MCYT baseline corpus: a bimodal biometric database

J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, J. Gonzalez, M. Faundez-Zanuy, V. Espinosa, A. Satue, I. Hernaez, J.-J. Igarza, C. Vivaracho, D. Escudero and Q.-I. Moro

Abstract: The current need for large multimodal databases to evaluate automatic biometric recognition systems has motivated the development of the MCYT bimodal database. The main purpose has been to consider a large scale population, with statistical significance, in a real multimodal procedure, and including several sources of variability that can be found in real environments. The acquisition process, contents and availability of the single-session baseline corpus are fully described. Some experiments showing consistency of data through the different acquisition sites and assessing data quality are also presented.

1 Introduction

One of the main problems that can be found in the development, testing and performance evaluation of biometric recognition systems, in both identification and verification modes, is the lack of public large multimodal databases acquired under real working conditions. The availability of multimodal biometric features corresponding to a large population of individuals, together with the desirable presence of biometric (intra)variability of each trait (multisession, acquisition channel/sensor, quality, etc.) makes database collection a complicated process, in which a high degree of co-operation among the participants is needed. For that reason, nowadays, the number of existing public databases oriented to performance evaluation of fingerprint- and signature-based biometric recognition systems is quite limited. Outstanding public databases are: the DB 4 NIST Fingerprint Image Groups [1] and FVC200x [2] fingerprint databases, and the Philips Research Laboratories Signature Database [3].

In this context, the Biometric Research Laboratory - ATVS, of the Universidad Politecnica de Madrid, has promoted the plan of action and the development of the MCYT project, in which the design and acquisition of a large-scale biometric bimodal database, involving fingerprint and signature traits, has been accomplished [4]. Although there are some other commercial and forensic partners within MCYT (Ministerio de Ciencia y Tecnología, Spanish Ministry of Science and Technology, partially funding the project) Project, the participation in the acquisition campaign has been conducted by a consortium of four academic institutions, namely: Universidad Politecnica de Madrid (UPM), University of Valladolid (UVA), University of the Basque Country (EHU) and Escola Universitaria Politecnica de Mataro, Barcelona (EUPMt).

MCYT database, which includes ten-print fingerprint and on-line signature modalities of each individual enrolled in the database, includes a significant number of samples of each modality, under different levels of control, in order to cope with the inherent variability of each feature at the acquisition process, as will be further detailed.

The scope of utility of the MCYT Database involves mainly the performance assessment in the design of automatic recognition systems in civil, commercial and forensic applications, allowing the development and evaluation of biometric recognition algorithms based on single biometric features, and also the fusion of them in a bimodal recognition system.

IEE Proceedings online no. 20031078

doi: 10.1049/ip-vis:20031078

Paper first received 6th May and in revised form 3rd October 2003

J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon and J. Gonzalez are with the Biometric Research Laboratory, ATVS, Universidad Politecnica de Madrid, Campus Sur, 28031 Madrid, Spain

M. Faundez-Zanuy, V. Espinosa and A. Satue are with Escuela Universitaria Politecnica de Mataro, 08303 Mataró, Barcelona, Spain

I. Hernaez and J.-J. Igarza are with Universidad del Pais Vasco/Euskal Herriko Unibertsitatea, Escuela Superior de Ingenieros, Alameda de Urquijo s/n, 48013 Bilbao, Spain

C. Vivaracho, D. Escudero and Q.-I. Moro are with Universidad de Valladolid, Dpto. Informatica, Edif. de Tecn. de la Inf. y las Telecom., Campus Miguel Delibes s/n, 47011 Valladolid, Spain

2 MCYT bimodal database

The basic idea behind the design of the MCYT database has been the optimisation of the extent of its significance which, in a multimodal database, is related to (i) the number of individuals enrolled, (ii) the number of modalities per individual and (iii) the number of realisations (samples) for each modality (which should include those variability factors that can be found in the acquisition process). Because this significance increases with each one of the above-mentioned parameters (i) to (iii), the design of multimodal biometric databases (see, for example, BIOMET database [5]), usually seeks the maximisation of each one of them (i.e. as many individuals as possible, as many modalities as possible and/or as many samples as possible).

In the design of the MCYT database where fingerprint and signature have been the selected biometric features, the maximisation of the significance has been carried out in two different ways. On the one hand, the number of individuals has been maximised while maintaining the number of realisations within a useful margin; on the other hand, the number of realisations has been maximised while maintaining the number of individuals within a useful quantity.

The former strategy has led to MCYT baseline corpus and the later one has led to MCYT extended corpus.

Regarding the MCYT baseline corpus, which constitutes the aim of this contribution, 330 individuals have been acquired in the four institutions participating in the MCYT project. In particular, 35, 75, 75 and 145 individuals have been acquired, respectively, at EUPMt, UVA, EHU and UPM. As a reference, the number of individuals considered in the MCYT baseline corpus is very near to the well known XM2VTS database [6], including speech and face data.

In the case of the MCYT extended corpus, about 100 more individuals are to be acquired, in a multi-session procedure, to incorporate intrinsic short-term signature variability, signature size variability, over-the-shoulder and time constrained signature forgeries and several sensor devices for fingerprint acquisition.

The MCYT baseline corpus has been divided into the MCYT_Fingerprint subcorpus and the MCYT_Signature subcorpus. Regarding the MCYT_Fingerprint subcorpus, for each individual, 12 samples of each finger are acquired using two different sensors (optical and capacitive). Therefore, $330 \times 12 \times 10 \times 2 = 79\,200$ fingerprint samples are included in MCYT baseline corpus. In the case of the MCYT_Signature subcorpus, 25 client signatures and 25 highly skilled forgeries (with natural dynamics) are obtained for each individual. Both on-line information (pen trajectory, pen pressure and pen azimuth/altitude) and off-line information (image of the written signature) are considered in the database. Therefore, $330 \times (25 + 25) = 16\,500$ signature samples are considered in the MCYT baseline on-line corpus. Next, both the MCYT_Fingerprint and the MCYT_Signature subcorpora are explained in detail.

3 Description of MCYT_Fingerprint subcorpus

In this Section, the acquisition protocol used during the development of the MCYT_Signature subcorpus is described. The whole process of fingerprint capturing is accomplished under the supervision of an operator. Two types of acquisition devices are used: (i) a CMOS-based capacitive capture device, model 100SC from Precise Biometrics [7], with a resolution of 500 dpi, and (ii) an optical capture device, model UareU from Digital Persona [8], also with a resolution of 500 dpi. In each case, a ten-print acquisition per individual has been carried out. Each input generates a bitmap file representing the image of the fingerprint, in an 8-bit greyscale. The file sizes and the image resolutions are: (i) 89 kbyte and 300×300 pixels, respectively, in the case of the capacitive device, and (ii) 102 kbyte and 256×400 pixels, in the case of the optical device.

With the aim of evaluating the automatic recognition systems under different acquisition conditions, the MCYT_Fingerprint subcorpus includes 12 different samples of each fingerprint, under different levels of control (high, medium and low), which will be further described. Therefore, in each capture session each individual provides a total number of 240 fingerprint images to the database (10 prints $\times$ 12 samples/print $\times$ 2 sensors).

The acquisition interface follows a fixed acquisition protocol. A viewer on the screen is available to the operator to help in controlling the finger position on the sensor. Based on the core and/or delta position, the operator decides when the acquisition and storage of the image are accomplished. The acquisition software automatically names, accordingly with the protocol, the file which contains the recently acquired fingerprint. The assigned file name perfectly identifies the individual, the type of sensor, the finger from which the image is stored, the number of sample, and the applied level of control. Figure 1 shows the aspect shown by the interface of the acquisition tool associated with the capacitive device, and Fig. 2 shows the same outline for the optical scanner.

Fig. 1 *Acquisition interface for the CMOS capacitive device*

In the viewers of both interfaces a rectangle appears, for each acquisition, in order to control the position of the finger on the screen sensor. The software automatically changes the size of this rectangle depending on the level of control of the captured image. The acquisition control is accomplished in three levels, namely

(i) Three samples with low level of control: the individual puts his/her finger on the screen sensor without any position restrictions, without watching the viewer. The operator must regard that at least one core and/or one delta of the fingerprint fall into the restricted area delimited by the rectangle of the interface viewer.
(ii) Three more samples with medium level of control: in this stage, the individual him/herself must observe the computer screen while the finger is located on the sensor. The image must be centred into the new rectangle of smaller size which appears on the interface viewer.
(iii) Six more samples with high level of control: the acquisition is accomplished as in the above stage, but the rectangle has now a smaller size. In this case, the position restrictions are more severe, and one core and/or delta of the fingerprint must always fall under this rectangle.

Figure 3 shows three examples of images from the MCYT_Fingerprint subcorpus, belonging to a same finger, acquired with the optical scanner under the three levels of

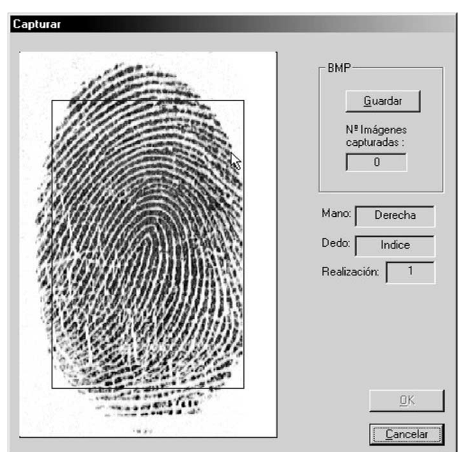
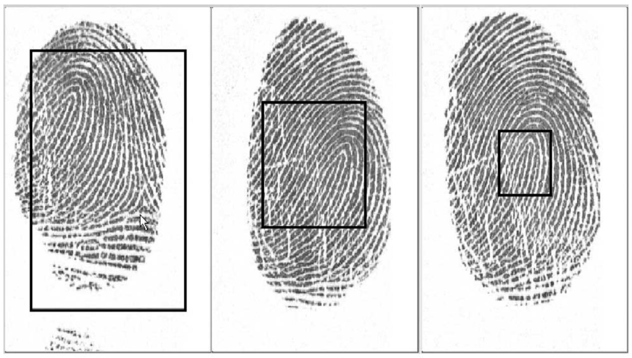


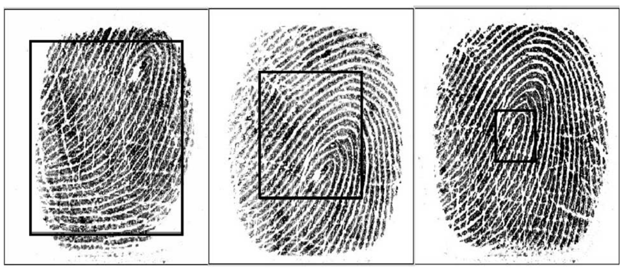
Fig. 2 *Acquisition interface for the optical device*



a b c

Fig. 3 *Examples of acquired images of the same fingerprint employing the optical scanner with the three different control levels*

a Low control
b Medium control
c High control



a b c

Fig. 4 *Examples of acquired images of same fingerprint employing capacitive scanner with three different control levels*

a Low control
b Medium control
c High control

control described above. Figure 4 shows the same examples for the capacitive scanner.

Furthermore, as it will be described in detail in Section 5.1, a subjective quality assessment, for a total number of 9000 samples (all optical samples from a subset of 75 subjects, from UPM site), have been accomplished. Regarding this quality measure, it can be stated that about 5% of the acquired images are of very bad quality; 20% of low quality; 55% of medium quality; and 20% of high quality. The significant percentage of low quality images is due to different factors which appear in the acquisition process: lack of impression in the image due to the adverse skin conditions (scars, marks, humidity, dirtiness, etc.), the particular configuration of the ridges in some fingers, the excess of pressure applied on the screen sensor, the background noise introduced by the acquisition device, and even the non-cooperative attitude of some individuals, producing in these cases a not well defined structure of the ridges.

4 Description of MCYT_Signature subcorpus

For each individual, the on-line signature capture session is achieved after the fingerprints are registered in the database. Since the acquisition of each on-line signature is accomplished dynamically, a graphics tablet is needed: the acquisition device used is a WACOM pen tablet, model INTUOS A6 USB [9]. The tablet resolution is 2540 lines per inch (100 lines/mm), and the precision is $+/-$ 0.25 mm. The maximum detection height is 10 mm (so also pen-up

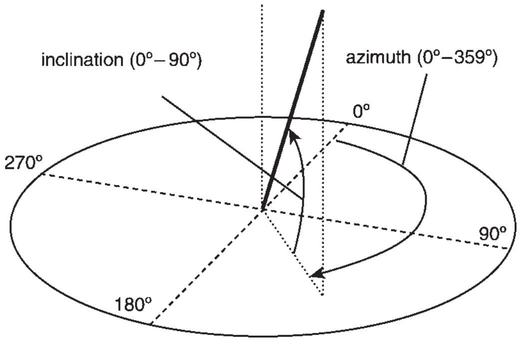


Fig. 5 *Azimuth and inclination angles of the pen with respect to the plane of the graphic card Intuos from Wacom*

movements are considered), and the capture area is 127 × 97 mm. This tablet provides the following discrete-time dynamic sequences (the dynamic range of each sequence is specified): (i) position in x-axis, x_t: [0–12 700], corresponding to 0–127 mm; (ii) position in y-axis, y_t : [0–9700], corresponding to 0–97 mm; (iii) pressure p_t applied by the pen: [0–1024]; (iv) azimuth angle γ_t of the pen with respect to the tablet (see Fig. 5): [0–3600], corresponding to $0°–360°$; and (v) altitude angle φ_t of the pen with respect to the tablet (see Fig. 5): [300–900], corresponding to $30°–90°$.

The sampling frequency of the acquired signals is set to 100 Hz, taking into account the Nyquist sampling criterion, as the maximum frequencies of the underlying biomechanical movements are always under 2030 Hz [10]. Each target user produces 25 genuine signatures, and 25 skilled forgeries are also captured for each user. These skilled forgeries are produced by the 5 subsequent target users by observing the static images of the signature to imitate, trying to copy them (at least 10 times), and then, producing the valid acquired forgeries in an easy way (i.e. each individual acting as a forger is requested to sign naturally, without artefacts, such as breaks or slowdowns). In this way, shape-based natural dynamics highly skilled forgeries are obtained. Following this procedure, user n (ordinal index) realises a set of 5 samples of his/her genuine signature, and then 5 skilled forgeries of client $n-1$. Then, again a new set of 5 samples of his/her genuine signature; and then 5 skilled forgeries of user $n-2$; this procedure is iterated by user n, making genuine signatures and imitating previous users $n-3$, $n-4$ and $n-5$. Summarising, user n produces finally 25 samples of his/her own signature (in sets of 5 samples) and 25 skilled forgeries (5 samples of each user, $n-1$ to $n-5$). *Vice versa*, for user n, 25 skilled forgeries will be produced by users $n+1$ to $n+5$.

The detection and segmentation of the input signature sample is automatically accomplished by the acquisition software. The signature start up is determined by the first sample obtained from the graphic card in which the pen-card contact exists, i.e. the first sample with non-zero pressure value, rejecting previous samples. The signature ending is determined by setting a 3 s timer to the first zero pressure sample found (i.e. a pen up). If no samples with non-zero pressure value are detected in this interval, the capture process is stopped, and the complete signature is stored. Otherwise, the timer is reset until the next pen up is found.

Finally, and as a reference, some example images from an MCYT_Fingerprint subcorpus are depicted in Fig. 6. Example data from an MCYT_Signature subcorpus are also shown in Fig. 7.

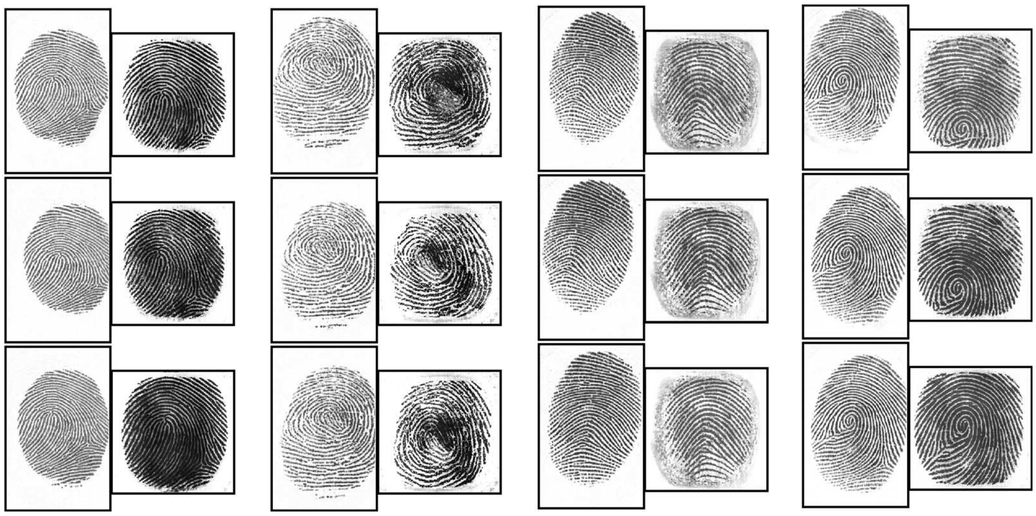


Fig. 6 *Fingerprint examples from MCYT_Fingerprint subcorpus*

Fingerprint images are plotted for the same finger for (i) both capacitive acquisition (left of each subplot) and optical acquisition (right of each subplot), (ii) the three control levels available in the database (from upper to lower row): low, medium and high and (iii) four different fingerprints in the database, one per column

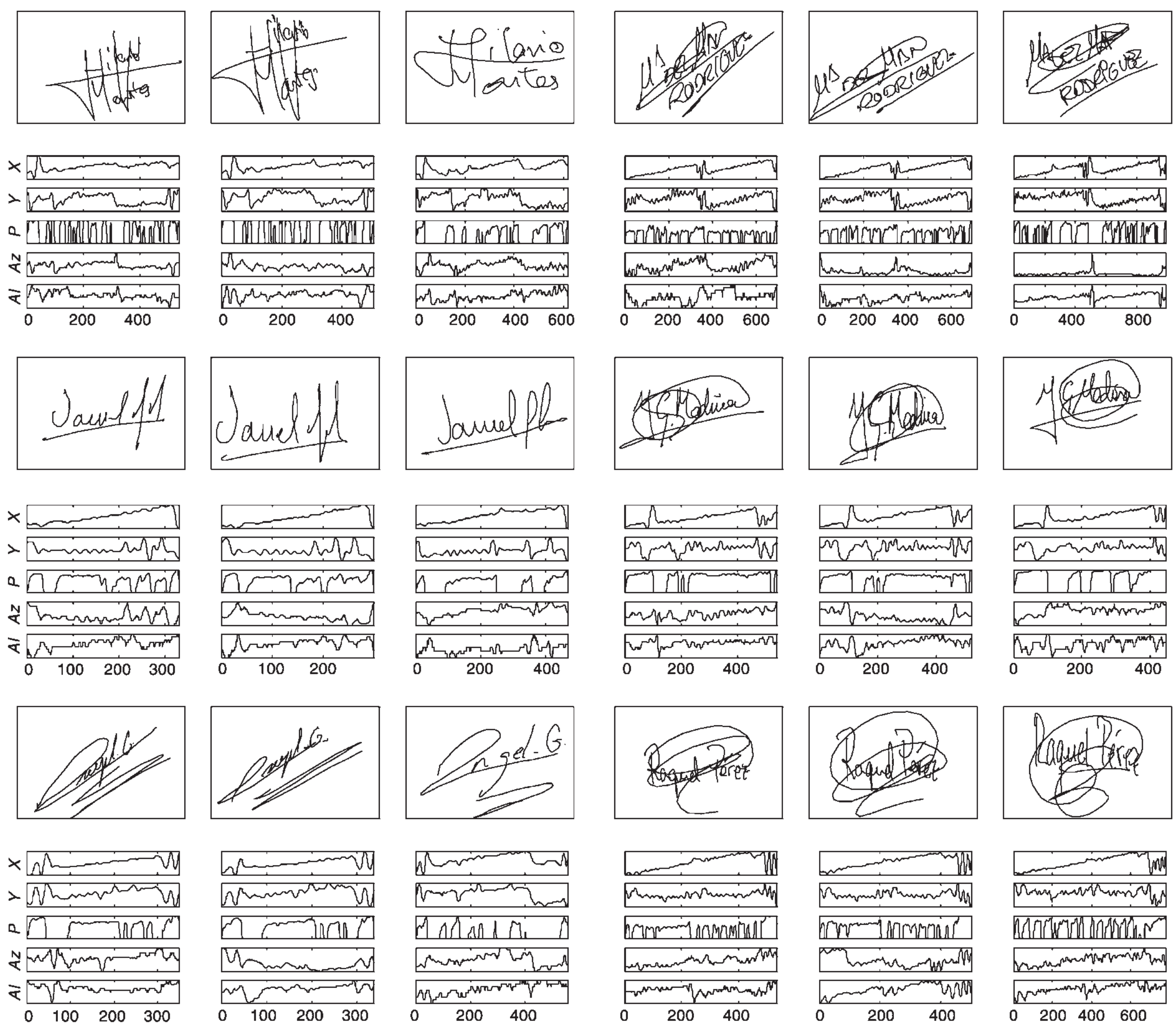


Fig. 7 *Signature examples from MCYT_Signature subcorpus*

For each row, the left half part (three signatures) corresponds to a subject and the right half part (three signatures) corresponds to another subject. For a particular subject, the two left samples are client signatures and the right one is a skilled forgery. In each case, graph plots below each signature correspond to the on-line information stored in the database

5 Algorithm benchmarking on MCYT data

In this Section, the problem of determining whether an MCYT database will produce statistically significant results or not is addressed. In [11] the minimum size of the test data set, N, that guarantees statistical significance in a pattern recognition task is derived. The goal in the above-mentioned work is to estimate N so that it is guaranteed, with a risk α of being wrong, that the error rate P does not exceed that estimated from the test set, $\hat{P}$, by an amount larger than $\varepsilon(N, \alpha)$, that is,

$$\Pr\{P > \hat{P} + \varepsilon(N, \alpha)\} < \alpha \tag{1}$$

Letting $\varepsilon(N, \alpha) = \beta P$, and supposing recognition errors as Bernoulli trials (i.i.d. errors), we can derive the following relation after some approximations:

$$N \approx \frac{-\ln \alpha}{\beta^2 P} \tag{2}$$

For typical values of α and β ($\alpha = 0.05$ and $\beta = 0.2$), the following simplified criterion is obtained:

$$N \approx 100/P \tag{3}$$

If the samples in the test data set are not independent (due to correlation factors that may include variations in recording conditions, in the type of sensors, in certain type of writers, etc.), then N must be further increased. The reader is referred to [11] for a detailed analysis of this case, where some guidelines for computing the correlation factors are also given. Another reference work regarding correlated errors is [12].

5.1 Algorithm benchmarking on fingerprints

No fixed protocol for training/testing has been established yet on the MCYT corpus. Anyway, if we assume that each client pattern is obtained by using one fingerprint sample and that the remaining 11 samples are used as client tests, we can obtain a bound on the error that can be tested with significance on the MCYT_Fingerprint set. To compute it, we also consider, for each user, all other users' samples as impostor test samples, so we finally have, for each sensor, that $N = 330 \times 10 \times 9\,(\text{client}) + 330 \times 329 \times 10 \times 12$ (impostor). So, with 95% confidence, an MCYT_fingerprint set guarantees statistical significance in experiments with an empirical error rate, $\hat{P}$, down to 0.0008% (note that this number should be increased, perhaps considerably, if error correlations are taken into account).

5.2 Algorithm benchmarking on signatures

In this case, we will consider two different experimental settings; the first will take into account only skilled forgeries, while the second will use casual forgeries. In the former, we assume that each client is modelled by using 10 signature samples. The remaining 15 client samples and the available 25 forgeries are used as tests. Therefore, if only skilled forgeries are considered, $N = 330 \times (15 + 25)$; and, with 95% confidence, an MCYT_signature set guarantees statistical significance in experiments with an empirical error rate, $\hat{P}$, down to 0.75%. Regarding experiments on casual forgeries, we assume an impostor test set that includes for each client all other clients' signatures as impostor samples, so $N = 330 \times 15\ (\text{client}) + 330 \times 329 \times (25 + 25)\ (\text{impostor})$, and the empirical error rate, $\hat{P}$, will be significant down to 0.002%.

6 Experiments

To examine the characteristics of the described MCYT database, some biometric recognition experiments have been carried by means of UPM verification systems [13, 14]. Regarding fingerprint verification, and taking into account the already mentioned high percentage of low/medium quality fingerprint samples in the fingerprint corpus, our main concern here is to determine the impact of the quality labels on the verification results. In the case of on-line signature verification, the major effect to be explored in the experiments is the variability between participating sites, which we believe will give us an idea of the database consistency.

6.1 Fingerprint verification experiments

To study the effect of the quality of the samples of the MCYT_Fingerprint subcorpus on the verification performance of an automatic recognition system, a subset of 75 subjects (750 different fingerprints) has been selected and manually supervised by an expert as described in [15].

Basically, each different fingerprint sample has been assigned a subjective quality measure from 0 (lowest quality) to 9 (highest quality) based on image factors like: captured area of the fingerprint, pressure, humidity, dirtiness, etc. From this expert-based classification, four subsets of the MCYT_Fingerprint subcorpus have been obtained, namely groups I, II, III and IV, including in each of them only the fingerprints with quality labels ranging from 0 to 9, from 1 to 9, from 3 to 9 or from 6 to 9, respectively.

For the experiments, the minutiae-based fingerprint verification system described in [13] has been used. Every fingerprint has been modelled with the minutiae pattern of one of the samples: (i) whose quality is that imposed by the quality group at hand and (ii) whose level of control (low, medium or high) is chosen at random. For a specific fingerprint, all client samples not used for training and in agreement with the quality imposed by the group at hand will be used as client data; and one sample of each one of the other 749 available fingerprints will be used as impostor data.

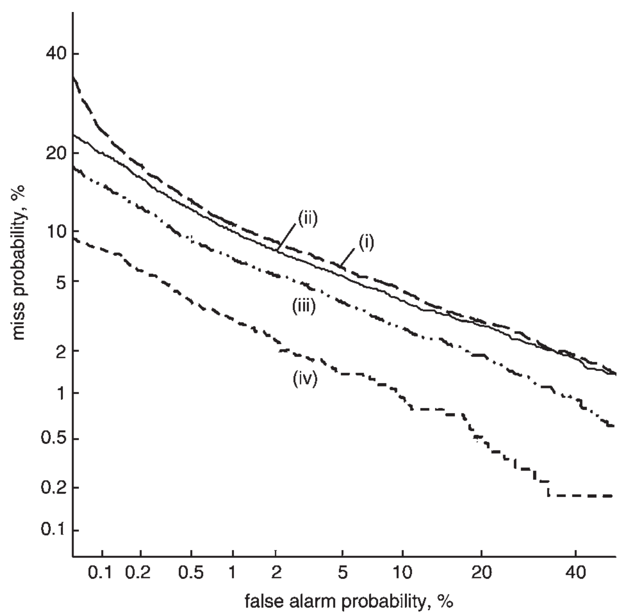


Fig. 8 *Fingerprint verification performance curves on MCYT_Fingerprint corpus when image quality is considered*

Curves (i)-(iv) correspond to evaluation with image quality groups I, II, III and IV, respectively (extracted from [15])

Verification performance results for the different quality groups I, II, III and IV are depicted in the form of DET plots [16] in Fig. 8. As expected, error rates decrease progressively from group I to group IV. In particular, 5.5% EER is obtained for Group I (all fingerprints), and 2.1% EER is obtained for group IV (only good quality fingerprints).

6.2 On-line signature verification experiments

As is well known, verification performance in on-line signature recognition is highly user-dependent, i.e. some clients could be easy to forge while some others could be (very) difficult to imitate. This situation has been exploited in different ways in referenced works, by using, for example, a different set of features per user [17], personalised weights in the feature set [18] or, most commonly, user-dependent verification thresholds [19, 14]. Anyway, this problem may bias some parts of the MCYT_Signature subcorpus, producing the undesired inconsistency of the corpus (i.e. biometric recognition systems reporting heterogeneous error rates when different parts of the database are considered).

In the following experiments, and to test the consistency of the MCYT_Signature corpus, the performance of the function-based on-line signature verification system is tested. This system is based on hidden Markov modelling [14], and verification experiments on the site-dependent subsets of MCYT_Signature is reported. For a specific subject, an identity model is trained using 10 signature samples. The remaining 15 client signatures and all the 25 skilled forgeries are used as tests.

Verification performance results for the different subsets are depicted in the form of DET plots [16] in Fig. 9. As can be observed, slight differences can be observed in verification performance between subsets: UPM and EUPMt subsets are about 1% EER, while UVA and EHU subsets get some 2% EER. Following the analysis given in Section 5, only the error rates from UPM (145 users) are statistically significant. Regarding the other sites, we cannot ensure that results are statistically significant, and the differences in performance between subsets can well be due to chance effects.

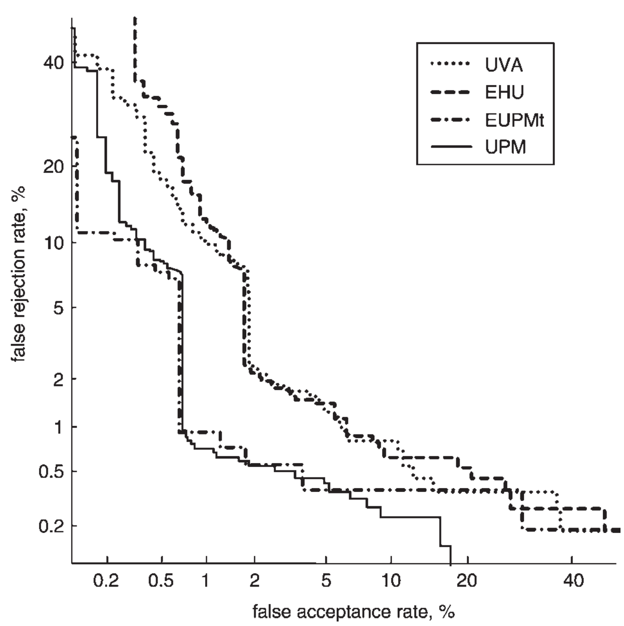


Fig. 9 *Signature verification performance curves on MCYT_Signature corpus for the different contributing sites*

The curves correspond to evaluation with UVA (75 individuals), EHU (75 individuals), EUPMt (35 individuals) and UPM (145 individuals) data

7 Database availability

The MCYT academic consortium approved the database being publicly available. Availability will be provided at the consortium homepage [20] in two separate steps, namely:

- From January 2004, a subset of the described baseline set will be available only for research purposes, just at low-price production costs. This subset will include 100 individuals from the UPM site. Regarding fingerprints, it will include 4 fingers per individual, and all the 6 samples with a high level of control acquired through the optical sensor. For the on-line signatures, it will include 10 genuine user signatures and 10 more forgeries for the same 100 individuals.
- From January 2005, the complete baseline set will be available, not limited to research use, at both commercial and research pricing.

8 Conclusions

In this paper, the structure of the MCYT bimodal biometric database is presented, and the MCYT baseline corpus, including fingerprint and signature traits of a total figure of 330 individuals, is described. The high number of participating individuals in its development, and the high number of samples in each modality (for different capture control levels and different sensor devices) permits us to take into account all the sources of variability included in the acquisition process, conferring to the MCYT database a remarkable statistical significance. In addition, the bimodal nature of the database also permits the evaluation of classification systems in which both biometric features are combined.

Experiments have also been reported both on MCYT_Fingerprint and MCYT_Signature subcorpora. Regarding the former, the effects of the image quality of the fingerprints on the verification performance of a standard minutiae-based recognition system have been studied. It has been demonstrated how, from a 5% EER verification result on a selected subset of MCYT_Fingerprint, the error rate can be decreased to 2% taking into account only high quality fingerprints. With respect to the latter, the variability between contributing sites has been explored, concluding that the MCYT_Signature subcorpus is reasonably homogeneous.

Ongoing work is being done to complete the MCYT extended corpus, where short-term signature variability, signature size variability, over-the-shoulder and time constrained signature forgeries and several sensor devices for fingerprint acquisition are considered. A more detailed statistical analysis is being currently carried out, taking into account the various factors of correlation between errors. Also, current research efforts in the frame of the MCYT project are oriented to the improvement of fingerprint [13] and signature [14] verification systems based on the MCYT corpus and the development of multimodal fusion schemes exploiting both traits [21].

9 Acknowledgments

The financial support from Ministerio de Ciencia y Tecnologia under project TIC00-1669-C04 is gratefully acknowledged. J.F.-A. also thanks Consejeria de Educacion de la Comunidad de Madrid and Fondo Social Europeo for supporting his PhD research.

10 References

1 NIST, http://www.nist.gov
2 Maio, D., Maltoni, D., Cappelli, R., Wayman, J.L., and Jain, A.K.: 'FVC2000: Fingerprint verification competition', *IEEE Trans. Pattern Anal. Mach. Intell.*, 2002, **24**, (3), pp. 402–412
3 Dolfing, J.G.A., Aarts, E.H.L., and Van Oosterhout, J.J.G.: 'On-line signature verification with hidden Markov models'. Proc. IEEE 14th Int. Conf. on Pattern recognition, August 1998, Brisbane, Australia, pp. 1309–1312
4 Ortega, J., Simon, D., Faundez, M., Espinosa, V., Satue, A., Hernaez, I., Igarza, J.-J., Vivaracho, C., and Moro, Q.-I.: 'MCYT: A multimodal biometric database'. Proc. COST-275 Biometric Recognition Workshop, Rome, Italy, Nov. 2002, pp. 123–126, available at http://www.fub.it/cost275
5 Garcia-Salicetti, S., Beumier, C., Chollet, G., Dorizzi, B., Jardins, J.-L., Lunter, J., Ni, Y., and Petrovska-Delacretaz, D.: 'BIOMET: a multimodal person authentication database including face, voice, fingerprint, hand and signature modalities'. Proc. 4th Int. Conf. on Audio- and video-based person authentication (AVBPA), Guildford, UK, June 2003, pp. 845–853
6 Messer, K., Matas, J., Kittler, J., Luettin, J., and Maitre, G.: 'XM2VTSDB: The extended M2VTS database'. Proc. 2nd Int. Conf. on Audio- and video-based person authentication (AVBPA'99), Washington, DC, USA, March 1999, pp. 72–77
7 Precise Biometrics, http://www.precisebiometrics.com
8 Digital Persona, http://www.digitalpersona.com
9 Wacom, http://www.wacom.com
10 Baron, R., and Plamondon, R.: 'Acceleration measurement with an instrumented pen for signature verification and handwriting analysis', *IEEE Trans. Instrum. Meas.*, 1989, **38**, (6), pp. 1132–1138
11 Guyon, I., Makhoul, J., Schwartz, R., and Vapnik, V.: 'What size test set gives good error rate estimates?', *IEEE Trans. Pattern Anal. Mach. Intell.*, 1998, **20**, (1), pp. 52–64
12 Guillick, L., and Cox, S.-J.: 'Some statistical issues in the comparison of speech recognition algorithms'. Proc. IEEE Int. Conf. on Acoustics, speech and signal processing (ICASSP), Baltimore, USA, May 1989, vol. 1, pp. 532–535
13 Simon-Zorita, D., Ortega-Garcia, J., Sanchez-Asenjo, M., and Gonzalez-Rodriguez, J.: 'Facing position variability in minutiae-based fingerprint verification through multiple references and score normalization techniques'. Proc. 4th Int. Conf. on Audio- and video-based person authentication (AVBPA 2003), Guildford, UK, June 2003, pp. 214–223
14 Fierrez-Aguilar, J., Ortega-Garcia, J., Martin-Rello, J., and Gonzalez-Rodriguez, J.: 'A novel function-based on-line signature verification system exploiting statistical signal modeling', submitted to *IEEE Trans. Syst. Man Cybern. C*, 2003, Special issue on Biometric systems
15 Simon-Zorita, D., and Fierrez-Aguilar, J.: MCYT_Signature Technical Report, ATVS-02/2003, Universidad Politecnica de Madrid, April 2003
16 Martin, A., Doddington, G., Kamm, T., Ordowski, M., and Przybocki, M.: 'The DET curve in assessment of decision task performance'. Proc. ESCA 5th European Conf. on Speech communications and technology (EuroSpeech'97) Rhodes, Greece, 1997, pp. 1895–1898
17 Bauer, F., and Wirtz, B.: 'Parameter reduction and personalized parameter selection for automatic signature verification'. Proc. 3rd Int. Conf. on Document analysis and recognition, Montreal, Canada, August 1995, pp. 183–186
18 Kim, S.H., Park, M.S., and Kim, J.: 'Applying personalized weights to a feature set for on-line verification'. Proc. 3rd Int. Conf. on Document analysis and recognition, Montreal, Canada, August 1995, pp. 882–885
19 Jain, A.K., Griess, F.D., and Connell, S.D.: 'On-line signature verification', *Pattern Recognit.*, 2002, **35**, (12), pp. 2963–2972
20 MCYT Consortium site, http://www.infor.uva.es/biometria
21 Fierrez-Aguilar, J., Ortega-Garcia, J., Garcia-Romero, D., and Gonzalez-Rogriguez, J.: 'A comparative evaluation of fusion strategies for multimodal biometric verification'. Proc. 4th Int. Conf. on Audio- and video-based person authentication (AVBPA 2003), Guildford, UK, June 2003, pp. 830–837