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“Palmprint Recognition by using 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. All “non-uniform” patterns are grouped into one pattern, so a lot of useful information is lost. In this study, propose to build a LBP histogram for a palm print image. The palm print 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.

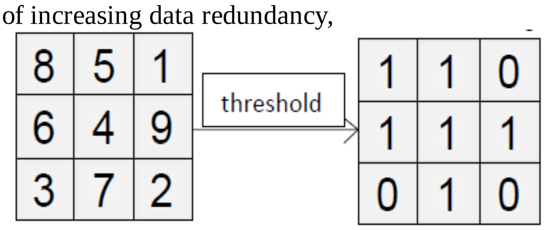
Key words: *local binary pattern, component based face recognition, texture features, face misalignment*

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 use friendly. How to extract discriminate information from an image is one of the key components for biometrics system. There are many phases of algorithms proposed in the past, such as principal component analysis (PCA), Gabor phase encoding, local ternary pattern LTP) and local binary pattern (LBP) for feature extraction. Along them, LBP method has shown in 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. Incorporating “suggest uniform” idea, many patterns, which are not “uniform” patterns, are clustered into one “non-uniform” pattern. By this way, many discriminate at that time “non-uniform” patterns fail to provide useful features. And the some criteria of “non-uniform”. pattern. By this way, many discriminate at that time “non-uniform” patterns fail to provide useful features. And the some criteria of “non-uniform” patterns increases also radius increases, so much information is lost. Recently, some works were proposed to address this issue. Many “nonuniform” patterns are isolated from the “non-uniform” cluster. Then such types of methods are learning based algorithms, which require some training samples to discover useful “non-uniform” patterns. Thus, the recognition performance based may be related with the training samples. In this paper, we propose a LBP algorithm for palmprint recognition. The LBPs for biggest radius is firstly extracted. This “non- uniform” patterns, the counterpart LBPs of smaller radius is extracted. Among the new LBP, those “non-uniform” proceeded to extract "uniform" patterns in even smaller radius. The procedure is iterated until the smallest radius is proceeded. The proposed scheme could fully initializing 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.

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 shows 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 interacting LBP approach can obtain the relationship among the original LBP operator . 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

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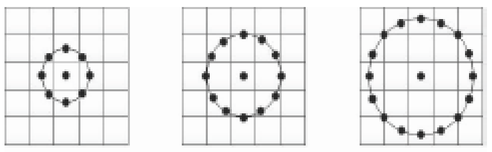
LBP [10] is a gray-scale texture operator that characterizes the local spatial structure of the image texture. Given a central pixel in the image, a pattern code is computed by comparing it with its neighbors:

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

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

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)). Above fig. gives examples of the 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.



(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:

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

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

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

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

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 creating 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. Flow Chart of Work

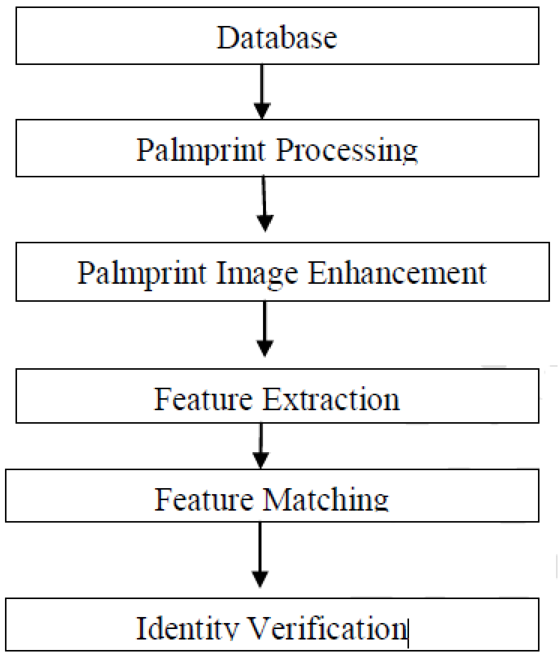


Fig. Flowchart of Palamprint matching system

(i) Database Creation:-
(ii) Pre-processing and Gabor filtering of data
(iii) Dimensionality reduction using PCA
(iv) Feature extraction for separation of class using LDA
(v) Fusion and classification using Euclidean distance classifier

(i) Database Creation

Database will be created by capturing images from webcam of laptop.The face and palm print image contains 400 samples images corresponding to 40 subjects with size of (640 x 480) will from database, some will be females, some will be fair and other dark skin people, each of various expression and posses.

(ii) Pre-processing and Gabor filtering of data

In pre-processing stage, all face and palm print images will be converted to gray scale and crop to (100x100) for face images and (100x100) for palm print images by the cropping process, all images have histogram equalizing in order to widen energy of all pixels. All images then will be normalized to produce image with equal amount of energy. Mean of these images will be computed for both modalities. The mean values here will be subtracted from the original face and palm print images to produce mean centre. All mean centre images then undergo Gabor filtering with the Gabor transform of 4 scales and 8 orientations to produce 32(4x8) images each. The size of these image will be too large

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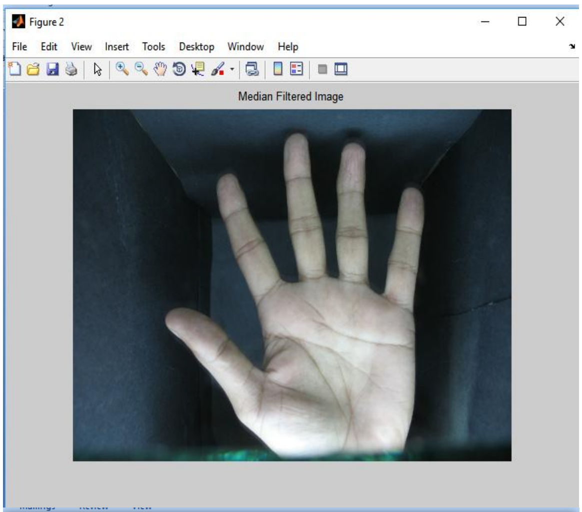
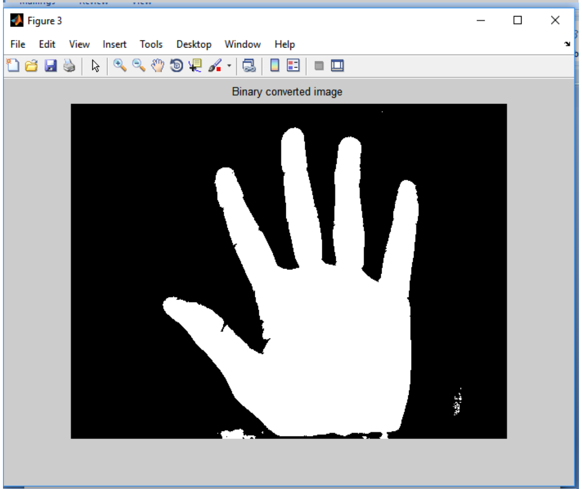
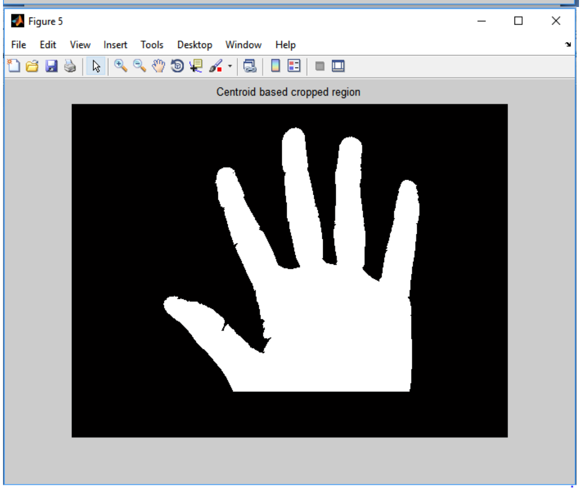
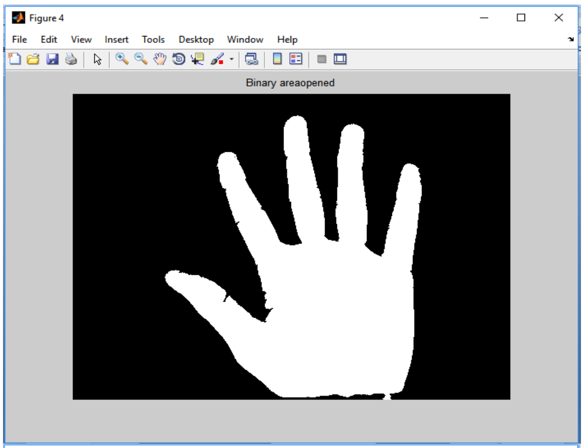
(filtered image size: 400 x 720), thus will consume a large memory and computational cost. Therefore, the filtered images here will be resized to a scale of 0.2 (reduced image size: 80 x 144).

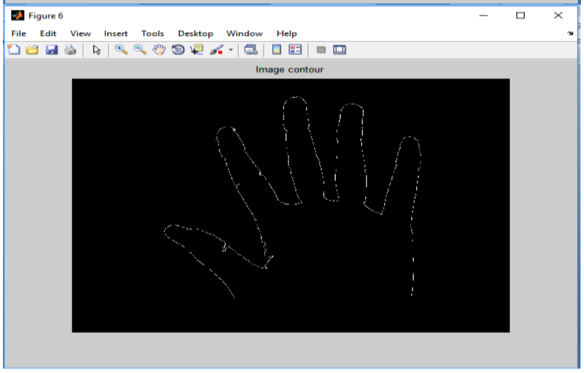
IV. Experimental Result

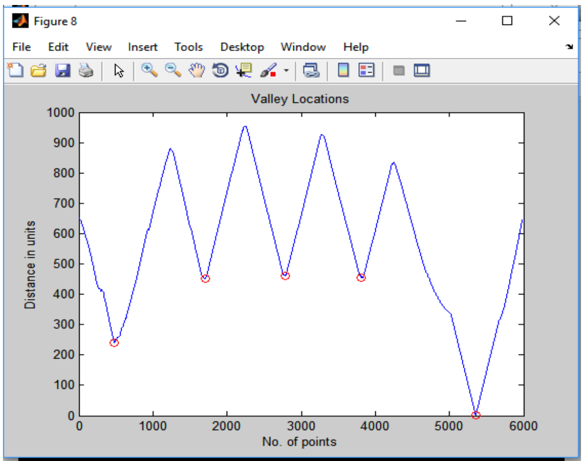


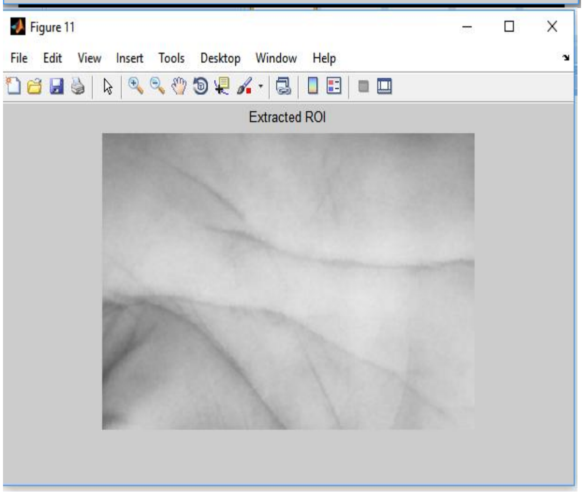


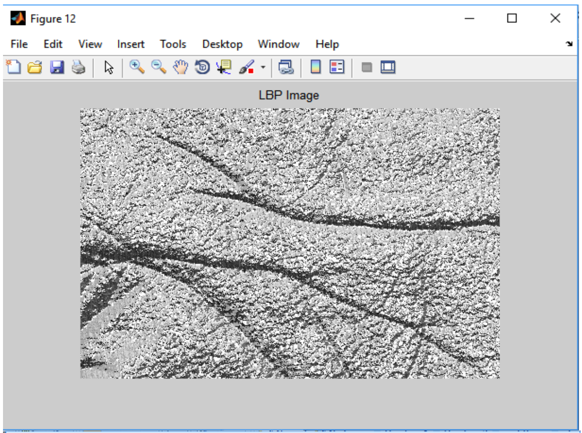


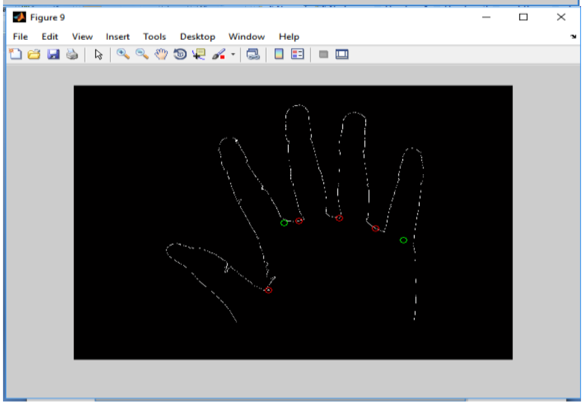












V. CONCLUTION

In this paper, to fully extract useful feature from an image, a 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 The feature size LBP is a little high. How to reduce the feature size but get good performance in recognition will be our future work.

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