Quality-based Fingerprint Verification

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***Abstract*— The performance of an automatic fingerprint verification system relies heavily on the quality of the captured fingerprint images. In this paper, we propose a new method using fingerprint image quality to improve the accuracy of fingerprint verification. Comparison to conventional fingerprint verification that only use the matching score, a final score is calculated by the matching score and quality score in our method. Experimental results show that our proposed quality-based method leads better accuracy than conventional method. The equal error rate (EER) of our method decreases significantly in each database, with 2.4% in FVC2000db1, 2.3% in FVC2000db2, 1.2% in FVC2002db1, 1.7% in FVC2002db2, 3% in FVC2004db1 and 3.5% in FVC2004db2, respectively.**

I. INTRODUCTION

Fingerprint verification is one of the most popular and reliable biometric techniques for automatic personal identification. During the past few years it has received more and more attention and been widely used in forensic and civilian environments, such as judicial investigation and access control [1,2].

However, the quality of fingerprint image affects the performance of a fingerprint verification system heavily. Factors that restrict the quality of a fingerprint image include: sensor conditions (e.g. dirtiness, noise and size), skin conditions (e.g. dryness, wetness, dirtiness, temporary or permanent cuts and bruises), user cooperation, etc. Some of these factors cannot be avoided and some of them vary along time. Due to resulting in spurious and missed features, poor quality images degrade the performance of overall system.

Several aspects of works have been studied to improve the accuracy of a fingerprint system. Firstly, some researchers pay effort to enhance the performance of the processing steps, such as segmentation, enhancement, feature extraction and matching. Secondly, multiple sources of fingerprint are used to increase more information, such as fingerprint multiple impressions and fingerprint videos. Thirdly, high-resolution fingerprint techniques attract increasing attention, and some algorithms have been proposed, such as ridge counts and sweat pores [3, 4] for matching.

Little literatures focus on how to use image quality factor directly to improve the performance of a fingerprint verification system.. In [5], neighboring ridge structures around a minutia are defined and analyzed to measure minutiae quality. Normal ridges with neighboring a minutia have regular structures in the parts of inter-ridge distance, connectivity, and symmetry etc. It is meaning of a possibility that the present minutia is a true minutia. In matching stage, minutiae for True Minutiae class is not nearly filtered, but ones for False Minutiae class is filtered, which improve the accuracy of fingerprint verification. In [6], the authors present a novel framework for evaluating and comparing quality indices in terms of their capability of predicting the system performance at three different stages, namely, image enhancement, feature extraction and matching. Other works mostly focus on approaches for fingerprint image quality computation, which can be divided into 1) those that use local features of the image; 2) those that use global features of the image; and 3) those that address the problem of quality assessment as a classification problem.

In this paper, a new method based on image quality is proposed to improve the accuracy of fingerprint verification. Together with matching score, fingerprint quality is seen as another factor to determine whether the pair of fingerprints is genuine. The validity of this method will also be theoretically analyzed. Compared with existing methods which utilize quality in the fingerprint matching stage, the proposed method is in the decision-making stage. That is to say, our method is independent of specific matching algorithm, and thus, has a better robustness.

The rest of the paper is organized as follows. Section 2 proposes a quality-based method of fingerprint verification and analyzes its validity to improve the accuracy. After that, experiment procedures are described and experiment results are presented in Section 3. Finally the paper is concluded in Section 4 with a discussion.

II. QUALITY-BASED FINGERPRINT VERIFICATION

A. *Quality Estimation*

Fingerprint quality is usually defined as a measure of the clarity of ridges and valleys and the "extractability" of the features used for identification such as minutiae, cores and delta points [6], etc. In good quality images, ridges and valleys flow smoothly in a locally constant direction. A lot of fingerprint image quality measures have already been proposed in the literatures [7, 8, 9, 10, 11, 12, 13]. In this paper, we adopt an effective strategy presented by Tabassi et al in [14] with some changes. Each different fingerprint image is assigned a subjective value q to estimate the quality by a human expert, which is viewed as a measure of separation between the match and non-match distribution of a given fingerprint. The value will be higher as the image quality increases.

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Then, local and global features are extracted. Methods that rely on local features usually divide the image into non-overlapped square blocks and extract features from each block. Blocks are then classified into groups of different quality. A local measure of quality is finally generated by averaging the quality information of different blocks. Some methods assign a relative weight to each block based on its distance from the centroid of the fingerprint image, since blocks near the centroid are supposed to provide more reliable information. In particular, we use the local measures proposed by Chen et al. in [6] which measures the spatial coherence using the intensity gradient and Shen et al. in [15] which proposed a method using a Gabor filter with m different orientations to filter each block. Methods that rely on global features analyze the overall image and compute a global measure of quality. In particular, we choose the global features proposed by Chen et al. in [6] which measures the energy concentration in the frequency domain.

Feature vector v is defined to compute the fingerprint image quality, which contains the above mentioned parameters: 1) the intensity gradient; 2) Gabor filter; 3) the energy concentration. Then, we train a regression function f that maps the feature vector v to the quality value q in training set with SVM. Based on the model, we predict the quality of a new fingerprint image.

B. Matching Algorithm

Since significant progress has been made in fingerprint verification, there are already many matching algorithms. In our method, we choose a typical minutiae-based matching technique which matches the fingerprint minutiae by using both the local and global structures of minutiae. The local structure of a minutia is a rotation and translation invariant feature of the minutia because it consists of the direction and location relative to other minutiae in its neighborhood. The global structure of minutiae reliably determines the uniqueness of fingerprint. Finally, both global structure and the local structure determine whether the two fingerprints are acquired from the same finger.

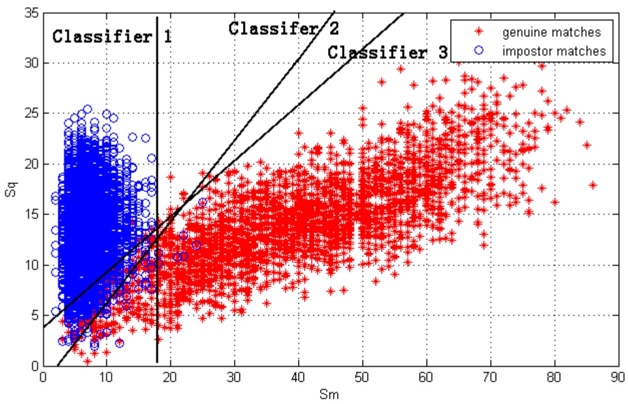

Fig. 1 a schematic diagram of linear classifiers with different slopes in the two-dimensional space.

C. Quality-based Fingerprint Verification

As mentioned in section B, minutiae-based matching is used to calculate the similarity of fingerprint pair. And the matching score S_m is compared with a threshold T. If $S_m > T$, the verification of fingerprint pair is accepted as a genuine request. Otherwise $S_m < T$, it is rejected as an imposter request. However, if the quality of fingerprint pair is too low, the matching score results in the false rejection of a genuine user or the false acceptance of an impostor. We use D_g to represent the situation that the pair is decided as genuine, and D_i to represent the situation that the pair is decided as an imposter. S_g denotes the fact that the two fingerprints come from a same finger, and S_i denotes the fact that the two fingerprints come from different fingers. When image quality degrades,

$$P(D_i \mid S_g) >> P(D_g \mid S_i) \quad (1)$$

That is to say, a genuine fingerprint matching is affected by image quality more severely than an imposter. Therefore, we need to adjust the threshold dynamically to ensure that genuine fingerprint matches of low-quality images are not all rejected.

We proposed a new method using both matching score $\mathrm{S_m}$ and image quality S_q to decide whether template fingerprint and input fingerprint come from the same finger. Compared to conventional verification method which only uses matching score $\mathrm{S_m}$ in decision stage, two- dimensional measure (S_m, S_q) of fingerprint pair is introduced in our method. We also give a formulation to calculate the final score S as follows:

$$\mathrm{S}=(1+w)*\mathrm{S_m} - w*\mathrm{S_q}, w \geq 0 \quad (2)$$

where S_q is the geometric mean of two matching fingerprint image quality values, and w is an empirical value, which is determined experimentally.

In the two-dimensional space, we define matching score $\mathrm{S_m}$ as x-axis and image quality S_q as y-axis. Equation (3) is transformed into the form

$$\mathrm{S_q} = \frac{(1+w)}{w}*\mathrm{S_m} - \frac{1}{w}*\mathrm{S},\ \mathrm{w}>0 \quad (3)$$

From Eq.(3), our method is in essence to find a linear classifier that can separate the match and non-match fingerprint pairs by optimizing two parameters w and S. Fig. 1 is a schematic diagram of linear classifiers in the two-dimensional space. The slope of the classifier is $(1+w)/w$ and the value of S is the final score that decides the final verification result. Experiment will be shown to test the effectiveness of our method in Section 3.

However, the two-dimensional similarity (S_m, S_q) may not be linear separable. So we use a nonlinear classifier SVM with RBF kernel to obtain better performance than a linear classifier. We treat each pair of matching fingerprint as a sample. The matching score S_m and quality value S_q are the two features of a sample. If the matching pair is genuine, the sample label is assigned as 1. Otherwise, the sample label is assigned as 0. Then, SVM is used to train the model with 10-fold cross validation, and the accuracy of prediction is recorded.

III. EXPERIMENT RESULTS

In this section, we design an experimental scheme to testify the effect of the proposed quality-based method for fingerprint verification. Experiments are conducted using three open fingerprint databases, that is, FVC2000, FVC 2002 and FVC2004. Each open database is composed of 4 sub-databases, of which db1 and db2 are preferred in our experiments. Each sub-database consists of 100 fingers and 8 impressions per finger.

Firstly, we measure the image quality of each fingerprint. 100 fingerprint composed of the first impression of each finger are chosen as training set and other 100*7 impression are left as test set. Each fingerprint image is assigned a subjective quality value by a human expert. And the vector containing the intensity gradient, Gabor filter and the energy concentration is extracted to train a regression model using SVM method. With the regression model, every fingerprint image quality is predicted in the test set.

Secondly, minutiae-based matching algorithm is carried out to get matching score of each pair in every sub-database. There will be a total number of 7750 matches, including 2800 genuine matches and 4950 impostor matches.

At last, we calculate the final score S according to Equation 2. Moreover, nonlinear classifiers (SVM with RBF kernel, neural network) are used to obtain better performance. The receiver operating curves (ROC) of every sub-database are plotted to describe the performance of our method and conventional method in Fig.2. We can find that the equal error rate (EER) decreases significantly in each sub-database, with 2.4% in FVC2000db1, 2.3% in FVC2000db2, 1.2% in FVC2002db1, 1.7% in FVC2002db2, 3% in FVC2004db1 and 3.5% in FVC2004db2, respectively. At the same time, we present the verification accuracy of every sub-database with different methods in Table I. In Table I, we can see that the overall matching performance can be improved with Equ.1, SVM with RBF kernel and linear kernel in each sub-database. In addition, non-linear classifier can lead better fingerprint verification accuracy than linear classifier.

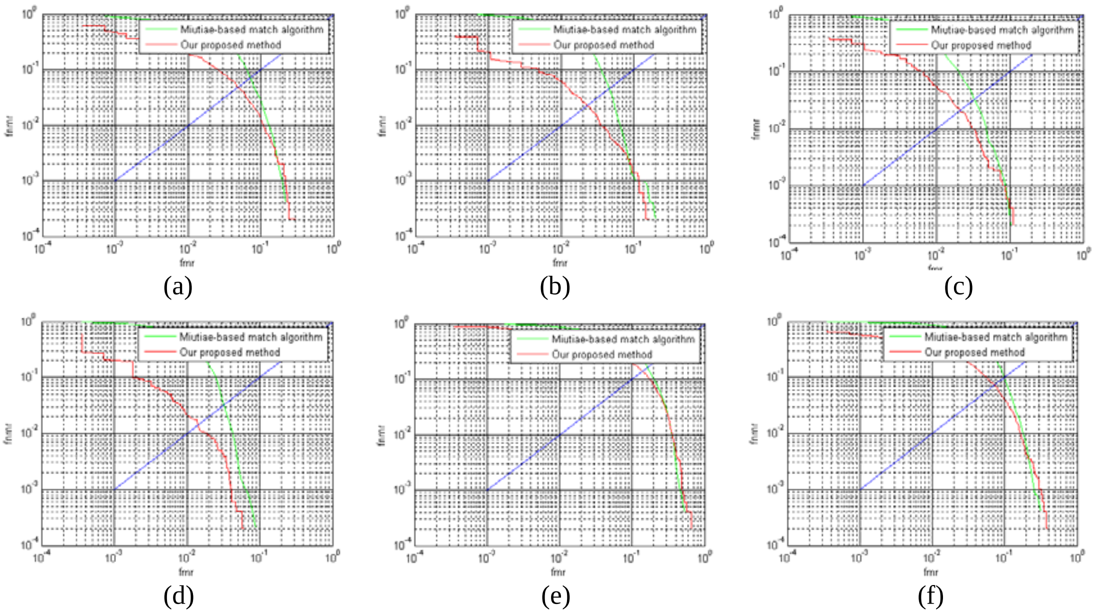

Fig. 2 ROC of conventional and our proposed method (w is chosen as 30) in each sub-database. (a)-(f) are FVC2000db1, FVC2000db2, FVC2002db1, FVC2002db2, FVC2004db1, FVC2004db2, respectively. Note that fmr means False Match Rate, and frr means False Reject Rate. We can find that the EER decreases significantly in each sub-database.

TABLE I
THE ACCURATE RATE OF FOUR METHODS

database	minutia-based match	our method (w = 30)	SVM with linear kernel	SVM with RBF kernel
2000db1	94.6968%	95.6387%	95.5613%	95.9097%
2000db2	96.9032%	97.9613%	97.9484%	98.1161%
2002db1	97.7290%	98.2710%	98.4516%	98.529%
2002db2	97.9742%	98.7355%	98.6839%	99.1613%
2004db1	87.5742%	88.1677%	87.8581%	88.8129%
2004db2	93.3032%	94.0000%	94.1548%	94.6323%

IV. CONCLUSION AND DISCUSSION

In this paper, image quality is utilized to improve the accuracy of fingerprint verification. The final score of each fingerprint matching pair is decided by both matching score and quality value. In fact, a threshold is adjusted dynamically in our proposed quality-based method. The formulation we proposed and machine learning methods are implemented in three open fingerprint databases. Experiment results show that quality-based method leads better accuracy in comparison to conventional fingerprint verification method.

Future work will focus on two aspects. One is to estimate the quality of fingerprint image more accurately, and the other is to select optimized equation to calculate the final match score.

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