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Fingerprint Recognition Using Level 3 Features

Neha Kesharwani[1], S.P.Ugale[2]

Department of Electronics and Telecommunication, K. K. Wagh Institute of Engineering Education and Research, Nashik India

Abstract: Fingerprints are a great source for identification of individuals. It is one of the oldest form of biometric identification. Fingerprint friction ridge details are generally described in a hierarchical order at three different levels,namely,Level1(pattern),Level2(minutia points),and Level 3(Pores and ridges contour) Although latent print examiners frequently take advantage of Level 3 features to assist in identification, Automated Fingerprint Identification Systems (AFIS) currently rely only on Level 1 and Level 2 features. Level 3 features carry significant discriminatory information. In our project we have presented an automated Fingerprint recognition system which uses level 3 features in combination with level 2 features which makes a matching system more accurate, efficient and beneficial.

Index Terms: Fingerprint recognition, high-resolution fingerprints, minutia, Level 3 features, extended features set, pores, ridges contour, string distance based matching.

I. INTRODUCTION

Recognition of persons on the basis of biometric features is an emerging phenomenon in our society [1, 2]. It has received increasing attention in recent years due to the need for security in a wide range of applications, such as replacement of the personal identification number (PIN) in banking and retail business, security of transactions across computer networks, high-security wireless access, televoting, and admission to restricted areas.

Traditional systems to verify a person's identity are based on knowledge (secret code) or possession (ID card). However, codes can be forgotten or overheard, and ID cards can be lost or stolen, giving impostors the possibility to pass the identity test. The use of features inseparable from a person's body significantly decreases the possibility of fraud. Furthermore biometry can offer user-convenience in many situations, as it replaces cards, keys, and codes. Many such biometric features can be distinguished: fingerprint, iris, face, voice, hand geometry, retina, handwriting, gait, and more. For several reasons, the fingerprint is considered one of the most practical features. Fingerprints are easily accessible, recognition requires minimal effort on the part of the user, it does not capture information other than strictly necessary for the recognition process (such as race, health, etc.), and provides relatively good performance. Another reason for its popularity is the relatively low price of fingerprint sensors. Fingerprints are one of the first biometrics to be widely used. The fingerprint of every individual is considered to be unique. No two persons have the same set of fingerprints. Also, Finger ridge patterns do not change throughout the life of an individual. This property makes fingerprints an excellent biometric identifier. So it is one of the popular and effective means for identification of an individual and used as forensic evidence. Fingerprint identification information is generally divided into three levels [3].Level 1 (pattern) is macro detail such as ridge flow and pattern type. Level 2 (points) is the Galton characteristics, or minutiae points, such as bifurcations and endings. Level 3(shape) includes all dimensional attributes of a ridge, such as ridge path deviation, width, shape, pores, edge contour, incipient ridges, breaks, creases, scars, and other permanent details.

Statistical analysis has shown that Level 1 features, or fingerprint pattern, though not unique, are useful for classification purpose, while Level 2 features or points have sufficient discriminating power to establish the individuality of fingerprints [3, 4]. FBI has set the standard for fingerprint resolution to be 500 dpi for forensic applications in order to reliably extract Level 2 features. However, human examiners perform not only quantitative (Level 2) but also qualitative (Level 3) examination since Level 3 features are also permanent, immutable and unique [4].

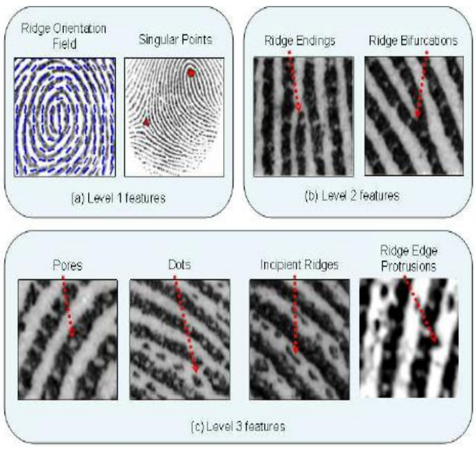

Fig. 1 Fingerprint features: (a) Level 1 (ridge orientation field and singular points), (b) level 2 (minutia, i.e. ridge endings and ridge bifurcations), (c) and level 3 (pores, dots, incipient ridges, and ridge edge protrusions).

II. IMAGE ENHANCEMENT

It is obvious that fingerprints are the most widely applied biometric identifiers. With the help of high performance computers, Automatic Fingerprint Identification Systems (AFIS) have gradually replaced human experts in fingerprint recognition as well as classification. However,

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fingerprint images contain noises caused by factors such as dirt, grease, moisture, and poor quality of input devices and are one of the noisiest image types. Therefore, fingerprint enhancement has become a necessary and common step after image acquisition in the AFIS.
To enhance the image,we used Gabor filters [22], which has the form

$$h(x,y:\emptyset,f) = exp\left\{\frac{-1}{2}\left[\frac{x_\emptyset^2}{\delta_x^2}+\frac{y_\emptyset^2}{\delta_y^2}\right] cos(2\pi f x_\emptyset)\right\} \quad (1)$$

Where $\emptyset$ is the orientation of the Gabor filter, f is the frequency of a sinusoidal plane wave, and δx and δy are the space constants of the Gaussian envelope along x and y axes, respectively. Here, $(x_{\emptyset,} y_\emptyset)$ represents the position of a point (x,y) after it has undergone a clockwise rotation by an angle (90-$\emptyset$).The four parameters $(\emptyset, f, \delta_x, \delta_y)$ of the Gabor filter are empirically determined based on the ridge frequency and orientation of the fingerprint image [22].

III. ALGORITHM ANALYSIS

A. Level 2 Feature Extraction

The level-2 features primarily refer to the Galton features or minutiae, namely, ridge endings and bifurcations. After the enhancement of the fingerprint image, the image is ready for minutiae extraction. For proper extraction, however, a thinning algorithm is applied to the enhanced image. It produces a skeletonised representation of the image.

Thinning is a morphological operation that is used to remove selected foreground pixels from binary images. It is used to eliminate the redundant pixels of ridges till the ridges are just one pixel wide. Thinning is normally only applied to binary images, and produces another binary image as output. It is the final step prior to minutiae extraction. It uses an iterative, parallel thinning algorithm. All the pixels on the boundaries of foreground regions that have at least one background neighbor are taken. Any point that has more than one foreground neighbor is deleted as long as doing so does not locally disconnect the region containing that pixel. Iterate until convergence.

Minutia Extraction

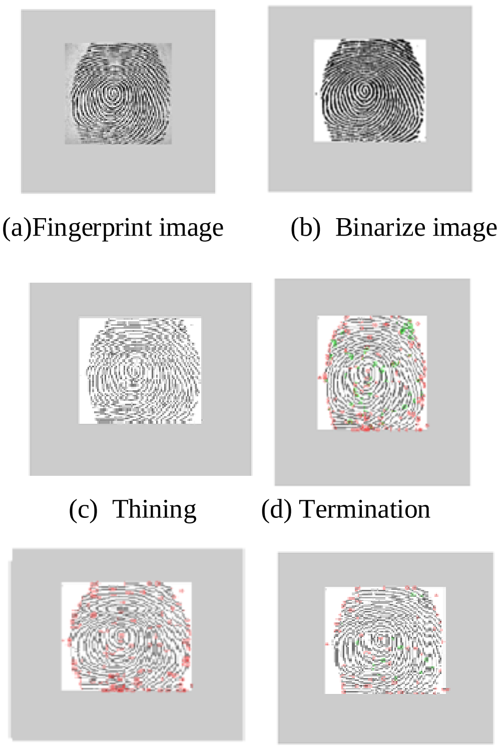
After the enhancement of the fingerprint image the next step is minutiae extraction. The method extracts the minutiae from the enhanced image. This method extracts the ridge endings and bifurcations from the skeleton image by examining the local neighborhood of each ridge pixel using a 3×3 window. The method used for minutiae extraction is the crossing number (CN) method. This method involves the use of the skeleton image where the ridge flow pattern is eight-connected. The minutiae are extracted by scanning the local neighborhood of each ridge pixel in the image using a 3×3 window. CN is defined as half the sum of the differences between the pairs of adjacent pixel.

The ridge pixel can be divided into bifurcation, ridge ending and non-minutiae point based on it. A ridge ending point has only one neighbor, a bifurcation point possesses more than two neighbors, and a normal ridge pixel has two neighbors. A CN value of zero refers to an isolated point, value of one to a ridge ending, two to a continuing ridge point, three to a bifurcation point and a CN of four means a crossing point. Minutiae detection in a fingerprint skeleton is implemented by scanning thinned fingerprint and counting the crossing number. Thus the minutiae points can be extracted.

A 3×3 window is used. The CN is given by

$$CN = .5\sum_{i=1}^{8}(P_i - P_{i+1}) \quad (2)$$

For a pixel q, the eight pixels are scanned in an anti-clockwise direction. The pixel can be classified after obtaining its pixel value. The coordinates, orientation of the ridge segment and type of minutiae of each minutiae point is recorded for each minutiae. After a successful extraction of minutiae, they are stored in a template, which may contain the minutia position (x, y), minutia direction (angle), minutia type (bifurcation or termination), and in some case the minutia quality may be considered. During the enrollment the extracted template are stored in the database and will be used in the matching process as reference template or database template. During the verification or identification, the extracted minutiae are also stored in a template and are used as query template during the matching.



(a)Fingerprint image (b) Binarize image
(c) Thining (d) Termination
(e) Bifurcation (f) remove spurious minutie

Fig. 2 Extraction of Minutia Features

B. Level 3 Feature Extraction

Level-3 features are often defined as the dimensional attributes of the ridges and include sweat pores, ridge contours, and ridge edge features, all of which provide quantitative data supporting more accurate and robust fingerprint recognition.

Pore Detection

Based on their positions on the ridges, pores can be 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 the two ridges. However, it is not useful to distinguish between the two states for matching since a pore may be open in one image and closed in the other image, depending on the perspiration activity. One common property of pores in a fingerprint image is that they are all naturally distributed along the friction ridge. As long as the ridges are identified, the locations of pores are also determined, regardless of their being open or closed.

To enhance the ridges, we use Gabor filters [22],
It is clear that ridges are well separated from the valleys after enhancement. The above procedure suppresses noise by filling all the holes (or pores) on the ridges and highlights only the ridges. By simply adding it to the original fingerprint image, we observe that both open and closed pores are retained as they appear only on the ridges. However, the contrast between pores and ridges is low. In order to enhance the original image with respect to pores, we employ a band pass filter to capture the high negative frequency response as intensity values change abruptly from white to black at the pores. Wavelet transform is known for its highly localized property in both frequency and spatial domains. Hence, we apply the Mexican hat wavelet transform [23] to the input image $f(x, y) \in R^2$ obtain the frequency response w as follows.

$$W(s, a, b) = \frac{1}{\sqrt{s}} \iint f(x, y) \emptyset \left\{ \frac{(x-a)}{s}, \frac{(y-b)}{s} \right\} d \quad (3)$$

Where s is the scale factor (=1.32) and (a, b) are the shifting parameters. Essentially, this wavelet is a band pass filter with scale s. After normalizing the filter response (0-255) using min-max normalization, pore regions that typically have high negative frequency response are represented by small blobs with low intensities. By adding the responses of Gabor and wavelet filters, we obtain the "optimal" enhancement of pores while enforcing the constraint that pores lie only on the ridges. Finally, an empirically determined threshold (= 10) is applied to extract pores. Note that our proposed pore extraction algorithm is simple and more efficient than the commonly used skeletonization- based algorithm, which is often tedious and sensitive to noise, especially when the image quality is poor.

(a)Fingerprint image

(b) Gabor Enhanced image

(C)Linear combine image

(d)Wavelet image

(e) pores detected

Fig.3 Pores Extraction

Ridge Contour Extraction

Ridge contours, which contain valuable Level 3 information including ridge width and edge shape, are observed to be more reliable features than pores.The ridge contour is defined as edges of a ridge. The algorithm to extract ridge contours can be described as follows:

a. The image is enhanced using Gabor filters .
b. Apply a wavelet transform to the fingerprint image to enhance ridge edges. The wavelet response is subtracted from the Gabor enhanced image such that ridge contours are further enhanced
c. The resulting image is binarized using an empirically defined threshold δ = 10.
d. Ridges contour can be extracted by convolving the binarized $f^b(x, y)$ with a filter H,given by

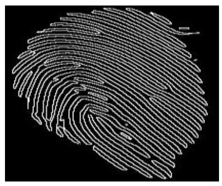
$$r(x, y) = \sum_{nm} f^b(x, y) H(x - n, y - m) \quad (4)$$

where filter H =(0,1,0;1,0,1;0,1,0) counts the number of neighborhood edge points for each pixel. A point (x, y) is classified as a ridge contour point if r(x,y)=1 or 2.

(a)Fingerprint image

(b) Gabor Enhanced Image

(c) Wavelet Image



(d) Extracted Ridges Contour

Fig.4 Ridges Contour Extraction

IV. FINGERPRINT MATCHING

A fingerprint matching module computes a match score between two fingerprints, which should be high for fingerprints from the same finger and low for those from different fingers.

Matching Algorithm

The features are extracted from a fingerprint image using a different extraction algorithm. Each feature is characterized by its location and the direction of the ridge on which it resides. The features obtained from two fingerprint images can be matched using **string distance**

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based matching algorithm. Dynamic programming has been commonly used in speech processing to deal with the time warping problem. Similar ideas can be used to solve the elastic distortion problem in fingerprint matching (Jain et al., 1997). Each set of extracted features is first converted into polar coordinates with respect to an anchor point. The 2D minutia features are, therefore, reduced to a 1D string. The string matching algorithm is applied to compute the edit distance between two strings. The edit distance can be easily normalized and converted into a matching score.

This algorithm can be summarized as follows:

1. Estimate the rotation θ between the two sets of features and the anchor minutia of eachset A1 and A2. Rotation is estimated through aleast-squares fitting. The values of parameters θ,A1 and A2 which result in the maximum number of matched minutia pairs within a bounding box are chosen as the best estimates;
2. Convert each set of features in to 1D string using polar co-ordinates anchored at A_1 and A_2,respectively;
3. Compute the edit distance between the two 1D strings. The matched pairs are retrieved based on the minimal edit distance between the two strings;
4. Output the normalized matching score as

$$\left\{\frac{No\ of\ matc\ hed\ pairs}{o_1+1}\ X\ \frac{No\ of\ matc\ hed\ pairs}{o_2+1}\right\} \qquad (5)$$

V. PERFORMANCE EVALUATION

Fingerprint identification system performance is measured in terms of its false positive identification rate (FPR) and false negative identification rate (FNR). A **false positive identification** occurs when the system finds a hit for a query fingerprint that is not enrolled in the system. A **false negative identification** occurs when it finds no hit or a wrong hit for a query fingerprint enrolled in the system.

FPR and FNR in terms of TP, TN, FP, FN

$$\text{FPR} = \frac{\text{FP}}{\text{FP+TN}} \qquad (6)$$

$$\text{FNR} = \frac{\text{FN}}{\text{FP+TN}}, \qquad (7)$$

Where TP (true positive) = Correctly identified
TN (true negative) = Correctly rejected
FP (false positive) = Incorrectly identified
FN (false negative) = Incorrectly rejected

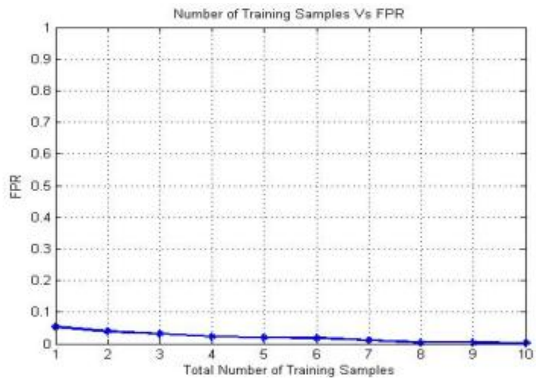

Fig 5 Graph of number of training samples vs FPR(Level 3 features)

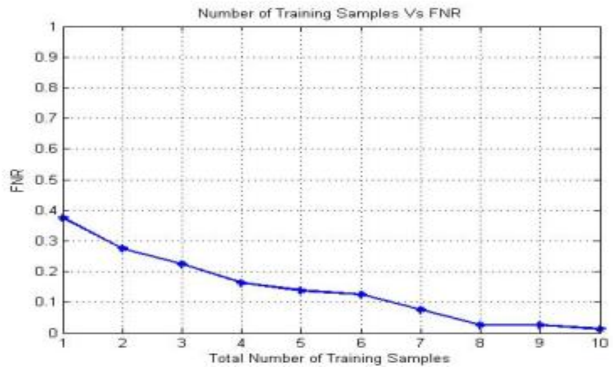

Fig 6 Graph of number of training samples vs FNR(Level 3 features)

Comparison of Level 2 features and Level 3 features in terms of Efficiency and time require for extracting those features:

By comparing both feature we got that the efficiency of level 3 features is more than level 2 features but it takes more time for extraction than level 2 features.

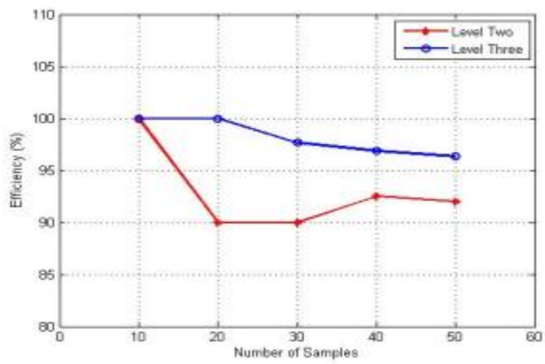

Fig7 Graph of number of samples vs. efficiency

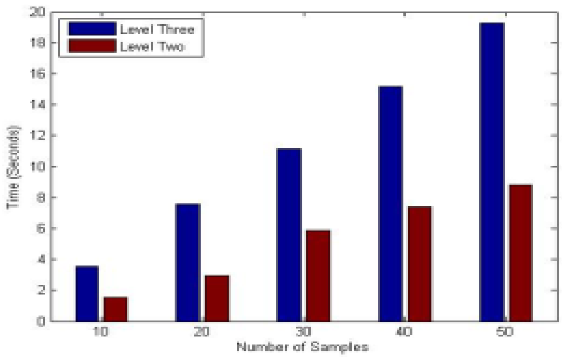

Fig8 Graph of number of samples vs. extraction time

VI. CONCLUSION

We have presented an automated fingerprint recognition system that utilizes Level 3 features which include all dimensional attributes of the ridge path deviation, width, shape, pores, edge contour, incipient ridges, breaks, scars and other permanent details. To obtain discriminative information at Level 3, we introduced algorithms based on Gabor Filters and wavelet transform to automatically extract pores and ridges contour. A string distance based algorithm is used for matching all the features. It is demonstrated that Level 3 features do provide additional discriminative information and should be used in combination with Level 2 features. The results of this study strongly suggest that by combining Level 3 features in addition to Level 2 features makes the fingerprint recognition system more accurate, efficient and beneficial. The extraction of level 3 features takes more time than level 2 features.

We are looking forward for discovering a better technique which reduces the extraction time and also a better enhancement method for fingerprint images captured by the digital camera by introducing some concepts of soft computing so that the output of preprocessing module increases the performance of the system. We are also trying to discover more optimal methods for matching fingerprints images.

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