A New Model of Fingerprint Retrieval Based on Features of Minutiae and Gabor

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***Abstract*—Fingerprint is the commonly used biometric property in security, commerce and forensic application. One common problem in pattern recognition is lack of samples, only a few fingerprint samples from each individual are available for training a classifier. This paper proposes an approach of fingerprint retrieval based on Bayes classifier by combining the features of Gabor and Minutia and attempted to tackle the problem of insufficient training samples by generating additional samples using spatial modeling. With the expanded training set, we are then able to employ a more sophisticated classifier such as a Bayes classifier for recognition. We apply the proposed method to build a fingerprint retrieval system that is accurate and efficient. In fingerprint indexing / retrieval, the problem of one-to-one matching is extended to one-to-N matching, the system searches through the entire database (FVC, NIST-4) of enrolled templates and returns a list of probable fingers (identifiers of individual) that the fingerprint may belong to. The accuracy and speed are evaluated using FVC database and the system performs better than that of K-NN classifier has the drawbacks of being comparatively slow and less accurate.**

***Keywords*—Fingerprint Indexing, FVC, NIST-4, Spatial modeling, Fingerprint Retrieval.**

I. INTRODUCTION

Fingerprints have been used for over a century and are the most widely used form of biometric identification A fingerprint is the feature pattern of one finger [1]. Each person has his own fingerprints with the permanent uniqueness. The fingerprint recognition problem can be grouped into three sub-domains: one is fingerprint enrollment, fingerprint verification and the other is fingerprint identification. Fingerprint verification is to verify the authenticity of one person by his fingerprint. It compares an input fingerprint with only one template of the claimed identity was extensively studied and promising results were reported [2] [3]. In fingerprint indexing/retrieval, the problem of one-to-one matching is extended to one-to- N matching without requiring the subject's claim of identity. Fingerprint identification refers to the process of matching a query fingerprint against a given fingerprint database to establish the identity of an individual. Its goal is to quickly determine whether a query fingerprint is present in the database and to retrieve those which are most similar to the query from the database. The critical issues here are both retrieval speed and accuracy. This method is especially useful for criminal investigation cases. The fingerprints, when analyzed at different scales, produce different types of features. At global level, patterns known as ridges and valleys exhibits a number of particular shapes called singularities, which are classified as: loop, delta and whorl. At the local level, ridge characteristics, called minutia. There are several types of minutiae, but the two most prominent ridge characteristics are: ridge ending (point where ridge ends abruptly) an d ridge bifurcation (points where ridge forks or diverges into branch ridges) as shown in Fig. 1. The rest of the minutiae are combination of each or those two types.

One common problem in pattern recognition is lack of samples in training a classifier. The number of samples available for recognition is limited. This paper mainly uses a database known as Fingerprint Verification Competition(FVC) contain only eight instances per finger in each set [4] [5].We have attempted to tackle the problem of insufficient training samples by generating additional samples from a genuine sample by using a Spatial modeling namely translational modeling and rotational modeling. The main objective of this research is to build a fingerprint retrieval system that is accurate and efficient. An early attempt of fingerprint retrieval based on Euclidean distance measure using a K-Nearest Neighbor(K-NN)classification[6] which is slow and less accurate. To overcome this problem we are going for an efficient classifier known as Bayes Classifier. With a lot more training samples, it becomes possible to train up a more sophisticated classifier instead of K-NN classifier.

A. *Outline of the Proposed Approach*

This paper mainly deals with Fingerprint Identification system. Identification is the traditional domain of criminal fingerprint matching. A fingerprint of unknown ownership is matched against a database of known fingerprints to associate a crime with an identity. Identification is also termed, one-to many matching. It is especially useful for criminal investigation cases. In this approach we are using fingerprint image present in the FVC database for training a classifier. In previous method Bayes classifier can be trained by using Gabor feature extraction, but here we are using both Gabor feature as well as minutia feature extraction for efficient retrieval. Fisher Linear Discriminant function is used for dimension reduction and Modified Quadratic

Discriminant for lower estimating errors. We can estimate the prior probabilities of the classes from their frequencies in the training data of a fingerprint using Bayes theorem.

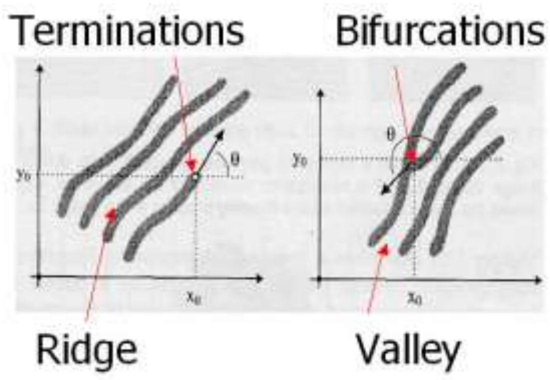

Fig 1: Fingerprint image with bifurcations and terminations

II. RELATED WORK

Real-time image quality assessment can greatly improve the accuracy of identification system. The good quality images require minor pre-processing and enhancement. Conversely, low quality images require major pre-processing and enhancement.

A. Pre-Processing

Pre-processing operation is used for enhancing the contrast of the fingerprint image. The main steps involved in the pre-processing include: (*a*) enhancement (*b*) binarization (*c*) segmentation, and (*d*) thinning .Quality of the acquired fingerprint depends on the condition of the finger and sensor used. Both factors may lead to poor quality between ridges, crossovers and bifurcation in the fingerprint image. So pre-processing operation should be performed before extracting the minutiae from the fingerprint. Pre-processing operation can be performed with various methods. For example histogram equalization will increase the contest of the image. Quality of the image can also be increased by using the filters. Low pass filter decrease the noise from the image, band pass filter decrease undesired noise from orientations which helps in preserving true ridges. Pre-processing is the initial step performed in a fingerprint for recognition.

1) Enhancement

Image enhancement can also be performed using Fourier transform based method and histogram equalization method. In spatial domain histogram equalization is applied. In frequency domain Fourier Transform is done. Divide the fingerprint image into sequence of squares each of size 32X32 pixels and perform a 2 dimensional Fast Fourier Transform (2D FFT) to the fingerprint image. Next the nonlinear function is applied to increase the power of useful information (orientation of ridges and valleys, to decrease noise etc). Where the nonlinear function is performed by multiplying the FFT of the block by its magnitude a set of times to increase the strength of the frequencies. Then inverse2D FFT is applied to transform the enhanced data to spatial representation. In the spatial domain, histogram equalization technique was applied for better distribution of the pixel values over the image to enhance the perceptional information. It means make the image clearer for further operation

B. Image Binarization

In this step, an 8-bit grey level fingerprint image is transformed into a 1-bit image with 1-value for ridges and 0-value for furrows. An optimized approach can be found for binarization. In our work, an enhanced binarization method was used which is based on the adaptive binarization approach. In this method, the pixel value is transformed to 1 if the value is larger than the mean intensity value of the current block (16×16pixels); otherwise, it is set to zero.

C. Segmentation

The objective of the fingerprint segmentation is to extract the region of interest (ROI) which contains the desired fingerprint impression. Fingerprint image segmentation highly influences the performances of Automatic Fingerprint Identification System (AFIS). In our work, the gradient based fingerprint segmentation approach [7]. was used and the segmentation results were found satisfactory even for the low quality images.

D. *Thinning*

The final image enhancement step typically performed prior to minutiae extraction is thinning. Thinning is a morphological operation that successively erodes away the foreground pixels until they are one pixel wide. A standard thinning algorithm [8] is employed, which performs the thinning operation in a binarized image by using two subiterations. This algorithm is accessible in MATLAB via the `thin' operation under the bwmorph function. Each subiteration begins by examining the neighbourhood of each pixel in the binary image, and based on a particular set of pixel-deletion criteria, it checks whether the pixel can be deleted or not. These subiterations continue until no more pixels can be deleted. The application of the thinning algorithm to a fingerprint image preserves the connectivity of the ridge structures while forming a skeletonised version of the binary image. This skeleton image is then used in the subsequent extraction of minutiae.

III. PROPOSED METHOD FOR FINGERPRINT RETRIEVAL

In this paper we propose to adopt the Bayes classifier and this requires the following issues to be addressed: 1) shortage of training samples;2)curse of dimensionality. Our main aim is to build a fingerprint retrieval system that is accurate and efficient. This can be done by concatenating the features of Gabor filter and Minutia features for efficient retrieval. Bayes classifier can be trained by two methods,

- Supervised classification (e.g., discriminant analysis) in which the input pattern is identified as a member of a predefined class
- Unsupervised classification (e.g., clustering) in which the pattern is assigned to a hitherto unknown class.

Our approach is based on Supervised Classification. In this research we are extracting Minutia and Gabor features for training a classifier. Basic fingerprint image consists of ridges, valleys, cores, deltas, pores etc. The ridge endings and ridge bifurcations are used for comparing two fingerprints with each other, denoted minutiae based matching. Commonly pixel with one neighbor is treated as ridge ending and the pixel with three neighbors is treated as ridge bifurcation. Fig. 2. illustrates ridge ending and ridge bifurcation which plays a vital role in fingerprint detection known as real minutiae. These ridge ending and ridge bifurcation do not change over time, therefore well suited for fingerprint matching. Fingerprint usually consists of *40* to *100* minutiae points. Minutiae location is represented by a coordinate location of the fingerprint image. Different systems represent minutiae location differently.

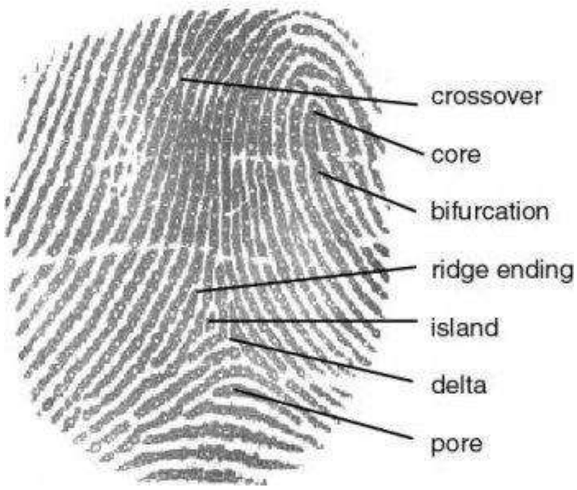

Fig .2.Basic fingerprint image

A. Minutia Extraction

The most commonly employed method of minutiae extraction is the Crossing Number (CN) concept. 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 neighbourhood of each ridge pixel in the image using a 3×3 window. The CN value is then computed, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight-neighbourhood. Using the properties of the CN as shown in Table 1, the ridge pixel can then be classified as a ridge ending, bifurcation or non-minutiae point. For example, a ridge pixel with a CN of one corresponds to a ridge ending, and a CN of three corresponds to a bifurcation.

TABLE I: PROPERTIES OF THE CROSSING NUMBER

CN	Property
0	Isolated point
1	Ridge ending point
2	Continue ridge point
3	Bifurcation point
4	Crossing point

Other authors such as Jain et al. [9] have also performed minutiae extraction using the skeleton image. Their approach involves using a 3×3 window to examine the local neighbourhood of each ridge pixel in the image. A pixel is then classified as a ridge ending if it has only one neighbouring ridge pixel in the window, and classified as a bifurcation if it has three neighbouring ridge pixels. Consequently, it can be seen that this approach is very similar to the Crossing Number method.

Fig. 3. Real and false minutia detected in the fingerprint

B. False Minutia Removal

Minutiae extracted from the fingerprint consist of real and false minutiae as shown in Fig. 3. The number of falsely detected minutiae depends upon the quality of the fingerprint. These false minutiae represented in Fig.4 must be filtered to remove as many false minutiae as possible without removing real minutiae. The redundant minutiae in the fingerprint are of the form

a) Minutiae Points adjacent to each other
b) Minutiae near the borders
c) Spike, break, bridge and hole

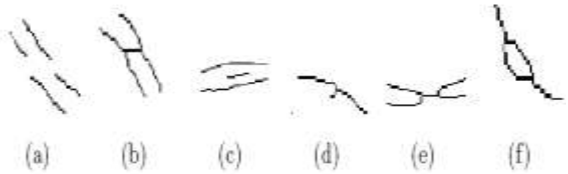

Fig. 4.(a) Broken ridges, (b) Bridge, (c) Short ridge, (d) Short ridge, (e) Short Ridge, (f) Hole.

I have chosen to implement the minutiae validation algorithm by Tico and Kuosmanen. This algorithm tests the validity of each minutiae point by scanning the skeleton image and examining the local neighbourhood around the point. The algorithm is then able to cancel out false minutiae based on the configuration of the ridge pixels connected to the minutiae point. Rather than using a set of ad hoc techniques to validate the minutiae, I have chosen to use the algorithm employed by Tico and Kuosmanen.

C. Gabor Feature Extraction

The Gabor function has been recognized as a very useful tool in computer vision and image processing, especially for texture analysis, due to its optimal localization properties in both spatial and frequency domain We filter an enhanced fingerprint image by Gabor filters in M (=12) directions to capture finer details of the ridge structures. The filtering orientations are ($0, \pi/12, 2\pi/12 \ldots. 11\pi/12$). The FVC 2000 and FVC 2002 databases, the center of feature extraction is exactly at the position of the registration point found [11]. This is due to the fact that many fingerprint images in the FVC databases have their registration point located close to the lower border of the frame..Now we can concatenate the features of both minutia and Gabor features for training a classifier.

D. Dimensionality Reduction

There are two main reasons to keep the dimensionality of the pattern representation (i.e., the number of features) as small as possible: measurement cost and classification accuracy. A limited yet salient feature set simplifies both the pattern representation and the classifiers that are built on the selected representation. Consequently, the resulting classifier will be faster and will use less memory. Moreover, as stated earlier, a small number of features can alleviate the curse of dimensionality when the number of training samples is limited. On the other hand, a reduction in the number of features may lead to a loss in the discrimination power and thereby lower the accuracy of the resulting recognition system. The original feature dimension is very high ranging from few hundred to thousand. The most famous example of dimensionality reduction is “principal components analysis”. This technique searches for directions in the data that have largest variance and subsequently project the data onto it. In this way, we obtain a lower dimensional representation of the data that removes some of the “noisy” directions. There are many difficult issues with how many directions one needs to choose, but that is beyond the scope of the note.PCA is an unsupervised technique and as such does not include label information of the data.To overcome this problem we are going for Fisher’s linear discriminant. Fisher's linear discriminant is a classification method that projects high-dimensional data onto a line and performs classification in this one-dimensional space. In the Fisher’s linear discriminant, we regularize the within-class scatter matrix.

E. Quadratic Discriminant Function

It is a compact Gaussian classifier. It re-parameterizes the covariance matrix into eigen values and eigen vectors and truncates the small eigen values to denoise the unstable estimation.Regularization in both Fisher’s linear discriminant and quadratic discriminant function may be required with reasonable constants. To achieve the optimal performance, these regularization constants have to be adjusted according to the number of training samples per finger and feature dimension. If there are not enough training sample patterns, covariance matrix cannot be estimated accurately. In the case that the dimensionality is large, these disadvantages markedly reduce classification performance [12]-[14]. In order to avoid these problems, in this paper, a new approximation method of the quadratic discriminant function is proposed. This approximation is done by replacing the values of small eigen values by a constant which is estimated by the maximum likelihood estimation. This approximation not only reduces the computational cost but also improves the classification accuracy.

F. Bayes Classifier

Bayes classifier is used for classification. Here we are using supervised classification [15]. The new recognition flowchart Bayes classification is drawn in Fig. 5.

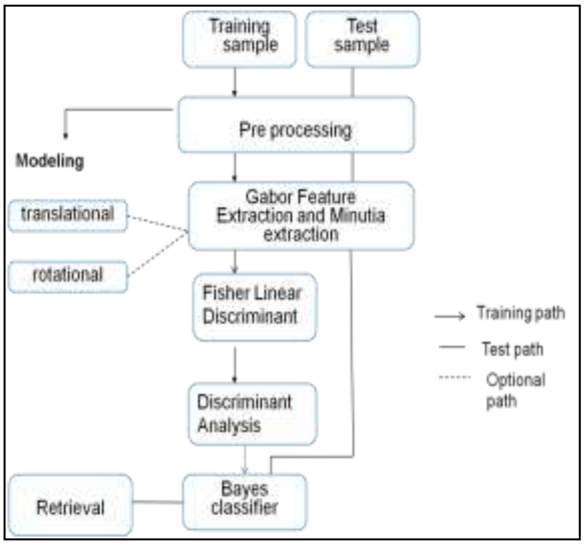

Fig.5.Outline of the proposed method

During training and testing we are concatenating the features of Gabor and minutia. We can estimate the prior probabilities of the classes from their frequencies in the training data. Training samples are the fingerprint images present in a database. Test samples are the query fingerprint image given instantly to check whether the query image is present in the database. We are using a Probabilistic approach for training a classifier.

IV. EXPERIMENTAL RESULTS

Most published fingerprint retrieval results on exclusive and continuous classifications as well as indexing are based on the FVC and NIST-4.To compare with other approaches test our approach on NIST-4 database, which contains 4,000 fingerprints of size 480 × 512 pixels, taken from 2,000 fingers with two instances per finger while a set of the FVC 2000 or FVC 2002 database contains 800 images taken from100 fingers (eight instances per finger). Efficiency and accuracy are two main performance measures widely used for fingerprint retrieval. In our experiments, the retrieval efficiency is indicated by a so called "penetration rate", which is the average percentage of the retrieved fingerprints for the finer matching over all query fingerprints. Smaller penetration rate indicates higher retrieval efficiency. The retrieval accuracy is calculated by the percentage of the query fingerprints whose corresponding database templates are correctly retrieved at a given retrieval efficiency. To compare with the K-NN classifier we implement our approach on data set 2. The retrieval results (penetration rate vs. retrieval accuracy) are shown in Fig. 6.

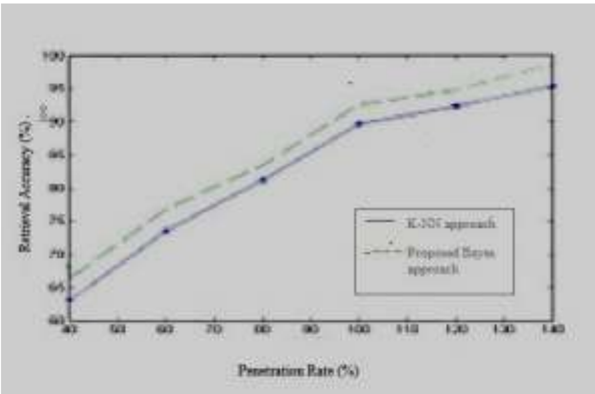

Fig.6. The comparison of the retrieval performances in our proposed approach and K-NN approach

The retrieval accuracy in our approach is 80.3% at penetration rate 20%, for 800 images. it shows the proposed approach can get high retrieval accuracy with better retrieval efficiency. In practice, the error rate of a recognition system must be estimated from all the available samples which are split into training and test sets. The classifier is first designed using training samples, and then it is evaluated based on its classification performance on the test samples. The percentage of misclassified test samples is taken as an estimate of the error rate. In order for this error estimate to be reliable in predicting future classification performance, not only should the training set and the test set be sufficiently large, but the training samples and the test samples must be independent. This requirement of independent training and test samples is still often overlooked in practice.

V. DATASET

There are two types of dataset widely used for fingerprint recognition, they are FVC and NIST-4.Main difference between two set, FVC contains eight instances per finger in each set, NIST-4 contains two instances per finger in each set. To train and evaluate the proposed method, we used FVC dataset. For comparing our approach we used NIST-4.

VI. CONCLUSION

This work proposed a fingerprint retrieval framework using the Bayes classifier uses Gabor and the minutia features. We can tackle the problem of speed by proposing the use of Fisher's linear discriminant and Bayes classification with the methods for regularization and handling of missing features. The speed of Bayes classification does not depend on the number of training samples per finger; one can capture many instances of the same finger for building up a large but comprehensive database without the fear of lowering the retrieval speed and accuracy. Regularizing the scatter and covariance matrices in the Fisher's linear discriminant and Bayes classifier is a useful strategy. The proposed techniques could be of practical uses in security, civilian, and forensic applications.A program coding with MATLAB going through all the stages of the fingerprint recognition is built. It is helpful to understand the procedures of fingerprint recognition and demonstrate the key issues of fingerprint retrieval.

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