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EMPIRICAL TESTS ON ENHANCEMENT TECHNIQUES FOR A HYBRID FINGERPRINT MATCHER BASED ON MINUTIAE AND TEXTURE

Loris Nanni[1], Cristiana Casanova[2], Sheryl Brahnam[3] and Alessandra Lumini[4]

[1]*Department of Information Engineering -University of Padua, Via Gradenigo, 6 - 35131- Padova - Italy E-mail: loris.nanni@unipd.it*

[2]*Faculty of Computer Engineering - University of Bologna, Via Venezia 52, 47521 Cesena, Italy*

[3]*Department of Computer Information Systems, Missouri State University, 901 S. National, Springfield, MO 65804, USA E-mail: sbrahnam@missouristate.edu*

[4]*DEIS, Università di Bologna, Via Venezia 52, 47521 Cesena, Italy E-mail: alessandra.lumini@unibo.it*

Abstract: *This paper focuses on the use of enhancement techniques for improving the performance of a hybrid fingerprint matcher based on the fusion of image-based fingerprint matchers and a minutiae-based matcher. A review of the existing literature is provided, and several methods are compared on all four FVC2004 databases. Through extensive testing, we find that the best performing system is obtained by an ensemble of image-based matchers with features extracted by local phase quantization and Tico's minutiae matchers.*

Contributions of this study include a fair comparison of different preprocessing techniques using the different matchers. We also study their fusion for improving the performance of stand-alone preprocessing techniques. In this way, we demonstrate that different enhancement methods can be used for building a multi-matcher method. We also propose a genetic optimization approach to improve the enhancement step using different optimization functions. Finally, we contribute all the source code used in our experiments (available at bias.csr.unibo.it/nanni/finger.rar). Providing a free Matlab toolbox that contains functions for minutiae extraction, enhancement, image-based matching, and minutiae-based matching (a system we show compares relatively well to commercial matchers) could form the basis for future work by other researchers in this and similar areas.

Keywords: *fingerprint identification; texture descriptors; minutiae; local phase quantization; multi-matcher ensemble.*

1. INTRODUCTION

Recent advances in biometric recognition have prompted companies such as IBM to predict that passwords will very soon give way to biometrics [1]. The development of biometric recognition has been fueled in part by the fact that security measures offered by passwords and answers to personal questions are frequently compromised and thus pose more of a security risk than security enhancement. Too often passwords are forgotten, naively shared with friends and coworkers, and surreptitiously recorded and observed. Basing security more on biometrics, such as fingerprint patterns, is a much more reliable and viable solution to contemporary security problems.

Biometrics is the science of measuring and discovering universal physical, biological, or behavioral characteristics that are unique to individuals. Biometric recognition is the automatic recognition or identification of individuals based on one or more biometric patterns. Facial appearance, fingerprints, and iris patterns are some popular biometrics utilized by contemporary biometric systems. These systems must contend with a number of difficult problems, including the variable quality of biometric samples, impersonation and fraud detection, and multimodal authentication. Moreover, common to all machine recognition systems is the difficult task of isolating and extracting features in the biometric samples that offer the most relevant information.

Fingerprints are one of the oldest and most frequently used biometrics. As a result, fingerprint matching continues to be the focus of much research [2]. In general, fingerprint matching algorithms can be classified into three categories: minutiae-based, correlation-based, and image-based. Minutiae-based approaches seek out the best alignment among a set of minutiae extracted from a fingerprint and template [3]. Correlation-based approaches estimate the degree of similarity between a sample and a template by calculating the spatial correlation between corresponding pixels [4]. Image-based approaches extract features by considering the texture of the image, or grey-level values, and then a distance metric is used or a classifier is trained to make a matching decision [5].

Most research has been focused on minutiae-based approaches. These methods typically provide the best classification results [5, 6], but image-based methods are gaining in popularity. This is due in part to the fact that image-based approaches are able to handle low quality images [5], a common problem with real-world systems. Moreover, powerful methods for extracting relevant features from images, such as Local Binary Patterns (LBP) [7-10] and Gabor filters [11], have been developed. Another advantage of image-based approaches is the potential of representing features as fixed length vectors that can then be combined with tokenized random number in a two factor authentication system [12] or used in multidimensional indexing techniques (as in R-Trees [13]) [14]. Moreover, recent experiments have demonstrated that the fusion between image-based and minutiae-based methods outperforms the best stand-alone approach [2, 6].

In image-based systems, the images being compared must be aligned in the same orientation. Four main categories of techniques (core alignment, minutiae alignment, core alignment and classification, and minutiae alignment and classification) have been developed to align fingerprints for comparison in the matching step (for a survey see [2, 14]).

In core alignment, each fingerprint is aligned to a template by considering a reference point, typically the core point. Finger Code [5] uses Gabor filters in the area around the core point. An improvement of Finger Code, proposed in [15], uses different matching functions to improve Finger Code performance. Other methods include those proposed by Theoh et al. [16], which uses a method based on Fourier-Mellin descriptors extracted from a wavelet transformed image, and by Zegarra et al. [17], who found in their comparison of wavelets that the Gabor wavelet achieves the best performance.

In Minutiae, or hybrid, alignment, [6, 18] two fingerprint images are aligned by considering their minutiae sets. In Ross et al. [6], Gabor filters were applied on a square grid, and the authors found that minutiae-based alignment is more robust than alignment based on the core point. Nanni and Lumini [19] applied Gabor filtering to different wavelet sub-bands. Performance was enhanced further using invariant local binary patterns (LBP) [14, 19]. Two other methods based on minutiae alignment include the fusion of LBP and Gabor descriptors in [8] and the convolution of Gabor filters starting from the minutiae localizations and orientations in [18].

In core alignment and classification, all fingerprint images are aligned using a single reference point, and a classifier is trained to distinguish between pairs of matching and non-matching fingerprints [20]. In minutiae alignment and classification, the minutiae alignment is constrained to pairwise alignment, which makes possible the extraction of a set of features from each pair to be mated. A two-class classifier is then trained to distinguish the genuine from the impostor sample. An example of minutia alignment and classification is [21], where a 17-D feature vector is extracted from both texture-based and minutiae-based descriptors using a greedy matching algorithm (it is interesting to note that few of the 17 selected features were image-based).

The aim of this work is to propose a new multi-matcher approach that performs comparatively well to commercially available matchers on all four of the FVC2004 datasets. A second goal is to make available to researchers a full-feature MATLAB toolbox (i.e., a toolbox that contains code for the all the steps needed for fingerprint matching using the FVC2004 datasets). To obtain our first goal, we have studied the fusion of different image-based minutiae-based matchers using different enhancement technique.

The remainder of this paper is organized as follows. In section 2 we discuss the fingerprint matching approach examined and proposed in this study. In section 3 we describe the enhancement techniques tested and proposed in this paper. In section 4 we report the experimental results obtained using the FVC2004 datasets. Finally, in section 5, we draw some conclusions and discuss directions for future research.

2. FINGERPRINT MATCHING SYSTEMS

Biometric verification is a difficult machine classification problem that is best handled by combining multiple descriptors to boost performance. Good descriptors are invariant to image rotation and scale. In addition, they are robust in terms of variations in illumination. In this section we describe the matchers used in our experiments. The minutiae are extracted from the image according to the approach proposed in the Matlab CUBS fingerprint toolbox.[1]

2.1. Minutiae-Based

According to [22], fingerprints can be characterized as weakly-order textures exhibiting a dominant ridge orientation at each point. The orientation field thus provides a good estimate of fingerprint patterns even in noisy images as a relatively small number of orientation angles can reconstruct a large area of the orientation field. In [3] a descriptor is proposed that captures information in a region of the orientation field by surrounding a minutiae position $m = [x, y]^T$ by L concentric rings, with each ring comprising k equally distributed sampling points. Using the minutia direction as the reference point, each point on the ring can be ordered in a counterclockwise direction.

Since this minutia descriptor is invariant to rotation and translation, it characterizes the minutia location irrespective of the position and orientation of the finger on the input sensor. The selection of sampling points is designed to preserve a minimum distance, and a similarity measure is used to determine whether a pair of minutiae in two fingerprints are correspondent or not (see [3] for mathematical details). As there can be difficulties distinguishing corresponding pairs of minutiae when similarity values are large with respect to more than one minutiae, a registration step is required to align the two fingerprint impressions. In the experimental section, we label this minutiae matcher TICO.

2.2. Image-Based

In order to apply an image-based method, the fingerprints are first aligned using their minutiae sets as in [8]. There are four general steps in the image-based method: enhancement, image alignment, tessellation by a square overlapping grid, and feature extraction. Different enhancement approaches are also tested (see the experimental results section). Before the feature extraction step, each image is initially decomposed into non overlapping square cells of dimension dim × dim. The following value is used in this study: dim = 50.

The Local Phase Quantization operator was originally proposed as a texture descriptor by Ojansivu and Heikkila [23]. It is based on the blur invariance property of the Fourier phase spectrum. The local phase information is extracted from the 2-D short-term Fourier transform. This is computed over a rectangular neighborhood superimposed over each pixel position of the image. Four complex coefficients, corresponding to 2-D frequencies, are considered. For more mathematical details, refer to [23]. The source code used was that developed by Ojansivu and Heikkila [23].

The matching value between two images is calculated by a distance function. We test several distance measures between feature vectors x_r and x_s, related to the unknown image and the template, respectively. We obtained the best performance with the city block (CB) metric:

$$dist_{CB}(x_r, x_s) = \sum_{j=1}^{n} |x_r(j) - x_s(j)|.$$

In the experimental section, we label the image-based matcher LPQ. In addition to LPQ, we also examine the normalized 2-D cross-correlation for comparing two sub-windows. We label this correlation-based matcher CORR.

2.3. Multi-Matcher

It is well known in the literature that by combining different matchers it is possible to improve the performance of the single matchers. In this work, we show that it is also possible to improve the performance of a matcher extracting the minutiae and the texture features from the same fingerprint using different enhancement methods. Obviously, this increases the computation time, but each enhancement can be performed separately. In this era, where the number of cores in each CPU is rapidly increasing, computation time will soon be less of a problem. For this reason, we explore the performance gains of combining different minutia and image-based matchers using different enhancement techniques.

3. ENHANCEMENT APPROACHES

Below we describe the enhancement approaches explored in this paper: Chikkerur (C) [28], Hong (H) [29], ROM (R) [31], TwoStep (T) [30], Hong + second step (HS), Chikkerur + second step (CS), and our proposed Genetic approach. Results of the enhancement methods are illustrated in Figure 1.

[1] www.cubs.buffalo.edu

[2] All the methods available in the *pdist* function of MATLAB

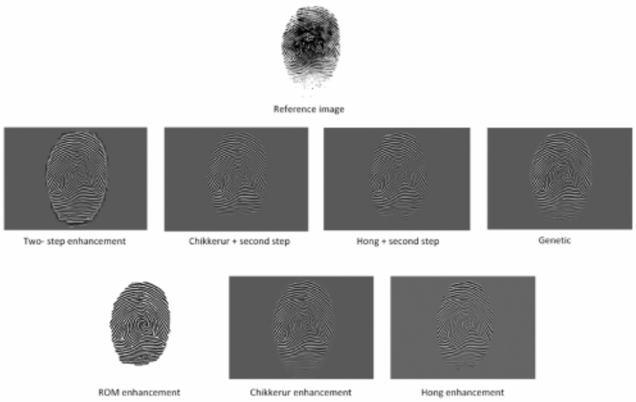

Figure 1. Results Obtained by Applying Different Enhancement Methods on the Reference Image

3.1. Chikkerur (C) [28]

The idea behind this method is to use Fourier analysis to estimate local ridge orientation and frequency information. The image is divided into 16 × 16 overlapping blocks upon which a filter in the Fourier domain is applied. The filter is based on the calculated local ridge orientation and frequency. It is possible, however, to have some problems around the singularities. The directional histogram is used to avoid this problem and to increase the bandwidth of the directional filter in these regions. The algorithm can also easily segment the fingerprint images: the mask in this case is obtained by thresholding, using Otsu's optimal thredsholding method, after which a contextual filtering is performed.

This method works better than methods that use Gabor filters [28] because the errors obtained during the application of Gabor filters are propagated to ridge frequency estimation resulting in imperfect reconstruction.

3.2. Hong (H) [29]

This approach can be divided into five stages. In the first sage, the images are normalized by calculating the mean and variance of the image. In the second and the third stages, the orientation and frequency are calculated. In the fourth stage, the region mask is estimated, and in the fifth stage, a bank of Gabor filters is applied to obtain the final enhanced image. The bank of Gabor filters are used as bandpass filters so that they select the frequency and orientation properties. Additionally, they also remove noise in spatial and frequency domains.

3.3. ROM (R) [31]

This approach has two main phases. The first phase obtains the global orientation pattern in the fingerprint structure, and the second phase refines areas with singularities. Both phases use a polynomial regression model. The difference between this approach and the others is that the construction of the model does not require prior knowledge of regions with singularities. This is because the model, rather than being fixed, is updated iteratively. Initially, a preliminary orientation modelling is calculated using a lower order Legendre polynomial. Regions in the orientation field with singularities are then refined and calculated. This is possible because areas in the orientation field are not as smooth as in the rest of the structure. Redefining the orientation field is accomplished by applying a higher order polynomial to the orientation field and combining it with the preliminary model.

3.4. TwoStep (T) [30]

This method is divided into two steps. In step 1 the image is enhanced with a spatial ridge compensation filter in the spatial domain. Local normalization is used to obtain a local orientation. In this way, it is possible to compensate for some of the defects in the images and to standardize the density distribution. To obtain the local orientation and correct the estimation, a gradient method and an orientation-smoothing method are applied.

In step 2, the image is enhanced in the frequency domain. To obtain information about local ridge frequency and orientation, a bandpass filter is applied. First, a gradient method (similar to the one used in step 1) and a FFT are applied to obtain local ridge orientation and local frequency estimation. Second, a frequency bandpass filter is applied on the filtered image. This is accomplished by dividing the image into subimages, and then applying FFT and angular and radial filters. Finally, the image block is filtered and reconstructed into the final enhanced image.

3.5. Hong + Second Step (HS)

In this method Hong's algorithm is applied first followed by TwoStep. In the case where there are problems with the quality of the greyscale images, Chikkerur algorithm is used to enhance the images.

3.6. Chikkerur + Second Step (CS)

In this method Chikkerur's algorithm is applied first followed by TwoStep. In the case where there are problems with the quality of the greyscale images, the simple Chikkerur's algorithm is applied to enhance these images.

3.7. Genetic Approach

In this paper, we propose adopting a genetic approach for improving the result of the enhancement step. A genetic algorithms (GA)[3] [35] is used to optimize the parameters of the enhancement algorithm. The chromosome is a bit string whose length is determined by the number of parameters of the enhancement method. Our selection strategy is cross generational. Assuming a population of size *N*, the offspring is 2*N*, and we select the best *N* individuals from the combined parent-offspring population. Uniform crossover is then used. In our experiments our population consists of 35 chromosomes, and each GA runs for 10 iterations. We chose the *C* approach for the enhancement method. For details on the bound of the parameters, see the attached Matlab code.

For the experimental section, we tested different optimization functions:

- WAVE, which maximizes the quality of the enhanced fingerprint considering a wavelet based quality extractor (see section 3.7.1);
- MEL, which maximizes the similarity between the enhanced fingerprint and a set of high quality images using 2dMEL (see section 3.7.2) to compare the reference fingerprint with the set of stored high quality fingerprints (for details how this set is chosen please see the section 4).

3.7.1. Wavelet

To obtain the best quality image, the whole image is considered and transformed using Pet Hat's[4] continuous wavelet (CWT) [19]. The following parameter values are used: scalen = 2 and angle = 0. The quality of a given image is calculated as the square root of the average of the absolute value of the wavelet coefficients. An example of an image with its CWT is seen in Figure 2. The Pet Hat wavelet is sensitive to features exhibiting sharp variations, an important characteristic since fingerprints are graphical ridge patterns. In Figure 2, it can be seen that CWT determines whether or not the ridge lines in a given image are well separated. Where the ridges are well separated, i.e., where the contrast between ridges and image background is sharp, the energy is highest.

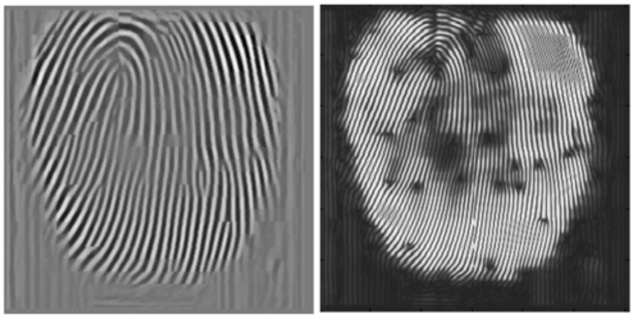

Figure 2. Pet Hat's Continuous Wavelet of a Given Fingerprint

3.7.2. 2dMEL [32]

This approach provides the measurement of image quality by investigating modalities to extract the information from images and by utilizing the machine learning approach. The first stage is to extract the 2D mel-cepstral features from images. The 2D ceptrum of an image is defined as:

$$\hat{c}(p,q) = F_2^{-1}(\log(|Y(u,v)|^2)),$$

where (*p*, *q*) are frequency coordinates, $Y(u, v)$ is the 2D Discrete Fourier transform of the image and, F_2^{-1} is the 2D Inverse Discrete Fourier transform. In this way, features are extracted. We obtain the feature vector by relating the reference image to the distorted image. Similarity is calculated using the difference between the two vectors. The vectors represent the timbral texture space. The similarity can be defined as:

$$\begin{aligned} \mathrm{x} &= |x_r - x_d| \\ &= |F_2^{-1}(\log(|G_r(m,n)|^2)) - F_2^{-1}(\log(|G_d(m,n)|^2))| \end{aligned}$$

where $G_r(m, n)$ is the bin energies from reference image, $G_d(m, n)$ is the bin energies from distorted image, x_r and x_d denote the two feature vectors, and *x* the absolute difference between the 2D mel-ceptrum coefficients. Finally, the quality score can be estimated reducing the numbers of the future vector into a single number. The idea is to have

$$Q = f(x),$$

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[3] It is implemented as in Gaot (Genetic Qptimization Toolbox Matlab Toolbox

[2] Implemented as in Matlab YAW Toolbox (YAWTB) http://www.fyma.ucl.ac.be/projects/yawtb

where Q is the quality score and x is the feature vector calculated as before. To calculate the function f the method proposed is to use the machine learning approach, Support Vector Regression, in this case. The function can be defined as

$$f(x) = W^T\varphi(x_i) + b,$$

where $\varphi(x)$ is a non-linear function of x, W is the weight vector, and b is the bias term.

4. EXPERIMENTAL RESULTS

All experiments were conducted using all four databases in the difficult FVC2004 benchmark database [24]. To collect the fingerprint images for this database, three different scanners and the SFinGE synthetic generator were used. Each of the four databases contains eight separate impressions from 100 fingers for a total of 800 images. The FVC2004 database is difficult because it contains many intra-class variations derived from large skin distortion[5], a well-known difficulty in fingerprint recognition. As a result, accuracy rates of the top ten algorithms using the FVC2004 competition was considerably lower than the accuracy rates obtained in the previous FVC2002 database.

In our experiments, each algorithm was tested using the FVC2004 testing protocol, i.e., for each database, the following two matching attempts were made:

1. Genuine recognition attempts, where the template of each impression is matched against the remaining impressions of the same user, while avoiding symmetric matches. In other words, if the template of impression j was matched against impression k, then template k was not matched against impression j;
2. Impostor recognition attempts, where the template of the first impression is matched against the first impressions of the remaining fingers, while avoiding symmetric matches.

The performance measured is the Equal Error Rate (EER) [24]. ERR is the error rate when the frequency of fraudulent accesses (called the False Acceptance Rate, or FAR) and the frequency of rejections, or of the people who should be correctly verified (called the False Rejection Rate, or FRR) assume the same value. It is a unique measure that characterizes the security level of a given biometric system.

The labels *AV* and *RA* in the following tables are related to the average *EER* and the respective rank of the given approach in all the tested datasets. The smaller the value of *RA* the better its performance since a classifier ranking best in all the datasets would have *RA* = 1.

Table 1
EER obtained by different matchers with different enhancement methods.

	LPQ						*TICO*					
	T	*C*	*CS*	*H*	*HS*	*R*	*T*	*C*	*CS*	*H*	*HS*	*R*
DB1	11.82	11.84	11.39	11.80	11.41	11.77	13.65	14.66	15.47	17.67	16.46	14.53
DB2	5.62	5.24	6.29	14.30	12.26	6.04	8.65	7.93	9.65	24.98	21.52	9.84
DB3	7.52	5.24	5.36	5.54	5.26	9.01	13.52	10.10	8.27	9.32	8.56	15.21
DB4	8.26	5.45	6.52	7.39	7.35	6.33	14.16	7.81	9.19	11.69	10.58	10.08
AV	8.30	6.94	7.39	9.75	9.07	8.28	12.49	10.12	10.64	15.91	14.28	12.41
RA	3.11	2.11	2.33	3.27	2.94	2.88	4.44	4.11	4.22	5.11	4.77	4.61

	CORR					
	T	*C*	*CS*	*H*	*HS*	*R*
DB1	13.28	12.84	12.87	14.25	12.72	15.16
DB2	4.92	5.14	6.69	15.71	11.91	8.97
DB3	8.82	5.94	6.37	7.01	5.91	13.06
DB4	6.63	3.83	5.31	6.66	6.12	6.23
AV	8.41	6.93	7.81	10.90	9.16	10.85
RA	3.11	2.33	2.77	3.88	3.00	3.94

[5] FV 2004 databases are markedly more difficult than FVC2002 and FVC2000 ones, due to the perturbations deliberately introduced http://bias.csr.unibo.it/fvc2004/databases.asp

In the first test we compare the matchers using the standard enhancement approaches detailed in section 3. In these tests LPQ outperforms the minutiae-based method. This performance gain in LPQ is due to the low quality of the images in the databases. It is interesting to note that in using these low quality images we obtain different performance conclusions than we do when using high quality images as in the easier FVC2002 datasets, where we obtain the following EERs (with *C* as enhancement methods): LPQ 2.48%; TICO 2.17%; CORR 1.71%; their fusion by sum rule 1.53%.

In our tests, *C* is the best enhancement method, while the old *H* is the worst approach. The main problem with these datasets is that some pairs of low-quality fingerprints that should be matched are not correctly aligned by TICO, so it is not possible for the image-based and correlation approaches to work well in this situation.

For comparison, in Table 2 we report the performance obtained by the complete NIST FIS2 ?ngerprint matcher (the bozorth3 package) using different enhancement methods (as reported in [36]). It is interesting to note that our proposed multi-matcher outperforms this free toolbox. Another interesting result reported in [36] is the low performance of *C*. This contrasts with our methods where *C* is the best approach. We conclude that the enhancement approach is matcher oriented. Another example of this is provided in [30] where *T* outperforms *C* but *C* outperforms *H*.

Table 2
EERs Obtained by the NIST Package with Different Enhancement Approaches

	No enhancement	*H*	*C*	*Proposed in [36]*
DB1	14.5	16.9	19.1	12.0
DB2	9.5	14.4	11.9	8.2
DB3	6.2	7.1	7.6	5.0
DB4	7.3	7.6	10.9	7.0
AV	9.37	11.5	12.37	8.05

In Table 3 we report some results of multi-matcher combination:

- $L + T$ is the sum rule between *LPQ* and *TICO* (as enhancement method *C* is used);
- $L + T + CO$ is the sum rule among *LPQ*, *TICO* and *CORR* (as enhancement method *C* is used);
- $W(L+T + CO)$ is the weighted sum rule among *LPQ*, *TICO* and *CORR* (note: the weights of *LPQ* and *CORR* is 1.5, while the weight of *TICO* is 1 and C is the enhancement method used);
- $F - W(L + T + CO)$ is the following: for each of enhancement method, *T*, *C*, *CS*, and *H*, a different $W(L + T + CO)$ matcher is built. These four $W(L + T + CO)$ matchers are then combined by sum rule.

The sum rule consists in summing the scores of all the methods in the ensemble. It should be noted that when more descriptors are combined, the scores related to each descriptor are normalized to mean 0 and standard deviation 1.

Table 3
EERs Obtained by Some Multi-Matchers

	$L + T$	$L + T + CO$	$W(L + T + CO)$	$W - W (L + T + CO)$
DB1	10.80	10.96	10.87	9.29
DB2	5.33	4.71	4.61	4.49
DB3	4.92	4.62	4.46	4.63
DB4	4.36	3.71	3.63	3.15
AV	6.35	6.00	5.89	5.39

In the literature it is well know that combing different matchers or different impressions of the same fingerprint improves performance (see [2]). In this paper we report our novel approach of building an ensemble by varying the enhancement methods (see the results of $F - W(L + T + CO)$).

In the next test, we report results using the images that were enhanced using the genetic algorithm (see Table 4). For the method 2dMEL, we first choose the best 10 images in each dataset using the wavelet-based image quality. A human expert then selects a subset of these images. In Table 4, each cell contains two values: the first is the EER obtained using the enhanced images and the second is the EER obtained applying the coherence filter[6] to the enhanced image.

As can be observed in Table 4, our proposed genetic enhancement algorithm improves the wavelet quality score of a given fingerprint image (while *MEL* does not works well). The average value

[6] It reduce the noise in an image while preserving the region edges, and will smooth along the image edges removing gaps due to noise.

of the quality score after the enhancement by C is 5.55 while after *WAVE* it is 6.57, but the EER is better with C compared to *WAVE*. In our opinion this is due to the fact that the wavelet quality score is a global value reflecting the whole image. In future work, we will apply the optimization in each subwindow (size 3 × 3). We note that the computation time could be a problem as *WAVE* took 60 seconds using a i5-3.3 Ghz machine with 8GB ram using MATLAB (it was 20 seconds using the parallel toolbox).

Table 4
EERs Obtained Using the Genetic Algorithm for Optimizing the Enhancement Step

	LPQ		*TICO*		*CORR*	
	MEL	*WAVE*	*MEL*	*WAVE*	*MEL*	*WAVE*
DB1	13.49	11.58	20.96	16.61	14.87	12.14
	13.88	11.70	22.53	16.56	15.28	13.04
DB2	6.55	6.52	10.74	10.11	6.44	6.15
	6.45	6.60	10.38	9.98	6.74	6.75
DB3	6.02	4.69	10.34	9.22	6.78	6.11
	5.61	4.64	9.58	8.34	5.91	5.37
DB4	9.26	6.62	13.04	9.34	7.99	4.67
	8.94	6.78	13.16	9.01	7.21	5.35
AV	8.83	7.35	13.77	11.32	9.02	7.26
	8.72	7.43	13.91	10.97	8.78	7.62

WAVE and *MEL* are useful for improving the ensemble of matchers we tested. In Table 5 we report results of the following two fusions:

1. FUS, which is fusion by sum rule of the matchers that belong to $F - W(L + T + CO)$ with LPQ and CORR based on WAVE as enhancement method.
2. FUSm, as in FUS, but in this case we combine LPQ and CORR using both *MEL* and *WAVE* as the enhancement method.

Table 5
Multi-Matcher Considering Also on the Images Enhanced Using the Genetic Algorithm

	F – W(L + T + CO)	*FUS*	*FUSm*
DB1	9.29	9.37	9.61
DB2	4.49	4.41	4.26
DB3	4.63	3.87	3.58
DB4	3.15	2.96	2.94
AV	5.39	5.15	5.09

It is interesting to note the FUS outperforms $F - W(L + T + CO)$ and that FUSm (despite the low performance of MEL) outperform FUS. This is further confirmation of the usefulness of combining different enhancement methods for improving performance.

In the last test, reported in Table 6, we validate our global quality method based on the wavelet. We divide the matches of the FVC2004 competitions into three groups: POOR, AVERAGE and GOOD. Each group contains 1/3 of the performed matches. POOR contains the matches with lowest quality, while GOOD contains matches with highest quality. Let w_A and w_B be the quality of two fingerprints (A and B), the quality of their match is defined as $w_A + w_B$.

In Tables 6 the label GLO denotes the performance of the matchers where all the matches are considered. The values between the round brackets is the ID of the best competitors in a given group (see http://bias.csr.unibo.it/fvc2004/ for more information on the competition). From the results reported in Table 6, we note that the winner of FVC2004 (ID 30) is the best method in the POOR group but it is outperformed in the AVERAGE and GOOD groups. The matching method of the winner of FVC2004 is based on ridge pattern and correlation. Probably this is the explanation of the good performance of this competitor in the POOR group. Moreover, it is clear that the performance in the GOOD group is higher that the performance in the AVERAGE group, and so on. This result validates our global quality method.

Table 6
EER Obtained in the Different Groups

	DB1	*DB2*	*DB3*	*DB4*	*AV*
CLO	1.97 (11)	1.58 (9)	1.18 (11)	0.6 (19)	2.06 (30)
POOR	2.80 (11)	2.9 (9)	1.34 (21)	0.93 (30)	2.5 (30)
AVERAGE	1.9 (11)	1 (9)	0.24 (11)	0.60 (19)	1.6 (11)
GOOD	1.2 (11)	0.65 (9)	0 (11)	0.15 (19)	0.73 (11)

5. CONCLUSION AND DISCUSSION

This paper focused on the study of texture descriptors in biometric verification. We proposed a multi-matcher approach that works well on the difficult FVC2004 database. Our method combines an image based approach, where LPQ is used as feature extractor, with a minutiae-based method, using the well know Tico approach, along with a correlation based technique. We also introduce a novel genetic-based enhancement method.

Our aim was to propose a multi-matcher approach that works quite well in the FVC2004 database. Our experimental section shows that we have succeeded in obtaining this goal. Moreover, we wanted to make our Matlab code available on the Internet since we were unable to find a toolbox that contained code for all the steps required in fingerprint matching (and work well on FVC2004 database[7]). Our free Matlab toolbox can be used to verify the results of our system on the FVC2004 images, and we hope that it may serve as the foundation for further explorations by other researchers in the field.

For obtaining a quite high performance system we have proposed new optimization functions based on a genetic approach for improving the result of the enhancement step. Moreover we have studied the fusion of different image-based/minutiae matchers each based on a different enhancement technique.

The main problem with the image-based approach is that two low-quality fingerprints are not correctly aligned by TICO (so the image-based cannot works well), as future work we want to test an ensemble of TICO's matchers each with a different parameter setting (our aim is to test if at least exist a parameter setting that permit to correctly align two low-quality fingerprints).

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