DOI: 10.5769/C2012007 or http://dx.doi.org/10.5769/C2012007

Fingerprint Image Quality Estimation Using a Fuzzy Inference System

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Abstract—Fingerprint image quality affects the performance of automatic fingerprint recognition systems, such as AFIS (Automated Fingerprint Identification System). This work proposes a new method for fingerprint image quality estimation using local features (contrast, curvature and ridge flow). A fuzzy inference system is used to combine these features into a single image quality score. Tests are carried out with fingerprint images from the Fingerprint Verification Competition 2006 (FVC 2006) DB2-A database and fingerprint matching software BOZORTH3 from NIST Biometric Image Software (NBIS). After the removal of 5%, 10% and 15% of the poorest quality fingerprints from the DB2-A, we obtained an improvement of 30.6%, 32.6% and 37.9% in EER (Equal Error Rate), respectively.

Keywords-Fingerprint Image Quality, Fuzzy Inference Systems, Digital Image Processing.

I. Introduction

A. Biometrics

Biometrics studies the measurement of living beings. One of its goals is to enable the recognition of individuals based on physiological or behavioral characteristics. Fingerprints, voice, iris, retina, face, handwriting, keystroke dynamics and hand shape are examples of these characteristics [1]. Biometric recognition provides greater convenience to users compared to other traditional security mechanisms such as passwords, smart cards and keys. An ideal biometric feature should be [1]-[3]: (a) immutable (does not vary over time), (b) distinct (sufficiently different between any two individuals), (c) universal (ideally, all individuals must possess it), (d) accessible (easy to collect by means of electronic sensors), and (e) acceptable (individuals do not care to have the characteristic captured). Fingerprints have such qualities. In addition, the cost and maturity of fingerprinting technology makes it the most widely used biometric feature [2]. Examples of applications include physical and logical access control, electronic banking applications, civil and criminal identification. As for police applications, fingerprints are used for identification of suspects and victims.

This work was sponsored by the Brazilian Ministry of Justice under the PRONASCI Program.

B. Motivation

The development of automatic fingerprint recognition systems began in the 1960s, and today, despite the maturity of this technology, many factors still influence its performance. Quality of the captured fingerprint image largely impacts recognition performance[4]. Processing of fingerprint images with poor quality can result in the detection of nonexistent features (*minutiae*) or prevent the detection of existing ones [5]. Possible causes for poor quality images include: excessively dry or humid fingertips, with cuts, scars or blemishes, excessive or insufficient pressure during collection, rotation or deliberate translation [6]. Fig.1 (a) and (b) are examples of poor and good quality fingerprints, respectively. These images are used throughout this paper to help explain the steps of the proposed system.

Since many factors that affect fingerprint images may not be controlled or avoided, quality assessment of captured samples is very important to an AFIS (Automated Fingerprint Identification System [7]). Possible uses of quality assessment in biometric systems are [8]: (a) monitoring (quality algorithms can be used as a monitoring tool), (b) indication for recapture (the quality of templates and samples captured during an access transaction can be controlled via recapture until the image is considered satisfactory), and (c) adjustment of the recognition system (some stages of the recognition system can be adjusted based on the estimated quality of the images).

Fingerprint quality assessment is useful to improve the performance of fingerprint recognition systems [9]. In many systems it is preferable to substitute low-quality images for better ones. Therefore, image quality estimation is a necessary step in fingerprint image processing.

Figure 1. Examples of (a) poor and (b) good quality fingerprints.

The objective here is to propose a new method to estimate the quality of fingerprint images using a fuzzy inference system that combines local fingerprint features (contrast, curvature, ridge flow) into an image quality score. The proposed method was tested on the DB2-A fingerprint image database of the 2006 Fingerprint Verification Competition (FVC 2006) [10] using the fingerprint matching program BOZORTH3 from the NIST Biometric Image Software (NBIS) [11],[12]. The goal of the tests is to verify the performance improvement in the matching process when poorest quality fingerprints are removed.

II. The Proposed Method

Previous works use one or more local/global features to estimate the quality of a fingerprint [8]. In spite of which features are used, none employs fuzzy inference systems to generate an overall quality score. The proposed method uses the concepts of fuzzy logic to combine local fingerprint features and estimate the fingerprint image quality. In the next subsections we describe the local features considered and present the fuzzy inference system that combines these features and generates a local quality map from which a image quality score is derived.

A. Local Features

The following fingerprint features were selected:

1) *Contrast:* non-uniform contact may result in noisy images with low contrast, leading to problems such as detection of non-existent *minutiae* or no detection of existing ones. The variance of an image block indicates the dispersion of gray scale intensities towards the observed average value. This attribute makes it useful to estimate the image contrast [13]. High quality blocks are more likely to present high variance, while low quality ones have lower variance [14]. To obtain the contrast map, the fingerprint image is divided into 8x8-pixel blocks and the variance of each block is then calculated. The value of the variance is assigned to all block pixels, resulting in images such as those of Fig. 2 (a) and (b), which were generated from the fingerprints of Fig. 1 (a) and (b), respectively. Lighter regions represent areas of higher contrast. Low contrast areas are represented by darker regions.

2) *Curvature:* we initially obtain an orientation map, which is a matrix of direction vectors representing the orientation of the ridges at each point of the image. The approach used for this map is based on gradient calculation[15]-[17]. Fig. 2 (c) and (d) represent the orientation maps for fingerprints shown in Fig. 1 (a) and (b).

The curvature map is obtained by measuring the variation of ridge angles on each block of the orientation map. *Minutiae* detected in high curvature regions are considered less reliable [11]. To estimate the curvature, we calculate the variance of the sines of the angles that belong to each block. This value is then assigned to all pixels of the block, thereby generating curvature maps as shown in Fig. 2 (e) and (f). Lighter areas represent blocks with high variance and, therefore, high curvature.

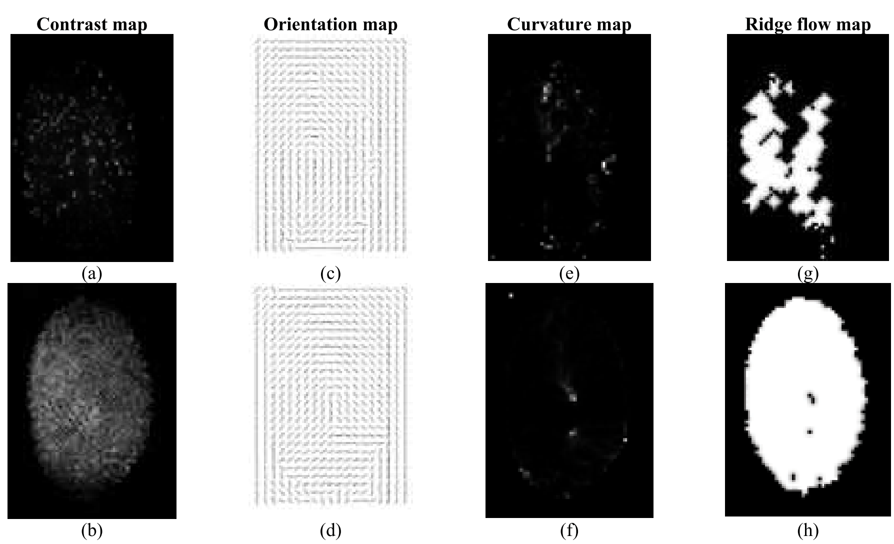


Figure 2. Local features: images (a), (c), (e) and (g) correspond to the fingerprint shown in Fig. 1 (a), while images (b), (d), (f) and (h) correspond to the fingerprint shown in Fig.1 (b).

3) *Ridge Flow:* the ridge flow map is obtained from the low flow map generated by MINDTCT. The low flow map indicates fingerprint regions where the ridge flow is not well defined. Usually, these areas have poor image quality. Image blocks with a well defined ridge flow are marked as 1, while the others are marked as 0, including image background blocks. To generate the ridge flow map, MINDTCT's low flow map is processed in two stages: (a) map smoothing, and (b) map resizing. The first step filters the flow map using a Gaussian low-pass filter. Each pixel in the filtered map corresponds to a 8x8-pixel block of the original fingerprint image. Therefore, it has a reduced size compared to the original fingerprint. So the second step resizes the flow map to the original image size using the nearest neighbour interpolation. The results are shown in in Fig. 2 (g) and (h) .

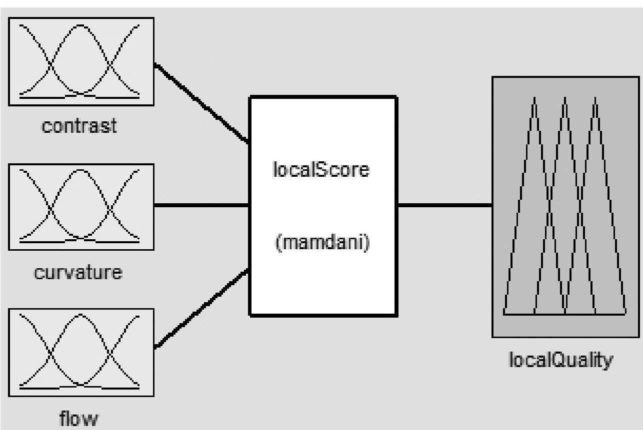


Figure 3. Illustration of the fuzzy inference system used to obtain the local quality map.

B. Local Quality Map and Local Quality Score

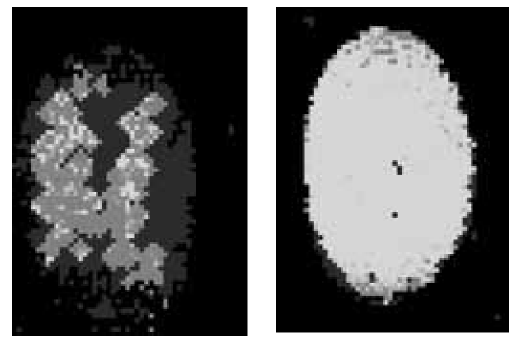
We propose a fuzzy inference system (FIS) [18]-[21], from now on referred to as *localScore*, that combines the local features into a single quality map. This system consists of three input variables - *contrast*, *curvature* and *flow* - and an output variable – *localQuality*, as shown in Fig.3.

For each input variable (*contrast*, *curvature* and *flow*), three Gaussian membership functions map their input values to *low*, *average* or *high* fuzzy sets. Regarding the output variable (*localQuality*) also three Gaussian membership functions, that represent *poor*, *average* and *good* fuzzy sets, are used. The adjustment of means and standard deviations of Gaussian functions was carried out empirically. Mamdani fuzzy inference method is used [22],[23].

Once input/output variables, membership functions and inference method are defined, the next step consists in defining the inference rules of the system. Three rules are used, based on experts' knowledge:

- IF (*contrast* is not *low*) and (*flow* is not *low*) THEN (*localQuality* is *good*)
- IF (*curvature* is *high*) or (*flow* is *low*) THEN (*localQuality* is *poor*)
- IF (*contrast* is *low*) and (*flow* is not *low*) THEN (*localQuality* is *average*)

As an example, the local quality maps shown in Fig. 4 (a) and (b) were obtained from the fingerprints shown in Fig. 1 (a) and (b), respectively. Darker areas represent poorer quality regions, while the lighter areas, higher quality regions. A local quality score can be calculated by the average local quality score of the map. For example, the local quality score calculated for the fingerprint image in Fig. 4 (a) is 3.58, while for the one in Fig. 4 (b) is 7.78. Fig. 5 summarizes the process for obtaining the local quality score.



(a) (b)

Figure 4. Local quality maps for the fingerprints shown in Fig. 1: (a) poor quality fingerprint; and (b) good quality fingerprint.

III. Experimental Results

The fingerprint image database DB2-A of the Fingerprint Verification Competition 2006 was used in our experiments. It contains 140 fingerprints, 12 samples of each finger, which makes 1680 images. Each image is a 400 x 600 bitmap with 256 gray levels. The DB2-A images were captured by optical sensor at 569 dpi.

The quality of all the fingerprints in the database is estimated using the proposed method and the whole test set is sorted in ascending order of quality score.

The objective of the experiments is to compare the performance of the verification process before and after the removal of the poorest quality fingerprints. For the verification process, we used MINDTCT and BOZORTH3 softwares, taken from the NBIS fingerprint processing package. The former is used to extract the *minutiae* of each fingerprint and the latter, for matching and obtaining a similarity score between fingerprints. The protocol used to compare the performance of the verification process is based on the protocol used to evaluate performance of the verification algorithms submitted to FVC 2006.

First, each fingerprint is compared to the remaining images of the same finger (genuine comparison). Consider two fingerprints: *x* and *y*. If *x* is compared to *y*, the symmetric comparison (*y* with *x*) is not made to avoid correlation in the similarity scores. The total number of genuine comparisons is ((12 x 11)/2) x 140 = 9240. From these data it is possible to obtain the False Rejection Rate or FRR, which is the probability of prints of the same finger to be considered as coming from different fingers.

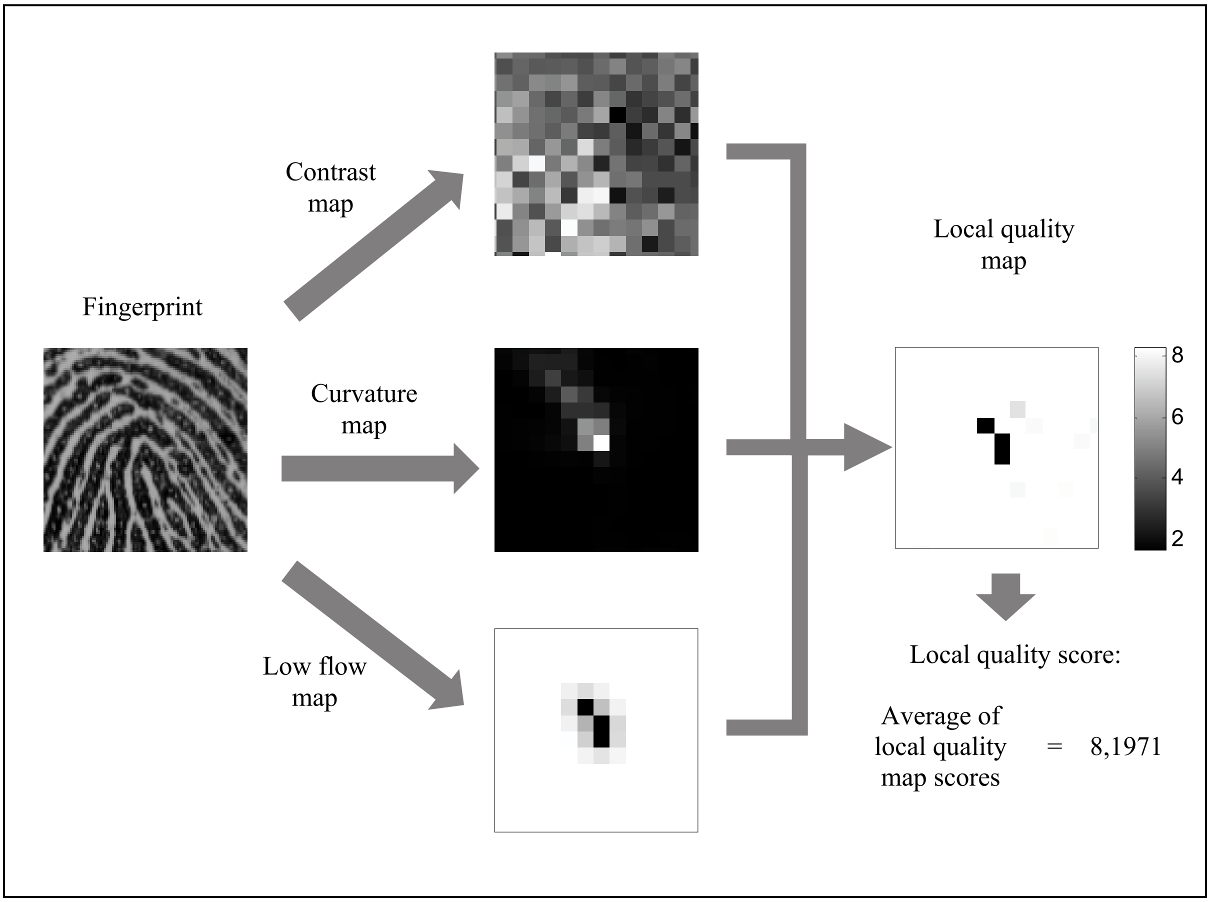


Figure 5. Local quality score estimation process

Then, the first print of each finger is compared to the first fingerprints of the other fingers (impostor comparisons). Also in this case, comparisons are not made symmetrical. The total number of comparisons between impostors is (140 x 139) / 2 = 9730. From these data it is possible to obtain the False Acceptance Rate or FAR, which is the probability of prints from different fingers to be considered as coming from the same finger.

From the data, it is possible to obtain the Detection Error Trade-off (DET) curve and the Equal-Error Rate (EER). The DET curve is a plot of FAR x FRR, where one may check the trade-off between these two types of error. EER is commonly used to measure performance of biometric systems. It is the rate at which both acceptance and rejection errors are equal.

Fig. 6 shows DET curves considering the entire database DB2-A and after removal of 5%, 10% and 15% of the images with poorest quality. Table I lists the EER values corresponding to each case. It is possible to verify the performance improvement of the fingerprint verification system with the removal of images of poorest quality. As one can see, the EER improvement after removal of the 5%, 10% and 15% poorest quality images over the complete image database is 30.6%, 32.6% and 37.9%, respectively. Alternatively, for a 1% FAR, the FRR for the complete database is about 2.27%. After the removal of the 5%, 10% and 15% poorest quality images, FRR is about 1.33%, 1.19% and 1.14%, respectively.

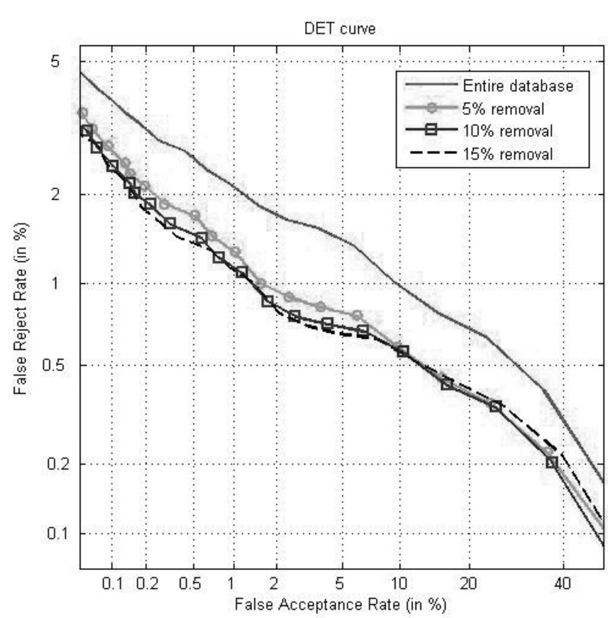


Figure 6 - DET Curves.

TABLE I. EER Values for the DB2-A Database

Image Database	EER
Entire database	1,6759
After removal of 5% of poor quality images	1,1621
After removal of 10% of poor quality images	1,1301
After removal of 15% of poor quality images	1,0394

IV. Conclusion

The performance of a fingerprint recognition system is directly affected by the quality of fingerprint images.

The use of fuzzy logic proved itself to be very useful for estimating the quality of fingerprints. With a fuzzy inference system, it was possible to define rules using experts' knowledge for combining local fingerprint features into a single quality score.

The proposed fingerprint quality estimation method improved the performance of the fingerprint matching. After removal of the 5%, 10% and 15% poorest quality fingerprints of the database DB2-A, an improvement in EER of 30.6%, 32.6% and 37.9%, respectively, was obtained.

Future works may include experiments with non minutia-based fingerprint matching approaches and also with other types of sensors, such as capacitive, heat or ultrasound devices.

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