Fingerprint Image Quality and Prediction of Matching Performance

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***Abstract*— Due to their high reliability, fingerprints have been extensively used as a biometric identifier. The performance of an automatic fingerprint authentication system relies heavily on the fingerprint image quality as seen in several studies. In this work, we present a new method to quantify fingerprint image quality which is relevant to matcher performance. The ultimate goal of this research is to determine and overcome the underlying causes of the poor match. Newly developed wavelet features and previously developed spatial features, as inputs to a fuzzy c-means classifier, are used predict matcher performance. Results are obtained for two different matchers, namely NFIS bozorth3 and Verifinger (Neurotechnologija), for two different optical sensors, Crossmatch Verifier 300 and Secugen Hamster III.**

***Index Terms*— fingerprints, image quality, fingerprint matchers, performance prediction, fuzzy classifier, Kullback-Leibler distances, principal component analysis, energy distribution analysis.**

I. Introduction

Authentication or identification of a user is important in many applications such as credit card authorization, building access control and bank ATM access. Biometrics refers to automatic identification (or verification) of an individual by using physiological or behavioral traits associated with the person (e.g., fingerprint, iris, voice, face, hand geometry, etc.). Biometric identifiers have an edge over traditional security methods because they cannot be easily stolen, shared or forgotten unlike passwords [1], [2].

Among all biometric identifiers, fingerprints are most widely used. Minutiae points (i.e., ridge ending and ridge bifurcations) are used by most fingerprint matchers for recognition [3], [4], [5]. Fingerprints images are usually obtained under different skin conditions (e.g., dry, wet, abraded, creased), which decide the quality of the fingerprint image. A poor quality fingerprint image (e.g., dry or smudged image) often produces many spurious minutiae points which may cause poor matching performance. Understanding the quality of an image in relation to matcher performance can determine what actions the system should take; such as whether to adjust the matcher, enhance the image, or consider the local quality, in order to improve performance (see Fig. 1).

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The basic aim of this research is to consider image quality in the context of matcher performance. A fuzzy cmeans classifier which uses wavelet-based distance measures (of both images) and spatial features (only of the verification image) in order to determine image quality (good, smudged, dry). Manually classified images are used for training. The results of the image quality determined by the fuzzy classifier are then compared to performance results from two matchers: NFIS bozorth3 and Neurotechnologija Verifinger.

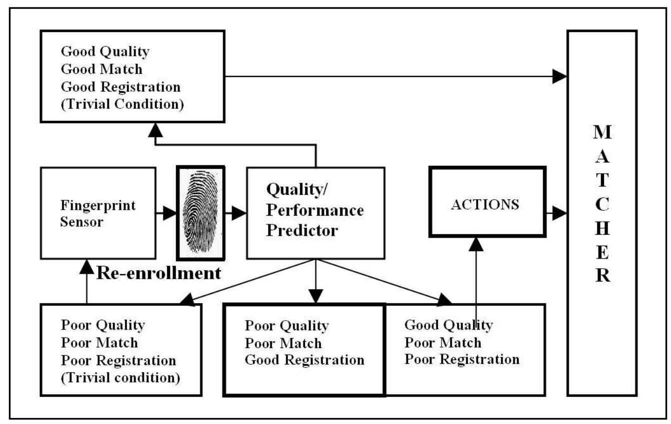

Fig. 1. Image quality and performance prediction.

II. Data Management

Fingerprint images were collected from two optical sensors, namely Crossmatch Verifier 300 and Secugen Hamster III. An enrolled image of good quality was collected followed by dry and smudged images for each subject. For dry fingerprint images, acetone was applied before scanning. For smudged, glycerin was applied (See Fig.2(a)-(b)) before each scanner, three datasets have been designed considering good, dry and smudged quality verification images as shown in Table 1.

TABLE I
DATA SET: DISTRIBUTION

Sensor	Type	Subjects	Images
CrossMatch (500 dpi)	good	28	100
	Dry	28	100
	Smudged	15	74
Secugen (500 dpi)	good	26	100
	Dry	8	20
	Smudged	31	100

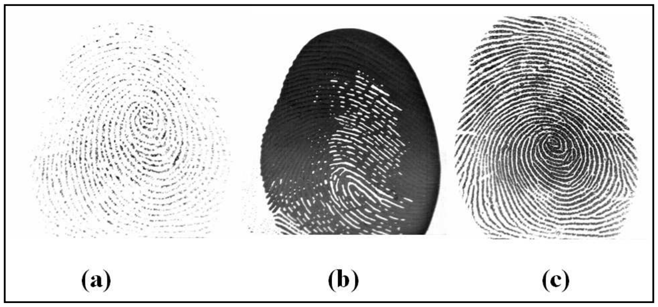

Fig. 2. Quality focused fingerprint collection using solvents (a) Dry quality image using acetone (b) smudged quality image using glycerin (c) good quality image

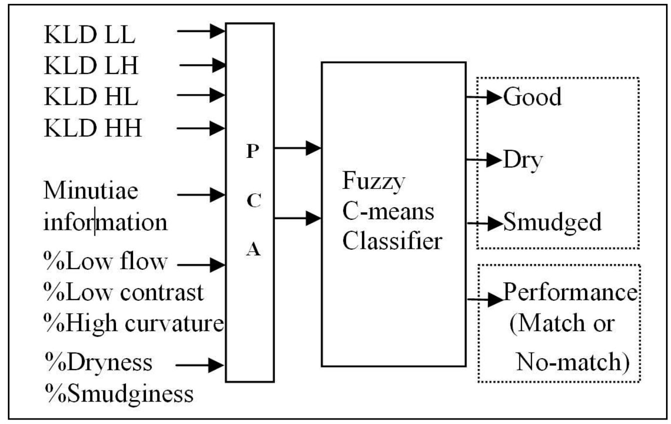

Fig. 3. Classification scheme with different features as input for predicting a match or a no match.

III. Methods

A. Inter rater statistics

In order to train the classification scheme for good, dry and smudged quality images, manual ratings were performed. To assess the consistency of manual classification, 30 images of each class were rated by four raters independently. Ratings were performed for each 32X32 block (i.e., 300 blocks for a 480X640 image). A simple protocol was explained to all the raters for rating good, dry and smudged blocks. Inter rater statistics are computed to determine the overall agreement between the raters [6].

The foreground blocks of the images were kept constant for all the raters, while the background blocks were not considered for calculating the overall agreement. For classification, an image level assessment was performed based on block classification by using For predetermined threshold on number of blocks of a particular category (see Table 2).

TABLE II
Data set: Distribution

Image Class Type	Average Kappa statistics at block level	Image level assessment Th= 0.4
Good	0.9809	1
Dry	0.7377	0.9667
Smudged	0.7924	0.6667

B. Features used for classification

Different features including quality maps of the verification image as well as joint features (i.e., KLD) of the verification and enrolled image are given as input to the fuzzy c-means classifier to determine the quality and to predict the matcher performance for the verification image, as shown in Fig. 3 .

Quality maps including low flow, high curvature, low contrast and minutiae information are obtained from NIST fingerprint image software (NFIS2) [7]. The dryness and smudginess analysis is performed using the US patent by Bolle et al. [8]. All these features are calculated for the verification image.

1) Wavelet based features: Asymmetric Kullback-Leibler distances (KLD) between different oriented wavelet sub bands of the two images at varying scales are used for texture comparison. The closed form for KLD between two generalized Gaussian density (GGD) functions is given by using equation (1). The linear phase Symlet filters are used which do not cause phase distortion or image artifacts. The wavelet sub band at each scale is modeled by using GGD [9].

$$
\begin{aligned}
D(p(.;\alpha_1,\beta_1)||p(.;\alpha_2,\beta_2)) &= \log(\frac{\beta_1\alpha_2\Gamma(1/\beta_2)}{\beta_2\alpha_1\Gamma(1/\beta_1)}) \\
&+ (\frac{\alpha_1}{\alpha_2})\frac{\Gamma((\beta_2+1)/\beta_1)}{\Gamma(1/\beta_1)} \\
&- \frac{1}{\beta_1} \qquad (1)
\end{aligned}
$$

where, α is scale parameter of the GGD function, β is shape parameter of the GGD function and 1, 2 subscripts refer to GGD functions of respective images.

C. Principal Component Analysis

Principal component analysis (PCA) is performed on the features described above, before being used as inputs to the fuzzy c-means classifier. The first two eigenvectors are selected and used as the direction of the plane to which the data points are projected.

D. Fuzzy c-means classifier

PCA output is used as an input to the fuzzy c-means classifier. The fuzzy c-means algorithm is designed to minimize c-means functional, which represents a nonlinear optimization problem. Stationary points associated with the c-means functional are found by Lagrange multiplier constraints. A simple fuzzy c-means algorithm is implemented using Picard iterations through first order conditions for the calculated stationary points. Instead of using the standard Euclidean distance norm, the adaptive norm is used, which adds to the capability of the classifier to induce hyper spherical clusters of different geometrical shapes and sizes. Validation uses error rates based on the misclassified data points.

50% images from each class are used for training the classifier and the rest are treated as test data. For dry, smudged and good quality images, the fuzzy c-means classifier is trained using the percentage of blocks of a particular quality out of the total number of foreground blocks determined by manual classification. For the performance component, match scores using NIST bozorth3 [7] and Verifinger (Neurotechnologija) are calculated.

First centroid is formed assuming that good quality will have good performance and poor quality images (dry and smudged) will have poor performance. These are considered to be trivial cases. To help facilitate equal distribution of the remaining classes, the remaining centroids are selected to be orthogonal to the first centroid in three dimensional space. A threshold of 60% for class participation is used for separating the trivial cases. A window of $58-68\%$ is used for both the dry and smudged non-trivial cases and good performance is decided if the good quality (or performance) class participation is more than the third class participation (e.g., dry being the third class with respect to smudged images), especially for the border points. The points which are closest to good quality centroid but are still outliers (with respect to 60% threshold) are treated as good quality poor performance.

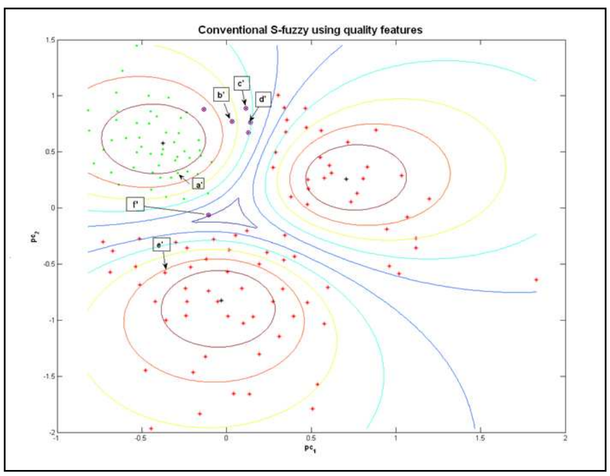

Fig. 4. Fuzzy c-means scatter plot for mapped data (2D) of Crossmatch dataset using only quality features

IV. Experimental Results

Results are obtained on images obtained from two optical scanners Crossmatch and Secugen. Classification rates are given in Table 3, when compared to manual classification of good, dry, and smudged quality. Next classifier results were assessed considering the match score where good quality is associated with good performance and poor quality (smudged, dry) is associated with poor performance. Comparison of the classifier results with match scores is as shown in Figures 4 and 5.

The effective use of designed predictor in improving the matcher performance is shown with the help of points (a- e) in figure 4 and the corresponding points (a-e) in figure 5.

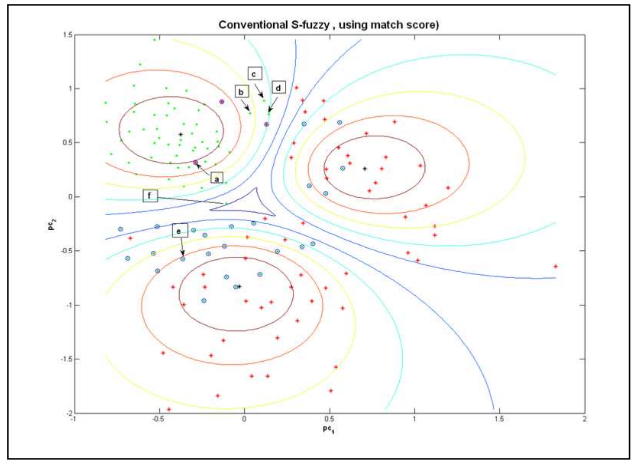

Fig. 5. Fuzzy c-means scatter plot for mapped data (2D) of Crossmatch dataset using match scores with quality features

TABLE III
Classification rates for designed datasets for both the matchers when compared to manual classification. (NIST/Verifinger data were used as part of the feature set.)

Dataset	Classification Rate NIST	Classification Rate VeriFinger
CrossMatch	94.89%	96.35%
Secugen	94.55%	90.91%

Five sample points are chosen for analysis as shown in figures 4 and 5 for analysis. Point a in figure 5 corresponds to a poor match score point (good quality), which lies in the vicinity of first good match centroid and hence treated as a outlier. This issue was not correctly addressed by the designed predictor (in terms of performance), as shown by point a in figure 4. In fact this is the only point that was incorrectly judged by the predictor.

The rest of the points (b-e) and their corresponding counterparts (b-e) demonstrate the capability of the system to predict the matching performance, based on the underlying quality of the fingerprint images. Points (b-d) (poor quality by manual classification) in figure 5 weigh more towards good performance centroid. The predictor determines the cause behind the points being on the good performance centroid boundary. Points (b-d) clearly show that these points do not produce good match scores as their quality indices are low. Pair of points (f-f) indicates the effectiveness of the predictor in correctly indicating the reasons behind good performance of apparently poor quality images. The correct prediction is shown by point f in figure 4.

The point f, which was manually classified as a dry image but has a good match score, is backtracked using our manual classification method (see Fig. 6). Out of 69 foreground blocks, 34 blocks have been marked as dry quality and 35 blocks have been marked as good quality blocks manually. Therefore this image is on a threshold to be classified as good or dry. Though we pre classified this image as a dry image, predictor predicts the good performance of this image accurately as this image being an outlier to dry quality class and close to good quality image class.

V. Conclusion

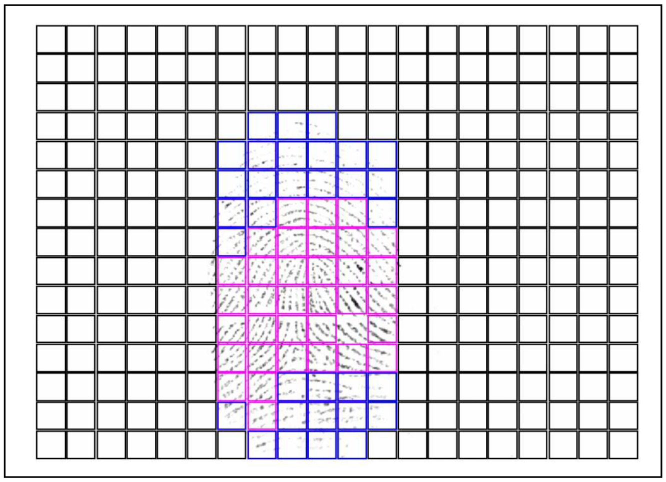

Fig. 6. Manual classification: (blue-dry blocks, magenta-good blocks, black-background blocks)

We have demonstrated a method by which performance of a fingerprint matching system can be predicted based on image quality. The model can be trained with matcher specific inputs to enhance the performance of the system. A fuzzy classifier has been developed which gives an associated confidence level with outputs of performance (good or poor) and quality (good, dry and smudged). By predicting the matcher performance, subsequent actions like matcher adjustment, preprocessing, local quality assessment or reenrollment of a fingerprint can be taken in order to improve the authentication. This is a vital task because image quality is an important factor in successful authentication.

Acknowledgment

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