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A Pore Based Partial Fingerprint Verification System Using Probabilistic Local Binary Pattern

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***Abstract*— Matching of partial fingerprint is an important challenge due to miniaturization of fingerprint sensors and small usable portion where partial fingerprint does not include details of minutiae points. Therefore sweat pores on fingerprint have proven to be useful feature. A common challenge to the pore based method is to extract pores from fingerprint images. Most of the Automatic Fingerprint identification system rely on level 1 and level 2 features which can be extracted using 500ppi resolution. But the pores are extracted using 1000ppi. In the research paper, the local binary pattern and its variations applied to fingerprint verification system is discussed.**

***Keywords*—Face Verification, Local Ternary Pattern, Probabilistic Local Binary Pattern, Uniform LBP**

I. INTRODUCTION

Fingerprint identification is widely used in the most biometric systems because it is considered as unique and permanent. It has been suggested that no two individuals have the exact same fingerprint and does not change throughout the lifetime. Low quality fingerprint image, distortion, the partial image problems (Fig.1), large fingerprint databases are all major areas of research needed to improve the accuracy of current systems.

Matching partial fingerprints presents several problems: The number of minutia points available in partial prints is few, thus reducing its discriminating power. Loss of singular points is likely and therefore, a robust algorithm independent of these singularities is required. Uncontrolled impression environments result in unspecified orientations of partial fingerprints, and distortions like elasticity and humidity are introduced due to characteristics of the human skin

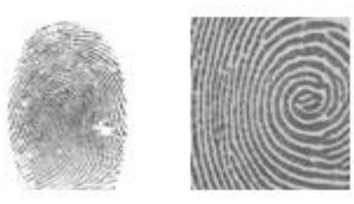


Figure.1 Fingerprint image with low resolution and partial fingerprint image

Fingerprint features (Fig.2) are generally categorized into three levels. Level 1 feature, (the macro details of the fingerprint such as ridge flow and pattern- type), Level 2

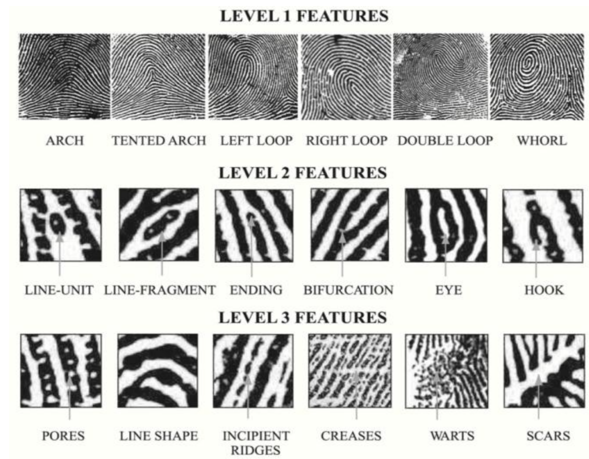


Figure.2: Fingerprint features

features, (minutiae, such as ridge bifurcations and endings), Level 3 features (includes ridge shape, pores, edge contour, incipient ridges, breaks, creases, scars). Among all the three levels, level 3 feature shows the most discriminating feature [3].

Locard stated that like the ridge characteristics, the pores are also permanent, immutable, and unique, and are useful for establishing the identity, especially when a sufficient number of ridges **are** not available. Locard further studied the variation of sweat pores and proposed four criteria that can be used for pore based identification: the size of the pores, the form of the pores, and the position of the pores on the ridges, and the number or frequency of the pores. It was observed that the number of pores along a centimeter of ridge varies from 9 to18, or 23 to 45 pores per inch and 20 to 40 pores should be sufficient to determine the identity of a person [1].

In this paper, we will focus on matching partial fingerprint against full fingerprint based on pores using Uniform LBP, Local Ternary Pattern, probabilistic LBP features. The paper is organized as follows: in section II gives brief description of background study of this work; section III Describes the phase I (Feature Extraction) of the fingerprint, Section IV Describes the phase II (matching and decision) of fingerprint verification system and section IV Concludes the paper.

II. Background Study

The state-of-the-art pore matching method was proposed by Jain et al. In the method, the fingerprint images were first aligned based on the minutia features on them by using a string-matching algorithm. Minutiae on the fingerprints were then matched and paired. Pores lying in a rectangular neighborhood to each pair of matched minutiae were cropped and rotated according to the directions of the two minutiae. Afterwards, they were matched by using the iterative closest point (ICP) algorithm The average distance between matched pores was taken as the pore match score. This score was then fused with the minutia match score by using the weighted summation scheme.

According to Qijun Zhao et.al proposed a direct approach for matching fingerprint pores. In this they have established an initial correspondence between the pores by pair wise comparing. Each pore is associated with a descriptor and it is directly obtained from the pixel values in the local circular neighborhood to the pore. Pore is rotated such that the ridge orientation at the location of the pore becomes horizontal and obtained a feature vector. Comparison of the descriptors is done and the similarity matrix is derived. RANSAC algorithm is used to refine the pore correspondences. A similarity score is calculated based on the pore matching results [2]. The method was not working effectively for the images with high noise in the background. In one another paper by Qijun Zhao et.al proposed a new approach to align partial fingerprints based on pores, Pores were extracted from the fingerprint images by using a difference of Gaussian filtering approach. After pore detection, a pore-valley descriptor (PVD) is proposed to characterize pores based on their locations and orientations, as well as the ridge orientation fields and valley structures around them. A PVD-based pore matching algorithm is then developed to locate pore correspondences. Once the corresponding pores are determined, the alignment transformation between two partial fingerprints can be estimated.

Local Binary Pattern: The local binary pattern (LBP) operator was first introduced as a complementary measure for local image contrast (Ojala *etal.* 1996). The first incarnation of the operator worked with the eight-neighbors of a pixel, using the value of the center pixel as a threshold. An LBP code for a neighborhood was produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result (Fig.3).

example

6	5	2
7	6	1
9	8	7

thresholded

1	0	0
1		0
1	1	1

weights

1	2	4
128		8
64	32	16

Pattern = **11110001**
LBP = 1 + 16 +32 + 64 + 128 = **241**

Figure.3: Local Binary Pattern

By selecting the smallest value of P-1 bitwise shift operations on the binary pattern, LBP is made rotation invariant.

There are some variations with the existing conventional LBP operator. The operator was extended to use neighborhoods of different sizes. Using circular neighborhoods and bilinear interpolating the pixel values allow varying the radius and number of pixels in the neighborhood. Let LBP $_{P,R}$ denotes p equally spaced pixels on a circle of radius R. as shown in the (Fig.4). The histograms are then computed from the binary patterns to form the feature vector.

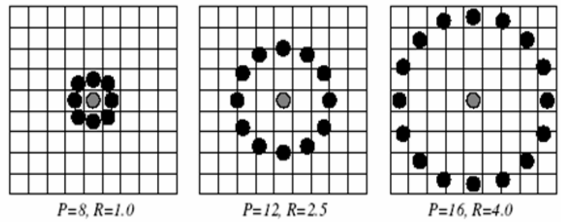


Figure.4 LBP with varying radius and number of neighboring pixels

Another extension to the original operator uses so called uniform patterns. A Local Binary Pattern is called uniform LBP if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. For example, 00000000, 00011110 and 10000011 are uniform patterns where as 01010001, 10100100 are nonuniform patterns. The number of bins in the uniform LBP is reduced by assigning all nonuniform patterns in one bin where as separate bins for every uniform pattern. Although the Uniform LBP is a good texture descriptor for face where the variation of the pixel intensity is less, it is less preferred to be used for fingerprint verification due to many variations in the fingerprint (i.e. ridges and valleys).

One more variation of the LBP is Local Ternary Pattern. Conventional LBP is sensitive to noise in the near uniform image regions. Local Ternary Patterns (LTP), as proposed by [5], overcomes this problem. In LTP the difference between a pixel **x** and its neighbor **u** is encoded by 3 values according to a threshold τ

τ=1 if $u \geq x + \tau$;

τ=-1 if $u \leq x - \tau$;

else τ =0.

The ternary pattern is split into two binary patterns according to its positive and negative components as illustrated in Fig.5. The histograms that are computed from the binary patterns are then concatenated to form the feature vector.

1	-1	1
-1		1
1	-1	0

1	0	1
0		1
1	0	0

0	1	0
1		0
0	1	0

Figure 5: Example ternary code divided into positive and negative LBP codes.

Third variation of LBP is Probabilistic Local Binary Pattern. In The LBP the centre may be smaller or greater than its neighbors; we use two different measures of probability p_g and p_s. If the neighbor is greater than the centre then it is denoted as p_g where as if it is smaller than it is denoted as p_s. Here, we suppose that the probability density can be molded as Gaussian, then the probabilities between the center pixel U and its neighbor V can be denoted as:

$$P_g(u,v) = \begin{cases} 1.0 - 0.5 * e^{-\frac{x^2}{\sigma^2}} & \text{if } I_u \geq I_v \\ 0.5 * e^{-\frac{x^2}{\sigma^2}} & \text{if } I_u < I_v \end{cases} \qquad (1)$$

$$P_s(u,v) = \begin{cases} 0.5 * e^{-\frac{x^2}{\sigma^2}} & \text{if } I_u \geq I_v \\ 1.0 - 0.5 * e^{-\frac{x^2}{\sigma^2}} & \text{if } I_u < I_v \end{cases} \qquad (2)$$

Where σ is the standard variance, x is defined as $x=|I_u - I_v| / I_u$ *and* I_u, I_v denotes the intensity values of the gray level image.
From the formula (1), we can see that if U is far greater than V, then p_g is near to 1, if U is far smaller than V, then p_g is near to 0, and if U is approximately equal to V, then p_g is near to 0.5.
The histogram which is plotted in the original LBP only one code (i.e. decimal equivalent to binary) corresponds to each pixel. Each pixel is added to the histogram. But in the given approach PLBP the above method will not work because here the probabilities are considered rather than binary code. The probability of each neighbor is found from the equations 1 and 2. The probability of each code is then derived by taking the product of all the neighboring probabilities and can be derived as

$$P_c(u) = {}_{i=1}\Pi^{8}\,(p_i) \qquad (3)$$

Where p_i is defined as

$$p_i = \begin{cases} p_g(u, xi) \text{ if } c_i=0 & (4) \\ Ps\,(u, x_i) \text{ if } c_i=1 \end{cases}$$

Where u is the centre pixel, x_i is the i_{th} neighboring pixel, c is the LBP code, c_i denotes the value of position i in c, and it values 0 (if the center is greater than the neighbor) or 1 (if the centre is smaller than the neighbor). Therefore, the histogram of PLBP can be denoted as

$$H_c^r = \sum_{u \in blockr} P_c(u), \text{ where } c=1\ldots.L \qquad (5)$$

III. PROPOSED SYSTEM

The Block diagram of the fingerprint verification system is shown in the Fig.6.

Phase I(Feature Extraction)

In this phase the image is acquired using a biometric sensor with resolution greater than 1000 ppi. In the next step the image is preprocessed using morphological opening and closing.

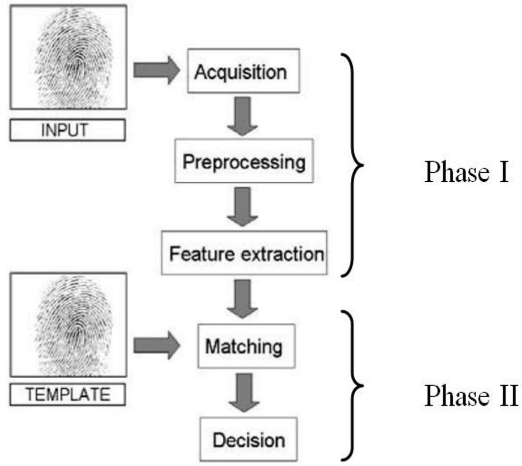
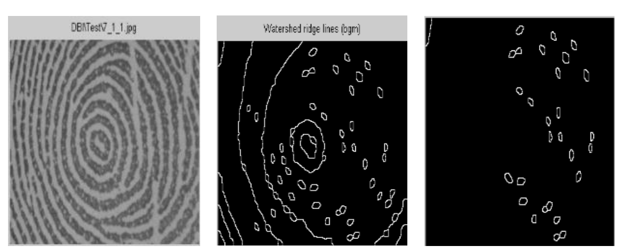


Figure 6: Fingerprint Verification System

Fingerprint pores which are used as feature can be extracted using watershed segmentation. The watershed transform finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low. Segmentation using the watershed transforms works well if we can identify, or "mark," foreground objects and background locations. Marker-controlled watershed segmentation follows this basic procedure:

- Read the color image and convert it to gray-scale.
- Develop gradient images using appropriate edge detection function.
- Mark the foreground objects using morphological reconstruction (better than the opening image with a closing).
- Calculating the regional maxima and minima to obtain the good forward markers.
- Superimpose the foreground marker image on the original image.
- Clean the edges of the markers using edge reconstruction. Compute the background markers.
- Compute the watershed transform of the function.(Fig. 7b)



(a) (b) (c)

Figure 7: (a) Sample fingerprint, (b) pores of a fingerprint,(c) filtered pores

Each watershed ridge lines are considered a cluster. Some of the watershed ridge lines might not be the pores (Fig.7 (b)) which can be eliminated by applying a threshold. If the number of pixels of a cluster is greater than the threshold then those clusters are removed as shown in the Fig.7(c)

A centroid of pore is an event in point processing. With regard to the features of pores, usually only the locations (or centroids) of pores are stable enough for matching. So the centroids of each pore are considered for matching two fingerprints. The centroids of the pores are calculated using the equations 6:

$$\rho^x = \frac{\sum_{cols}\sum_{rows} I_{ij} x_i}{\sum_{cols}\sum_{rows} I_{ij}}, \quad \rho^y = \frac{\sum_{cols}\sum_{rows} I_{ij} y_j}{\sum_{cols}\sum_{rows} I_{ij}} \qquad (6)$$

Where I_{ij} is the intensity of all the pixels which belongs to the pore and x_i, y_i is the x and y coordinates of the pore.

A. Phase II(Fingerprint Matching)

Extracted pores are used as anchor points for mapping to full image. For each pore, a sub window (33x33) is formed centered at that pore(Fig.8). Then the LBP operator as mentioned in section II is applied to each window to get a LBP histogram (Fig.9). In the 33x33 window we may get 11x11=121 LBP patterns. The resultant histogram is stored in the template of the partial image. Thus finally in the template for the partial image we have a set of histograms corresponding to all pores.

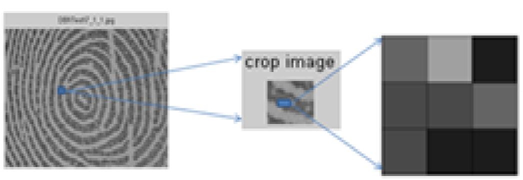


Figure 8: LBP for 33x33 window

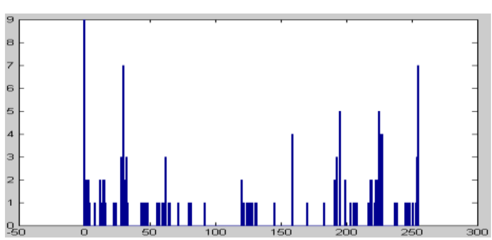


Figure 9: Histogram of LBP

The distance between the histograms of the partial fingerprints and full fingerprint database are found using the chi-squared formula given below

$$\chi^2(S,M) = \sum_{i=1}^{n} \frac{(S_i - M_i)^2}{S_i + M_i} \qquad (7)$$

Where S is the full fingerprints histogram where as M is the Query fingerprints histogram and n is the number of elements in the histogram.[3]

The match score between two images can be decided based on the number of matching points. The matching score is calculated as in the equation given below:

$$Match\ Score = \frac{Numi}{Total\ ni} \qquad (8)$$

The LBP only considers the sign of the difference between two values, but doesn't consider the magnitude of the difference, which may be very useful for example.

5	101	99
12	100	102
97	173	243

a.LBP=00111010

5	101	101
12	100	102
97	173	243

b.LBP=00111110

5	101	3
12	100	102
97	173	243

c.LBP=00111010

Figure 10: Patterns of LBP

As shown in Fig.10 a, b and c are different just in the right-top position. Apparently, a is more similar to b than to c, but we know that the LBP code of a is the same as c and different to b, which doesn't coincide with the truth. In this case the original LBP will result in some error. So, we can see that LBP sometimes can't capture the local detail of an image completely. Accordingly, in order to make LBP robust to noise, we propose probabilistic-LBP as described in section II, denoted as PLBP, which expresses the result of the comparison with probability rather than binary mode [4].

Now, let us review the Fig.10, apparently, the probabilities that the center is greater than the right-top position are almost the same in a and b, but different to c, which coincides with the truth. So adopting probability for LBP can not only encode the magnitude of difference, but also improve its robustness to noise.

IV.CONCLUSION

PLBP surely outperforms LBP operator as LBP has a limitation of loss of important detail like the magnitude of the difference between two compared pixels. Remarkable performance of PLBP in face recognition which also contains similar details such as texture and other features is identified. So, use of PLBP in fingerprint verification system will enhance the accuracy over conventional LBP. Hypothesis can be further confirmed through the Implementation of our proposed system.

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