MINUTIAE-BASED ENHANCED FINGERPRINT VERIFICATION ASSESSMENT RELAYING ON IMAGE QUALITY FACTORS

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ABSTRACT

In this paper we evaluate authentication performance of the minutiae-based fingerprint automatic recognition system, previously proposed [13], and recently completed, with the new large fingerprint image database, MCYT [10]. The scheme includes: image enhancement, characteristic extraction and pattern recognition. The design of this database permits to analyse the influence of the variability factors appearing in the image acquisition phase. We focus in two factors: the finger position over the acquisition sensor, and the quality of the acquired fingerprint images. The analysis is accomplished in cases of supervised and non-supervised databases. Score normalization is presented as an effective technique to improve the fingerprint verification system performance, yielding highly competitive EERs.

1. INTRODUCTION

One of the critical problems regarding performance evaluation of biometric recognition is the scarcity of public databases representing large population characteristics. The enormous acquisition effort derived from a thorough design of the database contents, makes usually this process incomplete, costly, and unrealistic, because: *i)* A database designed for open recognition evaluations, must be intended to be statistically representative of large populations. *ii)* Biometric features in realistic applications exhibit empirical variability [8], so acquisition under controlled conditions makes, in many cases, the available data worthless in order to develop, adjust and test real recognition applications. Characteristics of the MCYT_Fingerprint Database, such as the representation of variability factors and the large volume of enrolled individuals, described in Section 2, permit to evaluate the verification performance of the minutiae-based fingerprint automatic recognition system, previously proposed in [13]. In Section 3 the architecture and the implemented processing algorithms for this system are described, and in Section 4, results achieved in the different evaluation experiments are presented.

2. MCYT MULTIMODAL DATABASE

A large biometric database acquisition, based in our previous experience in biometric database acquisition [9], was launched in 2001 within the MCYT Project. The expected number of individuals in the database is roughly 400, although by the time this contribution is realized, less than 100 were fully available. A single-session fingerprint database acquisition process has been designed to include different types of sensors and different acquisition conditions. Two types of acquisition devices, producing 8-bit gray-scale images, are used: *i)* a CMOS-based capacitive capture device, model 100SC from Precise Biometrics [12], with resolution of 500 dpi, producing a 300×300 pixel image (about 90 kB file size), and *ii)* an optical scanning device, model UareU from Digital Persona [1], also with resolution of 500 dpi, producing in this other case a 256×400 pixel image (about 102 kB file size).

With the aim of including fingerprint *position variability*, the MCYT_Fingerprint Subcorpus includes 12 different samples of each fingerprint, acquired under human supervision and considering 3 different *levels of control*. These levels of control do not make reference certainly to fingerprint quality, but just consider position variability: the fingerprint core must be located inside a size-varying rectangle (displayed in the acquisition software interface viewer), as shown in Fig. 1; in Figs. 1*(a)-(c)*, 3 samples of the same fingerprint are shown, so fingerprint position variability can be clearly observed in this case. In all cases, human supervision ensures that fingerprint core is inside the proposed rectangle. Fingerprints are acquired by asking the person to remove the finger from the device and then to put it on again in order to avoid exact copies between consecutive samples.

Depending on the size of the rectangle, control levels will be referred to as *high*, *medium*, and *low*, namely: *i) Low control level:* In this case –see Fig. 1*(a)*-, 3 fingerprint samples are acquired, preventing the individual from watching the viewer (without visual feedback on fingerprint placing); *ii) Medium control level:* In this other case -see Fig. 1*(b)*-, the individual must produce 3 more samples, while watching his/her own finger location (with visual feedback on fingerprint placing); *iii) High control level:* Finally, 6 more samples, acquired with the same procedure described in *ii),* but this time the rectangle has even a smaller size, so a more severe position restriction is applied, as shown in Fig. 1*(c)*. Therefore, for each of the two sensors, every individual provides a total number of 120 fingerprint images (10 fingers×12 images/finger) to the database.

3. FINGERPRINT RECOGNITION SYSTEM

The implemented architecture of the automatic fingerprint recognition system can be divided in four phases: *1)* the fingerprint *image acquisition* from the sensor device; *2)* the *image enhancement* process, in order to reconstruct the fingerprint ridge structure; *3)* the fingerprint *feature extraction* from the enhanced image; and *4)* the *pattern matching* process, in which a biometric fingerprint pattern entering the system is compared with the database registered patterns. Since fingerprint acquisition for the MCYT_Fingerprint Database has been already described in Section 2, we will briefly focus in phases *2*, *3*, and *4*.

3.1. Image Enhancement

The aim of image enhancement stage is to provide a quality image, so that the feature extractor can obtain a precise biometric pattern. In terms of accuracy, it is common to make use of the *minutiae pattern* [3-7, 11, 13]. A point in the fingerprint image is designed as being a minutia if it is derived from an ending, beginning or bifurcation of a ridge. Image imperfections may induce misdetermination of the spatial coordinates and relative orientation of each minutia. If so, the recognition system reliability will decrease significantly, making necessary this image enhancement procedure.

Regarding our system, the complete improved sequence of stages that accurately extract the minutiae is: *i)* Normalization; *ii)* Orientation field calculation; *iii)* Interest region extraction; *iv)* Ridge extraction; *v)* Ridge profiling. Details from each stage are explained in [11, 13].

3.2. Feature extraction

The feature extraction process involves [5, 11, 13]: *i)* Thinning of the binary reconstructed ridge structure achieved after image enhancement, *ii)* Removal of all structure imperfections from the thinned image, and *iii)* Minutiae extraction, in order to generate a reliable biometric pattern. The thinning process is performed without modifying the original ridge structure of the image. For each detected minutia the following parameters are stored: *a)* the x and y coordinates of the minutia; *b)* the orientation angle θ of the ridge containing the minutia; *c)* in the case of an ending ridge, the x and y coordinates of the sampled ridge segment containing the minutia; *d)* in the case of a ridge bifurcation, the x and y coordinates of the sampled ridge segment of one of the bifurcation branches. The sampling interval is the mean distance between ridges in the image, and the maximum number of stored sampled points for each minutia is 10. Figures 2*(a)-(d)* show results achieved with the MCYT fingerprint *"dp_0080_0_5"* after feature extraction process.

3.3. Pattern Recognition

Given two biometric patterns, namely test and stored patterns, in the verification phase it must determined whether these fingerprint patterns have been produced by the same finger or not. Due to elastic deformations of the skin, imperfections in the image, and different interest regions of the acquired fingerprints, the two patterns must be aligned before fingerprint verification. Pattern alignment is achieved considering the relative position of the minutiae in the image. The matching process is accomplished seeking for correspondence between the two aligned structures. In the matching process, a score is defined to measure the similarity (edit distance) between the compared patterns. An elastic technique for minutiae comparison is used, permitting a certain spatial tolerance margin. To compensate for the nonlinear elastic deformations of the skin, the technique is also adaptive. For this purpose, a size-adaptive tolerance box adjustable to the spatial coordinate values of the explored minutiae, is defined [4, 5, 11].

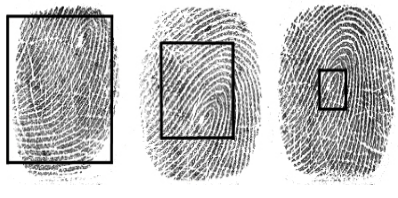

Fig. 1. Same MCYT fingerprint images acquired with optical scanner for: *(a)* low, *(b)* medium, and *(c)* high control levels.

Fig. 2. *(a) "dp_0080_0_5"* MCYT fingerprint. *(b)* Binary image after image enhancement. *(c)* Reconstructed thinned ridge structure and extracted minutiae. *(d)* Extracted minutiae and sampled ridge segments which constitute the biometric pattern of the fingerprint.

4. VERIFICATION PERFORMANCE EVALUATION

Four different goals have been pursued in the evaluation of the fingerprint recognition system, namely: *i)* to assess the performance and reliability of the processing algorithms, in the phases of image enhancement, characteristic extraction and pattern recognition, with large unsupervised databases, analyzing the influence of the position variability in the verification performance (see Section 4.1); *ii)* to explore a multiple-reference strategy to improve the similarity scores (see Section 4.2); *iii)* to apply a score normalization procedure aimed not to consider scores as absolute values but rather as relative values with respect to a reference population (see Section 4.3); and *iv)* to keep the above 3 goals over a supervised database in order to evaluate performance as a function of the quality degree of stored fingerprints images (see Section 4.4).

To accomplish this evaluation we have selected a database subcorpus consisting of the first 75 individuals acquired with the optical device; with such device, a total number of 120 images per individual are available and, consequently, the total number of involved fingerprints is 9,000 (120 images $\times$ 75 individuals).

In order to evaluate FAR (*False Acceptance Rate*), the set of impostors for each individual contains 1 high control level fingerprint from the remaining population, which means that there are 740 impostor images per individual (74 impostors $\times$ 10 images), and a total number of impostor attempts of 55,500 (740 images $\times$ 75 individuals). Number of client attempts to evaluate FRR (*False Rejection Rate*) will be further specified in each case. Results will be expressed in the form of DET curves (*Detection Error Tradeoff*).

4.1. Position Variability Assessment

The following experiments consider fingerprint position variability taking into account the above described levels of control contained in MCYT_Fingerprint database. Regarding the different experiments, we have selected the following sets: *1) Enrolled patterns*: for each fingerprint, 3 images of different control level can be used as patterns. *2) Test images*: the remaining 9 images per fingerprint are always used as test images.

4.1.1. Experiments considering position variability. In this set of tests we intend to evaluate the verification performance when comparisons between test and enrolled patterns are accomplished considering a higher or lower position variability level. Regarding position variability, 3 different experiments have been conducted, in which the enrolled pattern corresponds to a fingerprint of low, medium or high control level. Depicted curves *(a)-(c)* from figure 3, show, respectively, the results obtained for each of the above mentioned control levels. The number of comparisons for FRR evaluation, in each case, is 6,750 (9×10×75). In case *(a)*, when pattern has a low control level, we get 8.0% EER (this experiment will be denoted as *baseline* experiment); in cases *(b)* and *(c)*, we get 6.1% and 5.6% EERs, respectively. These experiments demonstrate that controlling position of pattern, but without controlling tests, results are yet improved (note improvement in cases *(b)* and *(c)* with respect to *(a)*).

4.1.2. Experiments controlling position variability. Another set of 3 experiments is accomplished to show verification performance when comparisons are performed between fingerprints of the same level of control (no position variability is considered). In each experiment, the enrolled pattern corresponds to a fingerprint of low, medium or high control level. Curves *(d)-(f)* from figure 3, show the results obtained when comparisons are accomplished between fingerprints of low, medium and high control level, respectively. The number of trials for FRR, in curves *(d)* and *(e)*, is 1,500 (2×10×75); and in curve *(f)*, is 3,750 (5×10×75). In cases *(d)-(f)*, we get respectively 7.8%, 4.2% and 3.3% EERs. Results demonstrate that controlling position of both pattern and tests improvement is highly significant for medium and high control levels.

4.2 Multiple Reference for Similarity Enhancement

In order to avoid an excessive position control level during acquisitions, in this section, each test fingerprint is compared with the Multiple Reference formed by the 3 enrolled patterns. The highest attained score from this matching procedure, is considered as the similarity value (MAX-Rule case). Results are shown in figure 3*(g)*. Attempts for FRR and FAR evaluation are those from section 4.1.A. A 2.3% EER value is achieved; this remarkable decrease of the EER permits us to conclude that system performance is improved if the set of enrolled reference patterns considers possible variability conditions due to the finger position during the acquisition process.

4.3. Score Normalization

This technique has successfully been applied in other biometric recognition systems [2]. The aim of score normalization is to increase the capability of the system to discriminate client scores from impostor scores, considering relative scores values with respect to a reference population. The problem of biometric recognition, formulated in terms of pattern classification, is a form of hypothesis test. Let F_i be any possible fingerprint sample from user *i*; F_c, a fingerprint sample of client *c*; $\overline{F_c}$, all the possible fingerprint universe different from client sample F_c; and X, an input fingerprint. It is verified the hypothesis that a fingerprint F_i, is indeed the authentic one F_c, if

$$\log P\left(X\middle|F_c\right) - \log P\left(X\middle|\overline{F_c}\right) > \Delta \qquad (1)$$

where $P(X|F_c)$ is the conditional probability of X given F_c. A positive value of verification threshold Δ, indicates a valid claim, and a negative value indicates an impostor attempt. The first term of left side of equation (1) is related to the scores provided by the system, and the second term is denoted as the normalization factor. An approach to estimate this factor is:

$$\log P(X|\overline{F}_c) \approx \log \sum_{F_i \in C, i \neq c} P(X|F_i) \qquad (2)$$

where C is a set of fingerprints, denoted as *cohort* set, selected to calculate the normalization factor. This set can be formed by the fingerprints taken from the global population, or by the fingerprints which better represent the population near the claimed fingerprint. If we assume that the sum in (2) is dominated by the nearest impostor fingerprint, the estimation of the normalization factor can be resume to:

$$\log P(X|\overline{F}_c) \approx \max_{F_i \in C, i \neq c} \left[\log P(X|F_i)\right] \qquad (3)$$

We have used this latter approach, denoted as *best reference* normalization, in our system evaluation, to better differentiate clients and impostors. The cohort set has been reduced to the maximum score (*best reference*), attained by the input fingerprint X against the set of fingerprints formed by the all the global fingerprint population except the claimed fingerprint. The two approaches depicted in figure 3: Curve *(h)* is attained applying normalizing scores obtained in curve *(g)*. In the case of curve *(i)*, once the normalization of scores in curves *(a)*, *(b)* and *(c)* is applied, the maximum normalized score is selected. As a conclusion, a notable performance improvement is achieve in both cases of score normalization, since the best 2.3% EER, achieved in curve *(g)*, is now significantly improved to values 1.0% in curve *(h)* and 0.9% in curve *(i)*.

4.4. Analyse of Image Quality Factors

In this section we shall analyse the influence in system performance of image quality characteristics of the stored fingerprints. Supervision of MCYT Database is accomplished with the classification of all fingerprints, by visual inspection, in different groups according to image quality. A sample belongs to a group if a predefined group quality threshold is exceeded. Formed groups are: *Group I*: initial group of 75 individuals which has no restrictions of image quality. *Group II*: from this group all individuals whose fingerprints have been considered as non suitable for automatic recognition are excluded. *Groups III* and *IV*: these groups include individuals whose fingerprints have medium and high quality rates, respectively. Therefore, 3 different categories of image quality are considered. To consider possible variability conditions due to finger position the Multiple Reference strategy is employed. Curves *(b)-(d)* in figure 4 shows the achieved results with groups *II*, *III* and *IV* respectively, in which EER values of 1.8%, 1.3%, and 0.4% can be derived. Attempts for FAR and FRR evaluations are 37,646 and 6,106, respectively for group *II*; 25,206 FAR and 4,864 FRR for group *III*; and 4,081 FAR and 1,759 FRR for group *IV*. Curve 4*(a)* permits to compare these results with those obtained in section 4.2. These results demonstrate that a better image quality is traduced in a highly improvement of the verification performance.

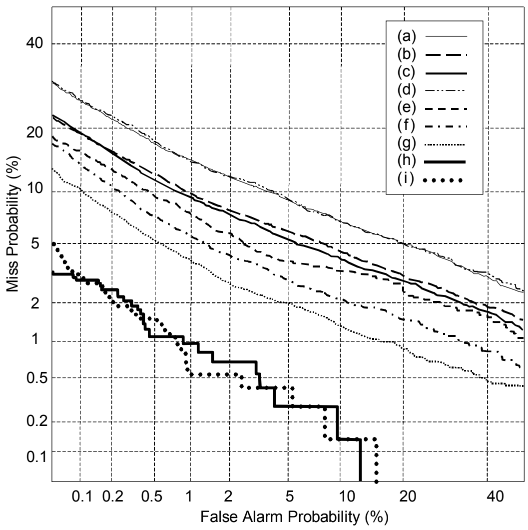

Fig. 3. DET curves without position control: *(a), (b)* and *(c)* correspond when enrolled pattern has low, medium and high control level. For position control: *(d), (e)* and *(f)* correspond to low, medium and high control level. *(g)*: MAX-Rule. *(h)*: score normalization of *(g)*. *(i)*: score normalization of *(a), (b), (c)* and selection of the maximum result.

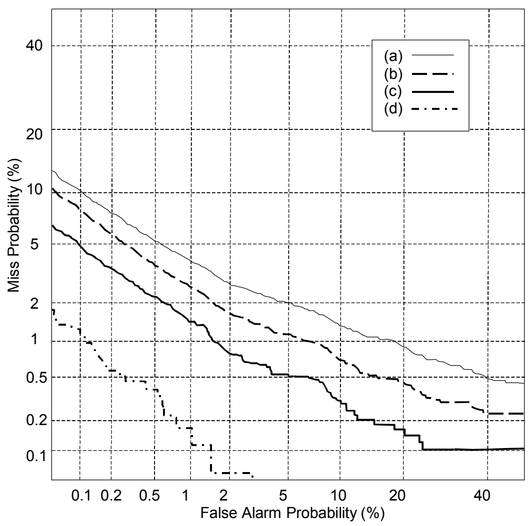

Fig. 4. DET curves when image quality and position control are considered. *(a)* MAX-Rule case from section 4.2. *(b)-(d)* correspond to evaluation with image quality groups *II*, *III* and *IV*, respectively.

5. CONCLUSIONS

The experiments accomplished in this paper have permitted to evaluate the performance of the proposed minutiae-based fingerprint automatic verification system, over a large individual population from MCYT, in which the variability factors of the acquisition process, by means of an optical device, are sufficiently represented. We have analysed the influence of controlling the position of the finger over the sensor screen during acquisition, and we conclude that the system EER decrease significantly if we increase: *i)* the control level of both the reference pattern and the test patterns (initial 8.0% EER for baseline scores has been improved to 3.3 % EER when high control level is applied to tests and reference); *ii)* the number of reference patterns, if possible variability conditions due to the finger position during the acquisition process is considered (2.3% EER with multiple references). Experiments with *best reference* technique demonstrate a great improvement in discriminating clients and impostors, resulting in an EER less than 1%. We have also analysed the combined influence of quality and position over a supervised database, in which an image quality rate to the different images has been assigned. We conclude that a great improvement in system performance can be achieved if both factors, position variability and image quality, are controlled (the 2.3% EER with MAX-Rule and without controlling image quality is highly decreased to a 0.41% EER when quality is supervised).

6. REFERENCES

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