNOWLEDGEMENTS

The first author would like to acknowledge the present work to Sir Bannari Amman for her ample and judicious blessings showered during the entire course of work

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ISSN: 2319-8753

International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 9, September 2013

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