OPEN ACCESS

International
Journal
Of Modern Engineering Research (IJMER)

# Study of Local Binary Pattern for Partial Fingerprint Identification

Miss Harsha V. Talele[1], Pratvina V. Talele[2], Saranga N Bhutada[3]
[1]Department of Computer Science, SSBT's College of Engineering, Jalgaon, Maharashtra
[2]Department of Information Technology, MIT College of Engineering, Pune, Maharashtra
[3]Department of Information Technology, MIT College of Engineering, Pune, Maharashtra

***Abstract***: *Fingerprints are usually used in recognition of a person's identity because of its uniqueness, stability. Today also the matching of incomplete or partial fingerprints remains challenge. The current technology is somewhat mature for matching ten prints, but matching of partial fingerprints still needs a lot of improvement. Automatic fingerprint identification techniques have been successfully adapted to both civilian and forensic applications. But this Fingerprint identification system suffers from the problem of handling incomplete prints and discards any partial fingerprints obtained. Level 2 features are very efficient if the quality of achievement decreases the number of level 2 features will not be enough for establishing high accuracy in identification. In such cases pores (level 3 features) can be used for partial fingerprint matching with the help of suitable technique local binary pattern features. Local binary pattern feature is used to match the pore against with full fingerprints. The first step involves extracting the pores from the partial image. These pores act as anchor points and sub window (32*32) is formed surrounding the pores. Then rotation invariant LBP histograms are obtained from the surrounding window. Finally chi-square formula is used to calculate the minimum distance between two histograms to find best matching score.*

***Keywords***: *Local Binary Pattern, Pores, Partial Fingerprint, Chi-Square*

## I. INTRODUCTION

Fingerprint can be used in forensic science to support criminal investigations, biometric systems such as civilian and commercial identification devices for person identification. It is believed with strong evidences that each fingerprint is unique. Each person has his own fingerprints with the permanent uniqueness. So fingerprints have being used for identification and forensic investigation for a long time. A fingerprint is composed of ridges and valleys on the surface of a fingertip. A fingerprint is a pattern of curving line structures called ridges, where the skin has a higher profile than its surroundings, which are called the valleys. In most fingerprint images, the ridges are black and the valleys are white. The fingerprint of an individual is unique and remains unchanged of over a lifetime. Automatic fingerprint identification is one of the most reliable biometric technologies. This is because of the well known fingerprint distinctiveness, persistence, ease of acquisition and high matching accuracy rates. Fingerprints are unique to each individual and they do not change over time. Even identical twins do not carry identical fingerprints. The uniqueness can be attributed to the fact that the ridge patterns and the details in small areas of friction ridges are never repeated.

The fingerprint identification problem can be grouped into two sub-domains: one is fingerprint verification and the other is fingerprint identification. In addition, different from the manual approach for fingerprint recognition by experts, the fingerprint recognition here is referred as Automatic Fingerprint Recognition System. Fingerprint verification is to verify the authenticity of one person by his fingerprint. The user provides his fingerprint together with his identity information like his ID number. The fingerprint verification system retrieves the fingerprint template according to the ID number and matches the template with the real-time acquired fingerprint from the user. The noise and distortion of captured fingerprints and the inaccurate of extracted features make fingerprint matching a very difficult problem. With the advent of high-resolution fingerprint imaging techniques and the increasing demand for high security, sweat pores have been recently attracting increasing attention in automatic fingerprint recognition.

The main modules of a fingerprint identification system (Figure 1) are:

1. Fingerprint sensing in which the fingerprint of an individual is acquired by a fingerprint scanner to produce digital representation.
2. In preprocessing the input fingerprint is improved and modified to simplify the task of feature extraction.

3. In feature extraction the fingerprint is further processed to generate discriminative properties.
4. Then in matching the feature vector of the input fingerprint is compared against one or more existing templates. Then score is calculated. The templates of approved users of the biometric system, also called clients, are usually stored in a database. Clients fingerprints can be checked against stored fingerprints. [5]

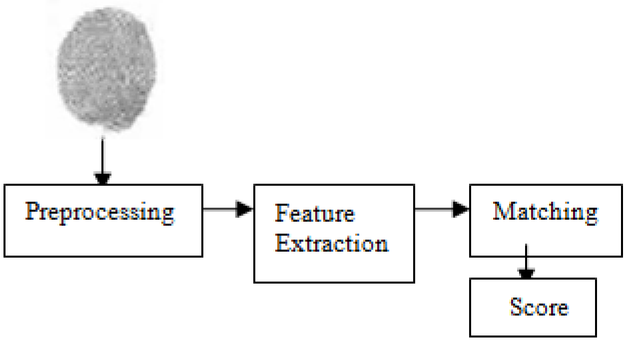



Figure 1: Main Module of Fingerprint Identification System

The need for recognition of partial fingerprints is increasing in both forensic and civilian applications. In forensics, latent fingerprints lifted from crime scenes are often noisy and broken, thus the usable portions are small and partial. In civilian applications, the invention of small hand-held devices, such as mobile phones, PDAs, and miniaturized fingerprint sensors present considerable demands on partial fingerprints processing. However, fingerprint scanners with a sensing area smaller than 1.0"x1.0", which is considered to be the average fingerprint size as required by FBI specifications can only capture partial fingerprints. A method for partial fingerprint recognition, the method comprising the steps of extracting features including ridge orientations, valley images, minutiae, and pores from at least two fingerprint fragments, aligning the fingerprint fragments, matching the pores and minutiae on the fingerprint fragments after applying estimated alignment transformation, calculating a final matching score based on a pore matching score and a minutiae matching score, identifying a person based on a result of the final matching score.

Matching partial fingerprints to a pre-filed complete fingerprint is usually encountered in forensic applications. In many cases, the partial fingerprint images that lifted from crime scenes are broken and unclear. Thus, the useable parts of the partial fingerprint images are restricted in small areas. Matching the partial fingerprint to the pre-filed images in database usually has the following problems:

1. The partial fingerprints obtained from a crime scene are normally small and noisy.
2. The number of minutia points available in such prints is less and further reduces the discriminating power.
3. Difficult to discover correspondence of obtained partial fingerprint to one of the fingers even if ten-prints are available.
4. Loss of core and delta is highly likely, so a robust algorithm that is independent of relying on these singularities is required.
5. Distortions like elasticity and humidity are introduced due to characteristics of the human skin.

The major challenges faced in partial fingerprint matching are the absence of sufficient level 2 feature minutiae and other structures such as core and delta. Thus common matching methods based on alignment of singular structures would fail in case of partial prints. Pores (level 3 features) on fingerprints have proven to be discriminative features and have recently been successfully working in automatic fingerprint identification systems. [7]. The Purpose of our paper is partial fingerprint identification is done by using level 3 feature pores with the help of local binary pattern to improve the matching accuracy.

## II. LITERATURE SURVEY

Level 1 feature, or patterns, is the macro details of the fingerprint such as ridge flow and pattern type. Level 1 level of detail cannot be used to individualize, but it can help narrow down the search. The line scan algorithm is very powerful algorithms that can be used for both full and partial fingerprints. The most notable advantages of these algorithms are the high accuracy in the case of partial fingerprints. At this time, the major drawback of developed algorithms is lack of pre-classification of examined fingers. Therefore, we use minutiae classification scheme to reduce the reference base for given tested finger. In 1892, Galton introduced Level 2 features by defining minutia points as either ridge endings or ridge bifurcations on a local ridge. Level 2 features, unlike Level 1 features, have individualization power and contribute the most in fingerprint matching. On average, a fingerprint generally contains 75-175 minutiae. At times, however, only a small number of minutiae are available in the captured fingerprint image and the extraction of additional Level 3 features may be necessary.

Locard introduced the science of poroscopy, the comparison of sweat pores for the purpose of personal identification in 1912. Locard confirmed that like the ridge characteristics, the pores are also permanent, immutable, and unique, and are useful for establishing the identity, particularly when a sufficient number of ridges are not available. Then Locard added the variation of sweat pores and proposed four criteria which can be used for pore based identification. The four criteria are 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 to 18, or 23 to 45 pores per inch and 20 to 40 pores should be sufficient to determine the identity of a person. Partial fingerprint identification is done by level 3 features based on pores extraction. There are three methods for partial fingerprint identification:

**1. State of the art pore matching method:**

First, gray scale images from the sensor are converted to binary format. The binary image is stored for later use and then processed further, resulting in a skeleton image. Finally, the skeleton image is processed to improve its functionality from a minutia or ridge analysis viewpoint. During the skeleton processing stage, its quality is improved by eliminating "ridge noise" components produced by pores and also by syntactic processing. The state-of-the-art pore matching method was recently proposed by Jain et al. In this method, the fingerprint images were first aligned based on the minutia features on them by using a string-matching algorithm. Then they were matched by using the iterative closest point (ICP) algorithm which is capable to handle sets of points with different numbers of points and can compensate for non-linear deformation between them.

**2. Adaptive pore model method:**

Manually marked and cropped hundreds of pores in several fingerprint images, including both open and closed pores. Based on the appearance of these real pores, we summarized three types of representative pore structures. Pore extraction results include Pores should reside on ridges only. To implement this constraint, we use the binary ridge image as a mask to filter the extracted pores. Pores should be within a range of valid sizes. We measure the size of a pore by counting the pixels in its region. The mean intensity of a true pore should be large enough.

**3. Dots and incipients for partial fingerprint matching method:**

A ridge unit may stay isolated that looks like a dot between normal ridges and thin and often fragmented ridges may also appear between normal ridges, known as incipient. As a result, our extraction algorithm for dots and incipients is designed based on ridge information and local orientation fields. The key component of our extraction algorithm is to estimate the local phase symmetry for ridge pixels. Because dots and incipients are isolated. They present slightly higher local symmetry than normal ridges. As a result, we employ wavelets based on complex valued Log Gabor functions to measure the local phase symmetry. Once local symmetry is estimated, it is multiplied with the skeletonized valley image. This is because dots and incipient ridges only occur in valleys between normal friction ridges.

However all these methods require high quality fingerprints so we use an automatic extraction of Local Binary Pattern of a pore for partial fingerprint identification.

## III. METHODOLOGY

Pores appear on fingerprint images as drops on the ridge. Pores are extracted from partial fingerprint image by using marker controlled watershed segmentation method. The concept of watershed is used in the field of topography. It determines a drop of water which is fall into a particular region. The watershed transform produces closed and adjacent contours including all image edges. The watershed produces a severe over segmentation.

**1. *Marker Controlled Watershed Segmentation:***

The marker-controlled watershed segmentation method is strong and flexible for segmentation of objects with closed contours, where the boundaries are represented as ridges. Markers are placed inside an object of interest. Internal markers are used to limit the number of regions by specifying the objects of interest and external markers are those pixels we are confident to belong to the background. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors.

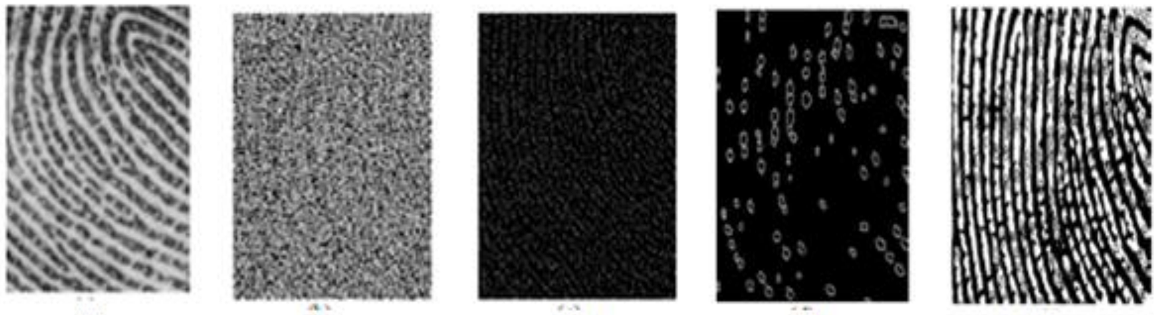
**2.** ***Creating Markers:***

The marker image used for watershed segmentation is a binary image consisting of either single marker points or larger marker regions, where each connected marker is placed inside an object of interest. Each initial marker has a one-to-one relationship to a specific watershed region, thus the number of markers will be equal to the final number of watershed regions. After segmentation, the boundaries of the watershed regions are arranged on the desired ridges, thus separating each object from its neighbors. The markers can be manually or automatically selected, but high throughput experiments often use automatically generated markers to save human time and resources. Various methods have been used for computing internal and external markers, many of which involve the linear filtering, non linear filtering and morphological processing.

**3.** ***Pore Extraction:***

We used simple algorithm to create foreground and background markers using Morphological image reconstructions. Read the original image as shown in Figure 3.1 (a). Then the watershed transform of the gradient fingerprint image is computed without any other processing. Watershed lines obtained which result in over segmented image as shown Figure 3.1 (b). Each connected region contains one local minimum in the corresponding gradient image. By computing the location of all regional minima in the fingerprint image as shown in Figure 3.1(c), we found that most of the regional minima are very shallow and represent detail which is irrelevant to our segmentation problem. The extraneous minima is eliminated by computing the set of low spots in the image that are deeper by a height threshold = 2. Then the markers are superimposed on the original fingerprint image. Next, background markers are created. The approach followed here is to mark the background by finding pixels that are exactly midway between the internal markers. This is done by computing the watershed transform of the internal marker image. The resulting watershed ridge lines appear in midway between the pores and hence they serve well as external markers. The marker image is shown in Figure 3.1 (d)

The internal and external markers are then used to modify the gradient fingerprint image using a procedure called minima imposition. The minima imposition technique modifies a fingerprint image so that regional minima occur only in marked locations. Other pixel values are pushed up as necessary to remove all other regional minima. The gradient fingerprint image is then modified by imposing regional minima at the locations of both the internal and the external markers. Finally watershed transform of the marker-modified gradient fingerprint image is computed. After superimposing the watershed ridgelines on the original fingerprint image, a much improved pore extraction is obtained as shown in Figure 3.1 (e)



(a) (b) (c) (d) (e)

Figure 3.1: Pore extraction results (a) Original image (b) Over segmented image (c) Regional minima (d) Marker image (e) Extracted pores

**Algorithm:**

1. Read the original image.
2. Develop gradient fingerprint images using appropriate edge detection function.
3. Compute the watershed transform of the gradient fingerprint image without any other processing which gives over segmented image.
4. Watershed lines obtained from gradient fingerprint images. Use the obtained watershed line as external markers by calculating regional minima.
5. Superimpose the foreground marker image on binarized fingerprint image.
6. Clean the edges of the markers using edge reconstruction.
7. Compute the background markers.
8. Compute the watershed transform of the function.[2]

## IV. IMPLEMENTATION

A common challenge to the pore-based fingerprint recognition systems is how to accurately and robustly extract pores from fingerprint images. Based on the position on the ridges, pores are often divided into two categories: open and closed. A closed pore is entirely enclosed by a ridge, while an open pore intersects with the valley lying between two ridges as shown in Figure 4.1.

### 1. *Local Binary Pattern:*

The local binary pattern (LBP) operator was first introduced by Ojala et al. 1996.LBP is a powerful method of texture description. The original 3X3 neighborhood is thresholded by the value of the center pixel. The values of the pixels in the thresholded neighborhood are multiplied by the binomial weights given to the corresponding pixels. Finally, the values of the eight pixels are summed to obtain the LBP number for this neighborhood. [1]

The standard version of the LBP of a pixel is formed by thresholding the 3X3 neighborhood of each pixel value with the center pixel's value. Let $g_c$ be the center pixel gray level and $g_p$ (p = 0,1,..7) be the gray level of each surrounding pixel. Fig.1 illustrate the basic LBP operation. If $g_i$ is smaller than $g_c$ , the binary result of the pixel is set to 0 otherwise set to 1. All the results are combined to get 8 bit value. The decimal value of the binary is the LBP feature.

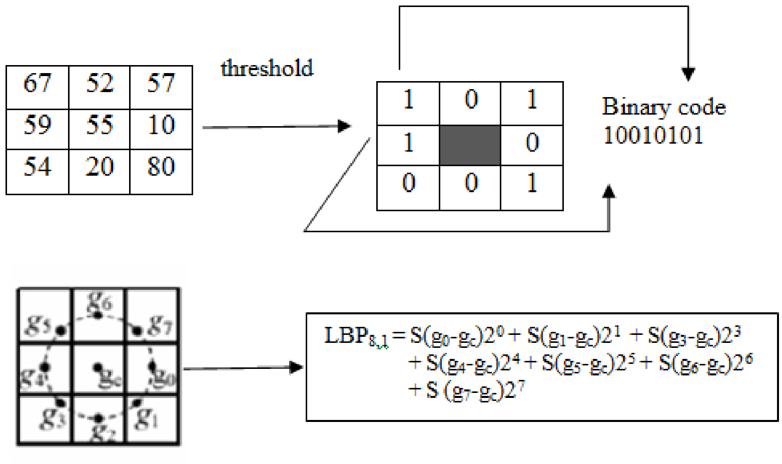



Figure 4.1: LBP operator of a pixel circular neighborhood with r=1, p=8

Let LBPp,r denote the LBP feature of a pixel 's circularly neighborhoods, where r is the radius and p is the number of neighborhood points on the circle .From Figure 4.1 we can write,

$$\mathrm{LBP}(P,R) = \sum_{p=0}^{p-1} S(g_p - g_c)2^p$$

The concept of uniform patterns is introduced to reduce the number of possible bins. Any LBP pattern is called as uniform if the binary pattern consists of at most two bitwise transitions from 0 to 1 or vice versa. For example if the bit pattern 11111111(no transition) or 00110000 (two transitions) are uniform where as 10101011 (six transition) are not uniform.

### 2. *Derivation of LBP Operator:*

Let us define texture T as the joint distribution of the gray levels of P (P > 1) image pixels:

$T = t(g_c, g_0, \ldots, g_{p-1})$

where gray value $g_c$ corresponds to the gray value of the center pixel of the local neighborhood and $g_p$ (P=0,1,…P-1) correspond to the gray values of P equally spaced pixels on a circle of radius R (R > 0). that form a circularly symmetric neighbor set.

Without losing information, the gray value of the center pixel ($g_c$) from the gray values of the circularly symmetric neighborhood $g_p$ gives:

$T = t(g_c, g_0 - g_c, g_1 - g_c, \ldots, g_{p-1} - g_c)$

Next, we assume that differences $g_p$ - $g_c$ are independent of $g_c$, which allows us to factorize the above equation :

$T = t(g_c)t(g_0 - g_c, g_1 - g_c, \ldots, g_{p-1} - g_c)$

Since $t(g_c)$ describes the overall luminance of an image, which is unrelated to local image text so it can be ignored and therefore does not provide useful information for image analysis :

$T = t(g_0 - g_c, g_1 - g_c, \ldots, g_{p-1} - g_c)$

Signed differences $g_p$ - $g_c$ are not affected by changes in mean luminance; hence, the joint difference distribution is invariant against gray-scale shifts. We achieve invariance with respect to the scaling of the gray scale by considering just the signs of the differences instead of their exact values:

$T = t( s(g_0 - g_c), s( g_1 - g_c) ,\ldots, s(g_{p-1} - g_c))$

Where,

$$S(x) = \begin{cases} 1, & \text{if } X \geq 0 \\ 0, & \text{Otherwise} \end{cases}$$

By assigning a binomial factor $2^p$ for each sign $S(g_p - g_c)$ , we transform the above equation into a unique $LBP_{P,R}$ number that characterizes the spatial structure of the local image :

$$\mathrm{LBP}(P,R) = \textstyle\sum_{p=0}^{p-1} S(g_p - g_c)2^p \qquad S(x) = \begin{cases} 1, \text{ if } X \geq 0 \\ 0, \text{ Otherwise} \end{cases}$$

The name "Local Binary Pattern" reflects the functionality of the operator, i.e., a local neighborhood is thresholded at the gray value of the center pixel into a binary pattern.[3]

### 3. *LBP Feature Extraction:*

However, adjacent LBP descriptors are not overlapped. Firstly, given an image, we split the image into several non-overlapped blocks. Then we extract the pores from fingerprint image by using marker controlled watershed segmentation method. Extracted pores are used as anchor points for mapping to full image. For each pore, a sub window is formed centered at that pore. Then for each block the feature histogram is calculated using local binary pattern. Through comparing the pixels between the neighbor points and central point, different weights are given according to different locations. We usually describe the neighborhood by a couple (P,R) , where P denotes the number of the sampled pixels in the area and R denotes the radius of neighbor. It is obvious that different types of images contain different feature details. Thus, it is the key issue that how to deal with the details in order to get good recognition performance and high efficiency. Specifically, we define the different weight on each block. Then we enhance the histogram vector according to the weight so as to strengthen the key information and eliminate the ineffective information. The single block strategy that segments a whole image symmetrically which obtain most of the features but still there are some problems.

The single-blocked strategy exacts the features in a easy way which leads to the decreasing of the recognition accuracy. Thus we can introduce the multi-blocked strategy that is to partition the same image into different blocks, and take the LBP feature vectors exacted by different partition into consideration. After that we deal with the problems bring by the single-blocked efficiently. In multi-blocked way, we need to combine the enhanced histogram in order to get the multi-blocked enhanced histogram. 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.

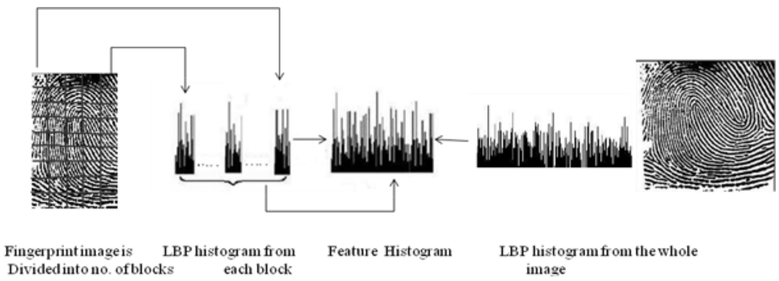



Figure 4.2: A fingerprint image is divided into number of blocks from which LBP histograms are extracted and concatenated into a single histogram

In the case of LBP, the matching of an image pair is done by computing the distance between the two LBP feature histograms of training and test samples. The larger the distance between the histograms the more dissimilar are the images. The algorithm for matching a partial and full image pair is based on distance between two lbp feature histograms. Minimum distance corresponds to best match. To get distance between two histograms, chi-square formula is used.

The Chi-Square distance between the two histograms S and M can be defined as:

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

Where $S_i$ and $M_i$ denote the $i^{th}$ bin value for two histograms respectively and n is the number of elements in the histogram. Chi square distance is an effective measurement of similarity between a pair of histograms, hence it is suitable for nearest neighbor. The "X" is the Greek letter chi; the "∑" is a sigma. Here we find out the distance between observed value and expected value and then sum all the value. For identifying a partial image in the set of full images, match score corresponding to each (partial image, full image) pair is obtained. The full fingerprint with maximum match score is identified as the best match.

Let Pp and Fp are list of histogram for pores in partial and full fingerprint mage respectively.
for p in Pp
dis = min(chi-square-distance(p, Fp))
if dis < threshold
  p is matched with distance dis
else p is non-matched

NIST special database 30 is used. It include all ten rolled fingerprints and the plain impressions at the bottom of the card scanned at both 500 dpi and 1000 dpi. This database has 36 paired fingerprint cards scanned at both resolutions and segmented into individual fingerprint images. Each partial fingerprint was matched with full fingerprint and then match score was calculated. [4]

Match Score =No. of Matched pores / Total No. of pores

Match scores represent the percentage of total number of pore matched out of total number of pores in partial image, it was necessary to choose threshold such that the match score was sufficiently high for all successful matches. The true detection rate RT means the ratio of the number of detected true pores to the number of all true pores and the false detection rate RF means the ratio of the number of falsely detected pores to the number of all detected pores were calculated on the fingerprint images.

## V. CONCLUSION

We present the partial fingerprint identification using local binary pattern features of pores. LBP feature provide good identification rate rather than other methods. This pore extraction method can detect pores more accurately and also help to improve the verification accuracy of pore based fingerprint identification system. The matching of partial and full image pair is based on distance between two local binary pattern feature histogram. For that we use chi-square formula to get the best result. Future work would involve making the fingerprint enhancement technique more efficient and effective for partial fingerprint identification. It also provide the fundamental issues of fingerprint permanence and improve the more accuracy of fingerprint recognition algorithms. Partial fingerprint identification also need to verify with different database which consists of large data and address robust feature extraction methods in case of scars, warts.

## REFERENCES

[1] S.Malathi, Dr.C.Meena "An Efficient Method for Partial Fingerprint Recognition based on Local Binary Pattern" IEEE International Conference on Communication Control and Computing Technologies, pages: 569-572, Oct 2010.
[2] S.Malathi, S.Uma maheswari, Dr.C.Meena "Fingerprint Pore Extraction Based On Marker Controlled Watershed Segmentation" in Proceedings of Second International Conference of Computer Automation and Engineering published by IEEE, pages: 337-340, February 2010 .
[3] Timo Ojala, Matti Pietikinen, and Topi Menp "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns" IEEE Transactions on Pattern Analysis and Machine Intelligence, pages: 971-987, 2002.
[4] American National Standards for Biometrics (NIST), http://fingerprint.nist.gov /standard/, May/2009.
[5] Abhishek Rawat "A hierarchical fingerprint matching system" July 2009.
[6] Chu He, Timo Ahonen and Matti Pietikäinen "A Bayesian Local Binary Pattern Texture Descriptor" IEEE International Conference on Pattern Recognition, pages: 1-4, Dec 2008.
[7] S. Mil'shtein, A. Pillai, A. Shendye, C. Liessner, and M. Baier "Fingerprint Recognition Algorithms for Partial and Full Fingerprints" IEEE Conference on Technologies for Homeland Security, pages: 449-452, May 2008.