Incorporating Image Quality in Multi-algorithm Fingerprint Verification

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Abstract. The effect of image quality on the performance of fingerprint verification is studied. In particular, we investigate the performance of two fingerprint matchers based on minutiae and ridge information as well as their score-level combination under varying fingerprint image quality. The ridge-based system is found to be more robust to image quality degradation than the minutiae-based system. We exploit this fact by introducing an adaptive score fusion scheme based on automatic quality estimation in the spatial frequency domain. The proposed scheme leads to enhanced performance over a wide range of fingerprint image quality.

1 Introduction

The increasing need for reliable automated personal identification in the current networked society, and the recent advances in pattern recognition, have resulted in the current interest in *biometric systems* [1]. In particular, automatic fingerprint recognition [2] has received great attention because of the commonly accepted distinctiveness of the fingerprint pattern, the widespread deployment of electronic acquisition devices, and the wide variety of practical applications ranging from access control to forensic identification.

Our first objective in this work is to investigate the effects of varying image quality [3] on the performance of automatic fingerprint recognition systems. This is motivated by the results of the Fingerprint Verification Competition (FVC 2004) [4]. In this competition fingerprint images with lower image quality than those in FVC 2002 were used. As a result, the error rates of the best matching systems in FVC 2004 were found to be an order magnitude worse than those reported in earlier competitions (FVC 2000, FVC 2002). Similar effects have also been noticed in other recent comparative benchmark studies [5].

We also investigate the effects of varying image quality on a multi-algorithm approach [6] based on minutiae- and ridge-based matchers. These two matchers

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provide complementary information commonly exploited by score-level fusion [7, 8]. Finally, we incorporate the idea of quality-based score fusion [9] into this multiple algorithm approach. In particular, an adaptive score-level fusion technique based on quality indices computed in the spatial frequency domain is presented and evaluated.

The paper is structured as follows. In Sect. 2 we summarize related work on the characterization of fingerprint image quality, and describe the fingerprint image quality measure used in this work. In Sect. 3 we summarize the individual fingerprint matching systems used here. The proposed quality-based score fusion scheme is introduced in Sect. 4. Database, experimental protocol, and results obtained are given in Sect. 5. Finally, conclusions are drawn in Sect. 6.

2 Assessment of Fingerprint Image Quality

Local image quality estimates have been traditionally used in the segmentation and enhancement steps of fingerprint recognition [10]. On the other hand, global quality measures have been traditionally used as indicators to identify invalid images. These indicators may result in failure to enroll or failure to acquire events that are handled either manually or automatically [2].

More recently, there is increasing interest in assessing the fingerprint image quality for a wide variety of applications. Some examples include: study of the effects of image quality on verification performance [3], comparison of different sensors based on the quality of the images generated [11], and comparison of commercial systems with respect to robustness to noisy images [5].

A number of fingerprint quality measures have been proposed in the literature. Most of them are based on operational procedures for computing local orientation coherence measures [12]. Some examples include: local Gabor-based filtering [10, 13], local and global spatial features [14], directional measures [15], classification-based approaches [16], and local measures based on intensity gradient [17]. In the present work we use the global quality index computed in the spatial frequency domain detailed in [17], which is summarized below.

2.1 Fingerprint Image Quality Index

Good quality fingerprint images bear a strong ring pattern in the power spectrum, indicating a dominant frequency band associated with the period of the ridges. Conversely, in poor quality images the ridges become unclear and non-uniformly spaced, resulting in a more diffused power spectrum. We thus assess the global quality of a fingerprint image by evaluating the energy distribution in the power spectrum.

A region of interest (ROI) in the power spectrum is defined to be a ring-shaped band with radius ranging from the minimum to the maximum observed frequency of ridges [17]. Fig. 1 shows three fingerprint images with increasing quality from left to right. Their corresponding power spectrums are shown in the second row. Note that the fingerprint image with good quality presents a strong

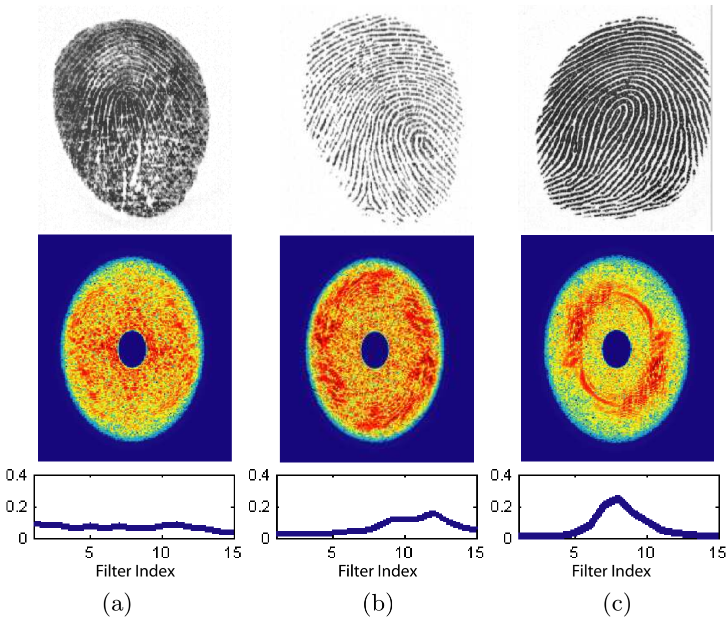

Fig. 1. Three sample fingerprint images with increasing image quality from left to right (top row), their corresponding power spectrum (middle row), and their energy distribution across concentric rings in the spatial frequency domain. It can be observed that the better the fingerprint quality, the more peaked is its energy distribution, indicating a more distinct dominant frequency band. The resulting quality measure for each fingerprint image from left to right is 0.05, 0.36, and 0.92, respectively.

ring pattern in the power spectrum (Fig. 1(c)), while a poor quality fingerprint presents a more diffused power spectrum (Fig. 1(a)). Multiple bandpass filters are designed to extract the energy in a number of ring-shaped concentric sectors in the power spectrum. The global quality index is defined in terms of the energy concentration across these sectors within the ROI.

In particular, bandpass filters are constructed by taking differences of two consecutive Butterworth functions [17]. In the third row of Fig. 1, we plot the distribution of the normalized energy across the bandpass filters. The energy distribution is more peaked as the image quality improves from (a) to (c). The resulting quality measure Q is based on the entropy of this distribution, which is normalized linearly to the range $[0, 1]$.

3 Fingerprint Matchers

We use both the minutia-based and the ridge-based fingerprint matchers developed at the Spanish ATVS/Biometrics Research Lab.

The minutiae-based matcher follows the approach presented in [18] with the modifications detailed in [3] and the references therein, resulting in a similarity measure based on dynamic programming.

The ridge-based matcher (also referred to as texture-based) consist of correlation of Gabor-filter energy responses in a squared grid as proposed in [19] with some modifications. No image enhancement is performed in the present work. Also, once the horizontal and vertical displacements maximizing the correlation are found, the original images are aligned and the Gabor-based features are recomputed before the final matching. The result is a dissimilarity measure based on Euclidean distance as in [19].

Scores from both matchers s'_M and s'_R are normalized into similarity matching scores in the range $[0, 1]$ using the following normalization functions:

$$\begin{aligned} s_M &= \tanh(s'_M/c_M) \\ s_R &= \exp(-s'_R/c_R) \end{aligned} \tag{1}$$

Normalization parameters c_M and c_R are positive real numbers chosen heuristically in order to have the normalized scores of the two systems spread out over the $[0, 1]$ range.

4 Quality-Based Score Fusion

The proposed quality-based multi-algorithm approach for fingerprint verification follows the system model depicted in Fig. 2.

The proposed method is based on the sum rule fusion approach. This basic fusion method consists of averaging the matching scores provided by the different matchers. Under some mild statistical assumptions [20, 21] and with the proper matching score normalization [22], this simple method is demonstrated to give good results for the biometric authentication problem. This fact is corroborated in a number of studies [21, 23]. Let the similarity scores s_M and s_R provided by the two matchers be already normalized to be comparable. The fused result using the sum rule is $s = (s_M + s_R)/2$.

Our basic assumption for the adaptive quality-based fusion approach is that verification performance of one of the algorithms drops significantly as compared to the other one under image quality degradation. This behavior is observed in

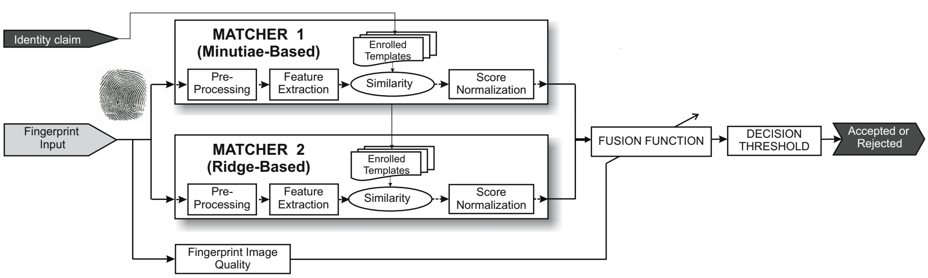

Fig. 2. Quality-based multi-algorithm approach for fingerprint verification

our minutia-based M with respect to our ridge-based R matcher. The proposed adaptive quality-based fusion strategy is as follows:

$$s_Q = \frac{Q}{2} s_M + (1 - \frac{Q}{2}) s_R, \tag{2}$$

where Q is the input fingerprint image quality. As the image quality worsens, more importance is given to the matching score of the more robust system.

5 Experiments

5.1 Database and Experimental Protocol

We use a subcorpus of the MCYT Bimodal Biometric Database [24] for our study. Data consist of 7500 fingerprint images from all the 10 fingers of 75 subjects acquired with an optical sensor. We consider the different fingers as different users enrolled in the system, resulting in 750 users with 10 impressions per user. Some example images are shown in Fig. 1.

We use one impression per finger as template (with low control during the acquisition, see [24]). Genuine matchings are obtained comparing the template to the other 9 impressions available. Impostor matchings are obtained by comparing the template to one impression of all the other fingers. The total number of genuine and impostor matchings are therefore 750×9 and 750×749, respectively.

We further classify all the fingers in the database into five equal-sized quality groups, from I (low quality), to V (high quality), based on the quality measure Q described in Sect. 2, resulting in 150 fingers per group. Each quality group contains 150×9 genuine and 150×749 impostor matching scores.

Distribution of fingerprint quality indices and matching scores for the two systems considered are given in Fig. 3.

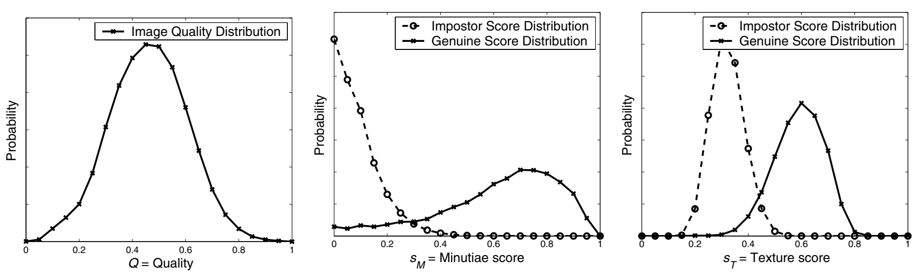

Fig. 3. Image quality distribution in the database (left) and matching score distributions for the minutiae (center) and texture matchers (right).

5.2 Results

Verification performance results are given in Fig. 4 for the individual matchers (minutiae- and texture-based), their combination through the sum fusion rule,

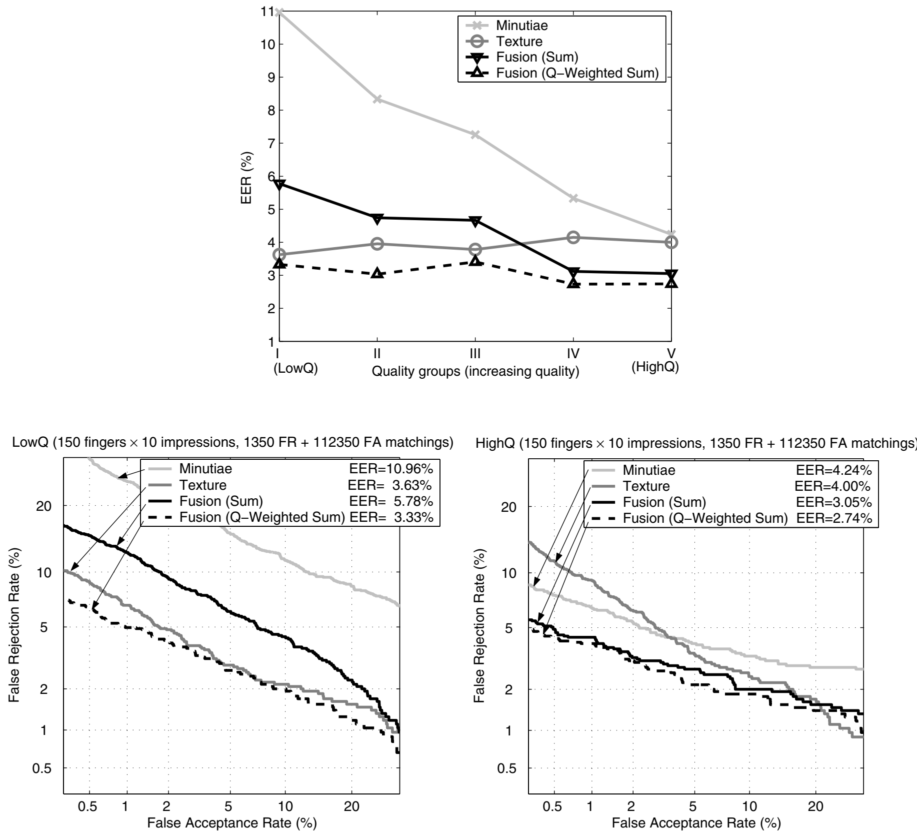

Fig. 4. Verification performance of the individual matchers (minutiae- and texture-based), their combination through the sum fusion fusion rule, and the proposed quality-based weighted sum for increasing image quality.

and the proposed quality-based weighted sum for different quality groups. We observe that the texture-based matcher is quite robust to image quality degradation. Conversely, the minutia-based matcher degrades rapidly with low quality images. As a result, the fixed fusion strategy based on the sum rule only leads to improved performance over the best individual system in medium to good quality images.

The proposed adaptive fusion approach results in improved performance for all the image quality groups, outperforming the standard sum rule approach, especially in low image quality conditions where the performance of individual matchers becomes more different.

Finally, in Fig. 5 we plot the verification performance for the whole database. Relative verification performance improvement of about 20% is obtained by the proposed adaptive fusion approach for a wide range of verification operating points as compared to the standard sum rule.

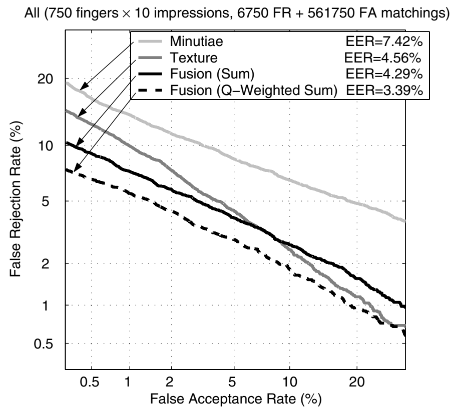

Fig. 5. Verification performance for the whole database

6 Discussion and Conclusions

The effects of image quality on the performance of two common approaches for fingerprint verification have been studied. It has been found that the approach based on ridge information outperforms the minutiae-based approach in low image quality conditions. Comparable performance is obtained on good quality images.

It must be emphasized that this evidence is based on particular implementations of well known algorithms, and should not be taken as a general statement. Other implementations may lead to improved performance of any approach over the other in varying image quality conditions. On the other hand, the robustness observed of the ridge-based approach as compared to the minutiae-based system has been observed in other studies. One example is the Fingerprint Verification Competition in 2004 [4], where low quality images where used and leading systems used some kind of ridge information [8].

This difference in robustness against varying image quality has been exploited by an adaptive score-level fusion approach using quality measures estimated in the spatial frequency domain. The proposed scheme leads to enhanced performance over the best matcher and the standard sum fusion rule over a wide range of fingerprint image quality.

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