

FINGERPRINT MATCHING USING MINUTIAE QUADRUPLETS

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ABSTRACT

Fingerprint matching faces several challenges resulting from the varying quality of fingerprint scanners, the weakness of some scanners in detecting fake fingerprints and the poor performance of fingerprint matching algorithms caused by the high intraclass variations between fingerprints of the same subject. The major contributions to the high intraclass variations include high displacement between an enrolled fingerprint and an input fingerprint of the same person; rotations and occlusions caused by non-uniform finger pressure on the scanner, differences in sensed fingerprint area, dry-skin or accidents; non-linear distortion as a 3 dimensional fingerprint image is sensed by a 2 dimensional fingerprint scanner. This paper proposes a new method of matching fingerprints using geometric features termed minutiae quadruplets. The performance of the properties of minutiae quadruplets were evaluated on unprocessed datasets of database_a (110 pairs of fingerprint images) of the Fingerprint Verification Competition (FVC) 2000 database. The evaluation resulted in genuine matches of 89 out of 110 fingerprints; and a receiver operating characteristics of about 20% off the zero axes. This entails that the properties of minutiae quadruplets may not be beneficial for fingerprint matching of unprocessed fingerprints but may be beneficial for matching of processed fingerprints.

KEYWORDS

Fingerprint, quadruplets, matching, minutiae, global matching, local matching, minutiae-matching, receiver operating characteristics.

1 INTRODUCTION

Fingerprint recognition is of interest to most biometric researchers because of its wide application in various security systems.

Existing global fingerprint matching algorithms are not efficient as they do not have much tolerance for variations in fingerprints of the same subject. The main challenges in fingerprint recognition include high displacement differences between the template and the input

fingerprints. In a fingerprint image scanned at 500 dpi, a finger displacement of 2 mm can result in a translation of about 40 pixels [1]. Another challenge is non-linear distortion as a 3 dimensional fingerprint image is sensed by a 2 dimensional fingerprint scanner. The skin has some plasticity property which results in non-linear distortion in successive image acquisitions of the same finger. There are also problems as a result of non uniform finger pressure, dryness of the skin, skin

injury, sweat and dirt. Feature extraction algorithms are imperfect and often extract genuine as well as spurious features in low-quality fingerprint images.

Approaches used in fingerprint matching can be minutiae-based [2], ridge feature-based [3] or correlation-based [4]. Minutiae-based matching consists in finding greatest number of minutiae matches between an input fingerprint called a probe and an enrolled fingerprint. This is the most popular and widely used approach. In correlation-based matching two fingerprints are overlapped and the correlation between corresponding pixels is determined for the different alignments. In ridge feature-based matching features of the fingerprint ridge pattern like local ridge orientation, frequency and shape are extracted for comparison. These features may be more reliable for comparison in fingerprints of low-quality images than minutiae features.

The features used for fingerprint comparison must be salient features that uniquely characterize each fingerprint template. The minutiae-based features are the bifurcation and ridge ends minutiae. Biometric recognition systems are pattern recognition and classification systems. A fingerprint recognition system is expected to match an input fingerprint, called a probe, to an impression of the same fingerprint already enrolled in the database. It is also expected not to match a probe with an impression of another fingerprint in the database. The classification of the fingerprint matching algorithm is right when there are true matches (true accepts) and true rejects (true non-matches). The classification is wrong when there are false

matches (false accepts) and false non-matches (false rejects). The performance of classification is not 100% efficient. The important issue is to limit the errors (false accept rate, FAR, and the false reject rate, FRR) as much as is possible.

2. EXISTING MATCHING TECHNIQUES

Minutiae-based matching can involve global matching or local matching. In global minutiae matching, highly discriminative features of the fingerprint are used in comparing the probe to the enrolled template. The least distance between minutiae in the probe and enrolled fingerprint is determined, whereas in local minutiae matching, structures are defined [5] based on some geometric or feature based technique which can be used in comparing fingerprint images for matches or non-matches. Global matching is accurate but has high computational complexity, low distortion tolerance, heavy template size and slow speed of computation. Local matching techniques on the other hand do not need highly distinctive features; they have a low computational complexity and less template size since the features are based on some secondarily derived structures for matching. Fingerprint matching can be done using the Hough transform [6] which is an approach normally used in global matching.

Several authors have developed local matching techniques for comparing fingerprints over the last two decades.

Sheng et al [7] developed a Memetic Fingerprint Matching Algorithm (MFMA) for comparing fingerprints of an input to the enrolled templates. They

generated a population of configurations from local features of minutiae from the probe and the templates, and determined matches in both using the degree of alignment of both templates.

Nilceu et al [8] combined minutiae-based matching with ridge feature-based matching in his approach. For the ridge-based features, matrices of ridge line were obtained and the match score from the alignments of these matrices determined which fingerprints constitute a match. In the minutiae-based matching features, the angle of inclination of a minutiae point and the x and y locations were utilized.

Jain et al [9] developed a hybrid matching technique that used both minutiae point information and texture based information that resulted in an improved performance. Texture based features (ridges) were extracted using Gabor filters.

Germain et al [10], the originator of the minutiae triplet matching technique, used properties of triplets of minutiae to match fingerprints. This remains the generally acceptable, state-of-the-art method of local minutiae matching technique. Germain et al also introduced a geometric and hashing method used for quickly searching the triplet features database.

Jie et al [11] combined minutiae features and core location in matching. The core is the maximum point of ridge curvature in a fingerprint image, and the core served as a reference point in the matching algorithm. Features with close distances from the core point in the probe and enrolled constitute a match.

Ng et al [12] developed an approach termed the adjacent orientation vector.

They extracted minutiae pairs then rotated and translated the pairs prior to matching to reduce rotation errors.

Ito et al [13] compared fingerprints based on the phase correlation technique by determining the 2D Inverse Discrete Fourier Transaction of the images prior to comparison.

3. MATCHING USING MINUTIAE QUADRPLETS

The method proposed in this paper uses properties of the quadruplets of minutiae points in a fingerprint for comparing fingerprints for matches.

3.1 Features for Matching

The features used for matching are the exterior angles of the minutiae quadruplets, the lengths of the two diagonals formed by the minutiae quadruplets, and the lengths of the two sides of the parallelogram formed by joining the mid-points of the four sides of the quadruplets.

(1) Let each exterior angle of quadruplets measured in a clockwise direction be

$$\alpha_1, \alpha_2, \alpha_3, \alpha_4$$

(2) Let the sum of two opposite exterior angles be

$$\alpha_1 + \alpha_3 = \alpha_2 + \alpha_4 \quad (1)$$

(3) Let the length of the two diagonals of the quadruplets be d_1, d_2 .

P_1 is the length that joins the two angles α_1 and α_3 .

P_2 is the length that joins the two angles α_2 and α_4 .

(4) Let the two lengths of the parallelogram formed be p_1, p_2 .

p_1 is the length opposite angle α_1 .

p_2 is the length opposite angle α_2 .

The set of the features for matching are

hence,

$$S = \{ \theta_1, \theta_2, \theta_3, \theta_4, \delta_1, \delta_2, \lambda_1, \lambda_2 \}$$

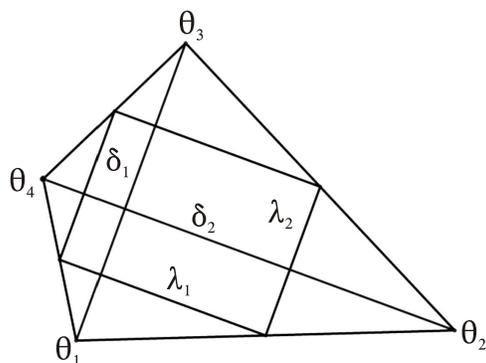


Fig. 1. The set of features used for matching in a minutiae quadruplet

3.2 Criteria for Matching

A query fingerprint would have all the features enumerated in the last sub section present in all the minutiae quadruplets extracted from the query fingerprint online. A hashed database would contain all features of quadruplets of minutiae of all fingerprints enrolled in the database in some hash table.

A range of features will be selected for matching against the query fingerprint based on the following criteria.

- (1) θ_1, θ_2 , and θ_3 remain the same or
 - (2) θ_1, θ_2 , and θ_4 remain the same or
 - (3) θ_3, θ_1 , and θ_2 remain the same or
 - (4) θ_4, θ_2 , and θ_1 remain the same.
- $\delta_1 + \delta_2 = k_1$ (a constant) (2)
 - $\delta_1 + \delta_4 = k_1$ (a constant) (3)
 - $\delta_2 + \delta_1 = k_3$ (a constant) (4)
 - $\delta_2 + \delta_3 = k_4$ (a constant) (5)

Hence, the criteria for matching are all features of quadruplets with either of the following similar set of features in the query fingerprint.

$$S_1 = \{ \theta_1, \theta_2, \theta_3, k_4 \} \tag{6}$$

$$S_2 = \{ \theta_2, \theta_3, \theta_1, k_2 \} \tag{7}$$

$$S_3 = \{ \theta_3, \theta_1, \theta_2, k_3 \} \tag{8}$$

$$S_4 = \{ \theta_4, \theta_2, \theta_1, k_1 \} \tag{9}$$

4. EXPERIMENTS AND RESULTS

The sample fingerprints used in the experiment were datasets from database_a of the Fingerprint Verification Competition (FVC) 2000 database. The FVC database is a standard database, neither proprietary nor subjective, used for the technological evaluation of fingerprint algorithms or sensors. The FVC database comprises unprocessed and noisy fingerprints with rotations, scaling and occlusions among different impressions of fingerprints from the same subject. 110 pairs of the unprocessed fingerprints in database_a were used for the evaluation.

4.1 Minutiae Features Extraction

Minutiae features were extracted from the fingerprint images using a features extraction algorithm written in C++ language. The fingerprint images were unprocessed and hence noisy. This led to the extraction of spurious minutiae as well.

The x, y coordinate locations of the bifurcation and ridge-end minutiae were extracted. The extracted features for every single image were stored in a template database.

4.2 Results

There were 110 pairs of fingerprint used in

the evaluation of the algorithm. The first set of 110 fingerprints termed the model was set apart and stored in a separate database. The second set of 110 fingerprints termed the probe was set apart in a second database. The fingerprints in the two databases are different impressions of the same subject. Every single fingerprint in the probe database was matched against every other fingerprint in the model database. In other words, a fingerprint in the probe database called a probe or input fingerprint was matched against all 110 in the model database. It is expected that the probe should match the genuine fingerprint in the model database and reject other 109

fingerprints. This process was repeated for all 110 probes in the probe database.

At the end of the matching exercise, there were 89 genuine matches (true accepts) and 21 false matches (false rejects). The pdf (probability density function) of the comparisons, the genuine and impostor distributions is shown in figure 2. The Receiver Operating Characteristics (ROC) of the false accept rate (FAR) versus the false reject rate (FRR) is shown in figure 3. The ROC of the genuine accept rate (GAR) versus the FRR is shown in figure 4.

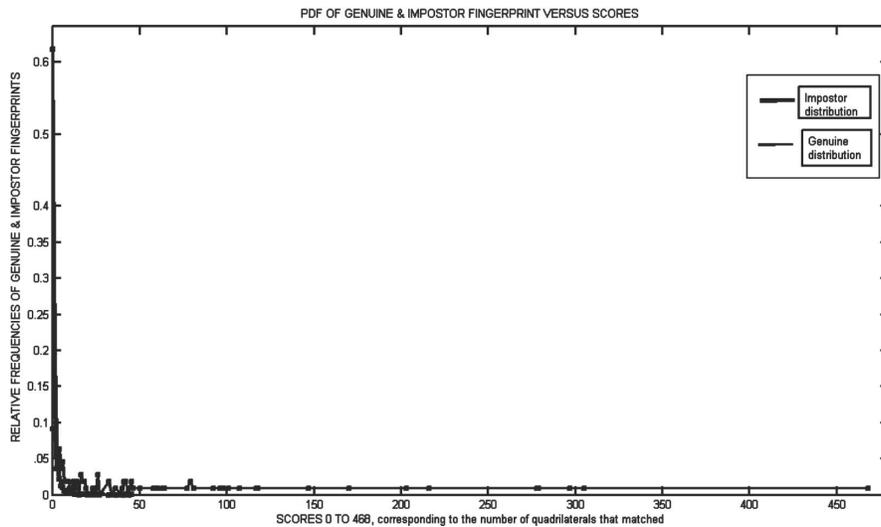


Figure 2: PDF of genuine and impostor distributions

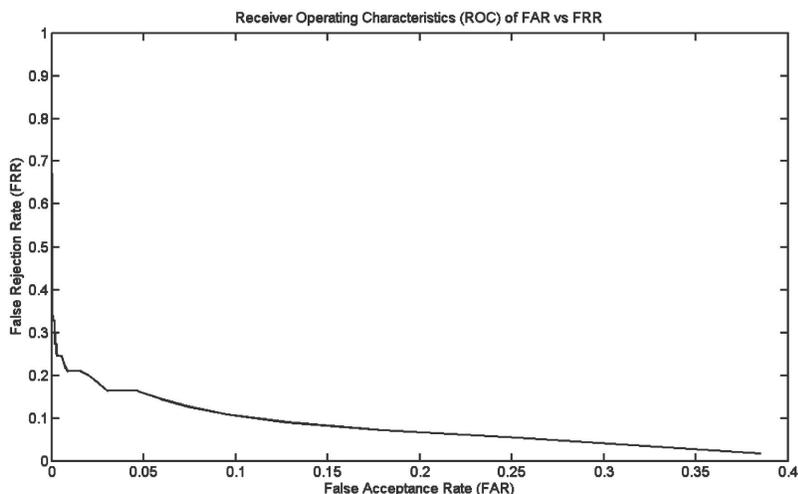


Figure 3: Receiver operating characteristics of the false reject versus false accept rates

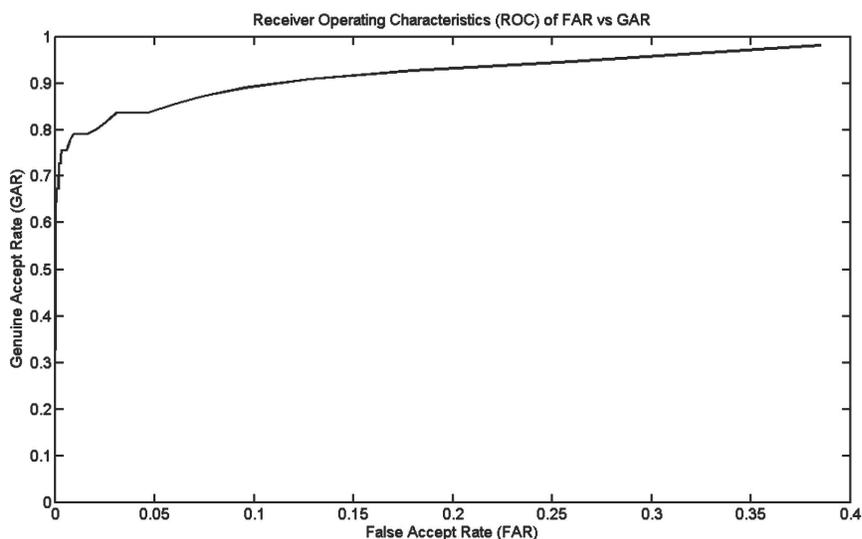


Figure 4: Receiver operating characteristics of genuine accept versus false accept rates

5. DISCUSSION OF RESULTS

The results in figures 2, 3 and 4 are discussed in this session.

5.1 PDF of Genuine and Impostor distributions

Figure 2 shows the pdf of the genuine and impostor distributions of the match scores of the fingerprint quadruplet features in the

fingerprint matching exercise.

The pdf in the fingerprint comparison evaluation is a curve of the relative frequencies, (that is, the number of occurrences of scores from a distinct population divided by the population) versus the scores. The match scores varied from 0 to 468 in this exercise and the relative frequencies of the genuine and

impostor populations that had these scores are plotted in figure 2. This is an overlapping distribution and hence has false accepts and false rejects. However, the scores of the impostor distribution did not exceed 50 while that of the genuine distribution was up to 468.

5.2 Receiver Operating Characteristics of the False Reject (FRR) versus False Accept Rates (FAR)

The graph that depicts the tradeoffs between FAR and FRR is known as the ROC. An ROC is a two-dimensional graph that relates the GAR to the FAR or the FRR to the FAR for various thresholds. The nearer a threshold point on the characteristics approaches the upper left corner or upper right corner (for GAR versus FAR) depending on order of the x-axis, the better the performance of the system. The nearer the ROC curve approaches the lower left corner or right corner (for FRR versus FAR), hence nearer the zero axis, the better the performance. The ROC of the FRR versus FAR is shown in figure 3. The false rejects were plotted against the false accepts using every score as a threshold. There were 469 threshold from scores 0 to 468. The ROC in figure 3 is about 20% off the zero axis.

5.3 Receiver Operating Characteristics of the Genuine Accept (GAR) versus False Accept Rates (FAR)

The ROC in figure 4 is a plot of the GAR versus FAR. The scores and the thresholds used in the plotting are the same with that of figure 3. A curve near to the upper left corner would be ideal however the curve is about 20% off the upper axis.

6. CONCLUSION

A new fingerprint matching algorithm based on the properties of quadruplets of minutiae is proposed in this paper and the performance of this algorithm was evaluated on the FVC 2000 standard database_a. The results show that the algorithm was able to perform 89 accurate comparisons out of 110 comparisons. There were 21 false comparisons. The performance of this algorithm would undoubtedly be better if tested on processed fingerprint datasets.

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