Minutia Verification and Classification for Fingerprint Matching

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Abstract

Raw image data offer rich source of information for matching and classification. For simplicity of pattern recognition system design, a sequential approach consisting of sensing, feature extraction and matching is conventionally adopted where each stage transforms a particular component of information relatively independently. The interaction between these modules is limited. Some of the errors in the end-to-end sequential processing can be easily eliminated especially for the feature extraction stage by revisiting the original image data. We propose a feedback path for the feature extraction stage, followed by a feature refinement stage for improving the matching performance. This performance improvement is illustrated in the context of a minutiae-based fingerprint verification system. We show that a minutia verification stage based on reexamining the gray-scale profile in a detected minutia's spatial neighborhood in the sensed image can improve the matching performance by $\sim 4\%$ *on our database. Further, we show that a feature refinement stage which assigns a class label to each detected minutia (ridge ending and ridge bifurcation) before matching can also improve the matching performance by* $\sim 3\%$*. A combination of feedback (minutia verification) in the feature extraction phase and feature refinement (minutia classification) improves the overall performance of the fingerprint verification system by* $\sim 8\%$*.*

1 Introduction

The human visual system relies on image data for decision making because of the richness of the image context. Ideally, we would like to design pattern recognition systems which make decisions based on *all* the information available in the input image. However, traditionally, for simplicity of design, a sequential approach is often adopted to feature extraction and matching where each stage transforms a particular component of the information relatively independently and the interaction between these components of information is limited. Often, the rather simplistic model used in each component (stage) is not sufficient/effective to capture the essence of the sensed data. One of the problems with the staged approach is that the limited use of information in each stage results in feature extraction and/or matching performance artifacts. Thus, though the sequential (staged) approach is efficient from design and processing point of view, it may introduce errors in the feature extraction and recognition results. We believe that by revisiting the original image data, some of the mistakes in the end-to-end sequential processing can be eliminated, resulting in an improvement in system performance. Performance can also be improved by feature refinement. See Figure 1 for our proposed changes to a sequential feature extraction system.

We illustrate the above approach in the fingerprint matching domain. Most of the existing automatic fingerprint verification systems first detect the minutiae in a fingerprint image and then match the input minutiae set with the stored template [1, 2]. A typical algorithm described in [1] uses a sequential approach to feature extraction (see

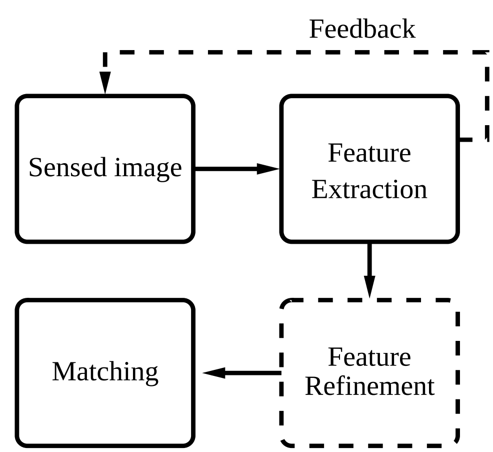


Figure 1. A general pattern recognition system with proposed feedback in feature extraction and a new feature refinement stage.

Figure 2). The feature extraction first binarizes the ridges in a fingerprint image using masks that are capable of adaptively accentuating the local maximum gray-level values along a direction normal to the local ridge direction. Minutiae (ridge bifurcation and ending; see Figure 3) are determined as points that have one neighbor or more than two neighbors in the skeletonized image. However, the orientation estimation in a poor quality image is extremely unreliable, resulting in the detection of many false minutiae. Several researchers have proposed minutia-pruning in the post-processing stage to delete spurious minutiae [1, 3, 4] but the pruning is based on rather ad-hoc techniques. In this paper, we propose a feedback system for minutiae extraction which is based on an analysis of the gray scale profile in the neighborhood of potential minutiae. We also propose a feature refinement stage where the minutiae are classified into two major classes: ridge bifurcation and ending. The goal in the feedback system (minutia verification) is to learn the characteristics of minutiae in gray level images which can then be used to verify each detected minutia. This step will replace the rather ad-hoc minutia-pruning stage used in [1]. Each detected minutia is filtered through this verification stage and is either accepted or rejected based on the learnt gray level characteristics in the neighborhood of a minutia. The minutia classifier is based on supervised training using Learning Vector Quantization [5].

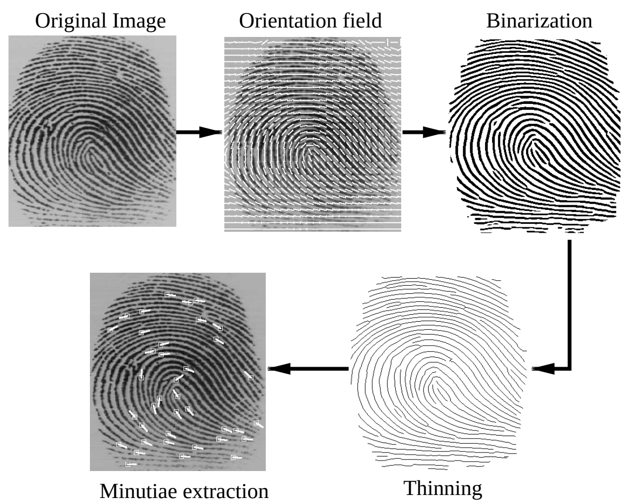


Figure 2. Minutiae extraction algorithm.

Figure 3. Examples of fingerprint minutiae; ridge endings (□) and bifurcations (○).

We show that the feature refinement (minutia classification into bifurcation and ending) can further improve the matching performance. We use a rule-based classifier to classify a minutia into the two categories. The matching algorithm proposed in [1] is modified to match minutiae of the same type in the sensed image and the template. The modification of minutia matching algorithm used in [1] with minutia verification and minutia classification significantly improves the matching accuracy.

2 Minutia Verification

Our minutia verification algorithm can be divided into three stages; (i) feature extraction, (ii) training (learning the minutiae characteristics), and (iii) verification.

2.1 Feature Extraction

We use the minutiae detection algorithm developed by Jain et al. [1] for our study. Each detected minutia has the following three attributes: the x and y position and the direction of the ridge in which the minutia resides. We extract a 64×64 region centered at the x and y position of the minutia and oriented in the direction of the minutia. The extracted region is normalized to a constant mean and variance to remove the effects of sensor noise and gray-scale deformation because of finger pressure variations. In our experiments, we set the values of both mean and variance to 100. We enhance the contrast of the ridges by filtering each 64×64 window with a appropriately tuned Gabor filter [6]. We set the frequency f of the Gabor filter to the average ridge frequency $(1/K)$, where K is the average inter-ridge distance. The average inter-ridge distance is approximately 10 pixels in a 500 dpi fingerprint image. The values of parameters δ_x and δ_y for Gabor filters were empirically determined and each is set to 4.0 (about half the average inter-ridge distance). Since the extracted region is in the direction of the minutia, the filter is tuned to $0°$ direction. We perform the filtering in the spatial domain with a mask size of 33×33. The Gabor response for each pixel in the region is scaled to eight gray levels. We extract a 32×32 region (see Figure 4) from the center of the 64×64 region to avoid boundary problems in normalization and filtering and concatenate the rows to form a 1024-dimensional feature vector.

2.2 Training

In the training phase, minutiae and non-minutiae feature vectors are fed to a Learning Vector Quantizer to learn the characteristics of minutiae and non-minutiae regions. We use the IBM_HURSLEY database that contains 900 fingerprint images from 269 different fingers for training and testing. The multiple impressions for each finger in the database were taken at significantly different times. The images are of different sizes but all the images have been scanned at 500 dpi resolution with 256 gray levels. A fingerprint expert has marked the “true” fingerprint minutiae in these images. We use the first 450 images for training and the remaining 450 images from different fingers for testing.

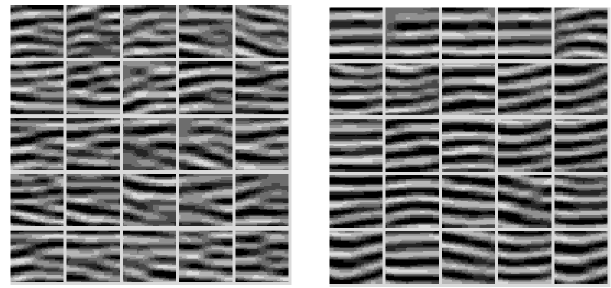
We extract approximately $15,000$ feature vectors corresponding to all the true minutiae from the images in the training database. We also extract an equal number of negative samples (non-minutiae) by randomly sampling the images in the training set and making sure that there is no minutia in its immediate 32×32 neighborhood. For the true minutia, we use the direction of the minutia provided by the expert. For the negative examples, we compute the direction of the 32×32 block using the hierarchical orientation-field algorithm [1].

2.3 Testing

We use two methods to test the LVQ-based minutiae vs. non-minutiae classifier. In the first method, we evaluate the classifier using the ground truth minutia information in the test database. In the second method, we extract the minutiae from the test database using the minutiae extraction algorithm described in [1]. An automatically detected minutia may be slightly perturbed from its original location because of the noise introduced during the binarizing and thinning processes. So, we extract twenty five 32×32 windows in the neighborhood of each detected minutia and verify each window. The decisions from the verification of these 25 windows are combined in a simple manner. If the classifier yields a positive verification for any of the 25 windows, the minutia is accepted. Figures 5 (a)-(c) compare the minutiae detection without pruning, with pruning, and with pruning replaced with minutia verification for a good quality fingerprint. Minutia verification is more effective for poor quality fingerprints.

3 Minutia Classification

The American National Standards Institute proposes four classes of minutia: ending, bifurcation, trifurcation, and undetermined. The most discriminable categories are ridge ending and bifurcation (see Figure 3). Most of the fingerprint matching algorithms do not use minutia type information because the two types of minutiae get interchanged due to finger pressure difference or noise. However, we show that a consistent classification of minutia can indeed



(a) (b)

Figure 4. Examples of gray level profiles in the neighborhood of (a) minutiae and (b) non-minutiae. These 32×32 subimages, scaled to to 8 gray levels, are used for training a LVQ.

improve the overall matching performance. In minutiae extraction algorithm, if a pixel in the thinned image has only one neighbor then the minutia is classified as an ending, and if a pixel has more than 2 neighbors, then the minutia is classified as a bifurcation. The matching algorithm in [1] is modified to match endings only with endings and bifurcations only with bifurcations. In our experience, there are significantly more number of bifurcations present in a typical fingerprint than endings. See Figure 5 (d) for minutia classification results.

4 Experimental Results

We first evaluated the performance of a minutiae-based fingerprint verification system [1]. The test consisted of evaluating the LVQ-based classifier on the ground truth data. Approximately $15,000$ 1024-dimensional feature vectors each for minutiae and non-minutiae were extracted from the images in the training database. The testing was done on feature vectors extracted only from the minutiae samples in the test database. The trained LVQ-based classifier with one hundred code book vectors per class gives an accuracy of $\sim 95\%$ on the training data and $\sim 87\%$ on the test data. A real test for the utility of the verification module is the gain in matching accuracy. So, we replaced the minutia-pruning stage in the algorithm in [1] with the proposed minutia verification stage. In the ROC curve shown in Figure 6, the dotted line represents the matching accuracy on the test set and the solid line represents the performance when the pruning stage in [1] is replaced with the proposed minutia verification scheme. These ROC curves show that the overall performance of the fingerprint verification system increases by $\sim 4\%$ at all the operating points.

The benefits of using minutia type information is illustrated in Figure 7. The solid line in the figure represents the performance when the minutia type information is used. Figure 8 shows the performance improvement when minu-

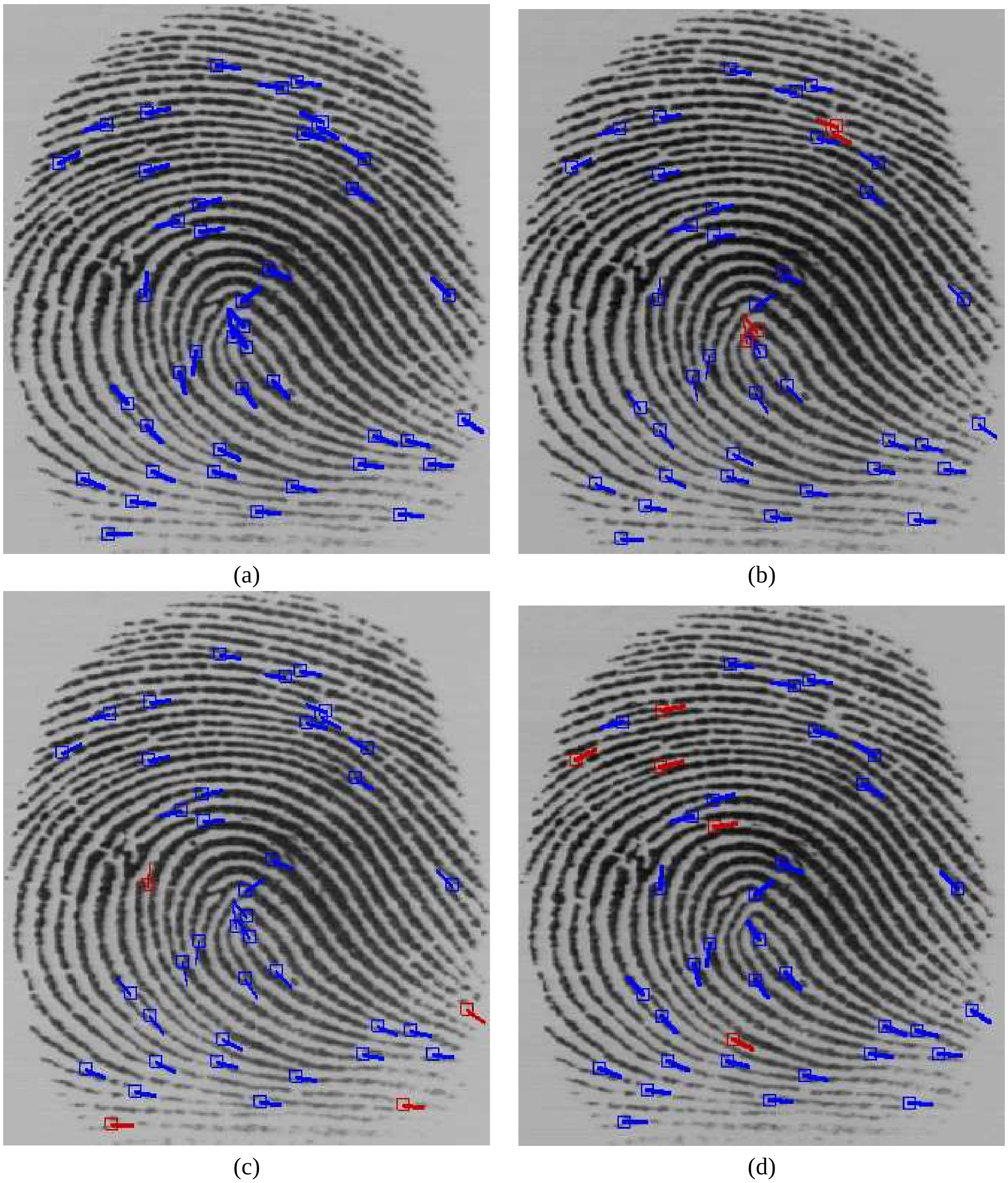


Figure 5. Minutiae detection and classification; (a) Minutiae detection using the algorithm in [1] without pruning, (b) results of minutia-pruning, minutiae marked with red were pruned, (c) result of minutia verification instead of pruning, minutiae marked with red were rejected, (d) result of classifying minutiae shown in (b); minutia bifurcations are marked with blue and endings are marked with red.

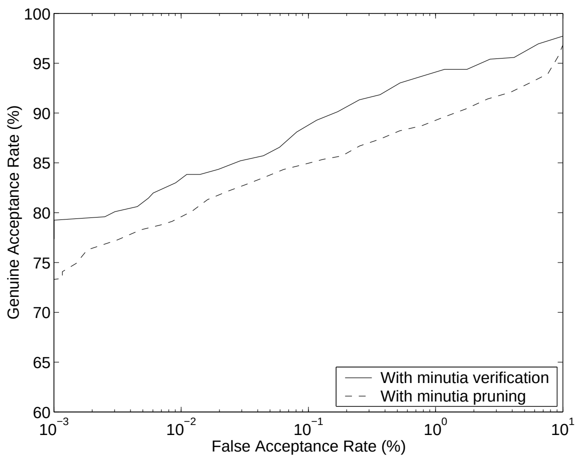


Figure 6. ROC for fingerprint matching when minutia verification is used.

tia verification and classification are combined. The classification is done before the verification but the classification information is not used during the verification. The performance of the fingerprint verification system in [1] is significantly improved by using minutia classification and verification.

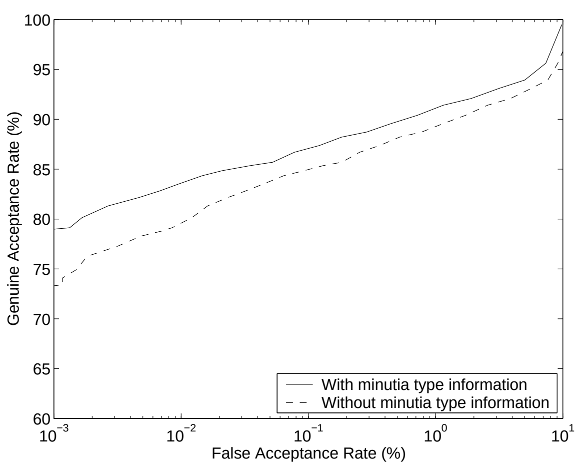


Figure 7. ROC for fingerprint matching when minutia classification is used.

5 Discussions and future work

We have shown that the performance of a minutiae-based fingerprint verification system can be improved by providing feedback in feature extraction (verification of each detected minutia by an analysis of grey-level profile of its spatial neighborhood in the original image). Performance can also be improved if the features are refined and more discriminable attributes can be extracted (minutia type information) before matching. The proposed minutia verification scheme can be extended for detection of minutiae in a fingerprint image.

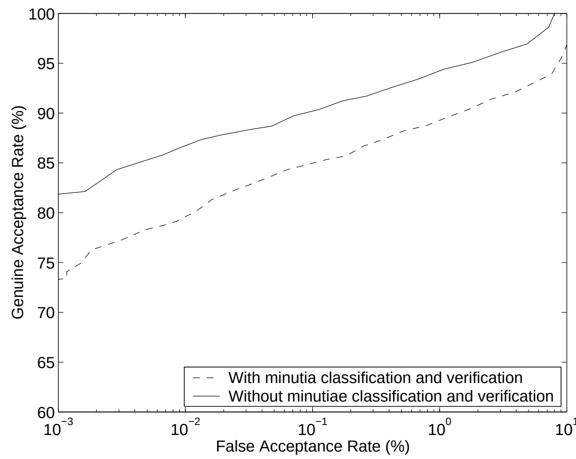


Figure 8. ROC for fingerprint verification when both minutia classification and verification are used.

We are working on a continuous classification of the minutiae into several categories, one of the categories being non-minutiae. A classification label and a confidence value will be assigned to each minutiae and we will modify the matching algorithm to account for the confidence values.

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