A SECURE MULTIMATCHER SYSTEM FOR FINGERPRINT VERIFICATION

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ABSTRACT

In this work we propose a multimatcher system for fingerprint verification for obtaining a system that is almost comparable with the state-of-the-art commercial matchers. One of the main problems in fingerprint identification, given the frequency of low quality images, is to adjust, as optimally as possible, the alignment of two fingerprints for comparison. In this paper we describe a multimatcher system that varies the preprocessing method using different wavelet decompositions of the original fingerprint image. After the alignment step, we also propose some variants of the widely used TICO method that utilize different descriptors (minutiae-based, correlation-based, and texture-based methods) for describing the area around the minutiae. Moreover, since our alignment method is based on texture features describing the appearance of the fingerprint pattern in a broad region around the minutia, we find that we can also couple it with Biohashing for obtaining a more secure fingerprint authentication approach. Results are validated on all four FVC2004 DBs and on the easier FVC2002 DB2. We also investigate the fusion among the proposed methods with the competitor systems in the FVC2004 competition. The MATLAB code used in our experiments is freely available for download at http://www.dei.unipd.it/wdyn/?IDsezione= 3314& IDgruppo_pass=124&preview=".

Keywords: fingerprint identification; texture descriptors; minutiae; biohashing; multimatcher.

1. INTRODUCTION

Biometrics is the science of measuring and discovering universal physical, biological, or behavioral characteristics that are unique to individuals. Popular biometrics utilized by contemporary biometric systems includes facial appearance, iris patterns, and fingerprints. Biometric recognition is based on the automatic recognition or identification of an individual based on one or more biometric patterns. Advances in biometric technology are focused on producing better recognition accuracy, security, and cost effectiveness. Basing security on biometrics is a much more reliable and viable solution to contemporary security problems than basing it on passwords, badges, and USB keys, all of which can be forgotten or lost, recorded or cloned, shared, and stolen. Because biometric authentication is directly dependent on physiological or behavioral aspects possessed by a given subject, biometrics represents the only form of authentication that directly authenticates a user. As the need increases for organizations to secure critical systems, ad hoc networks [26], and sensitive data, biometric technology will continue to grow in importance. Moreover, it is extremely important to begin securing biometric systems since an individual's biometric information lasts a life-time and usually cannot be changed.

Fingerprints are one of the oldest and most frequently used biometrics [6], mainly because fingerprints are easy to acquire, unique, and immutable. As a result, fingerprint recognition systems are the focus of much research [15] [30]. These systems must deal with several problems, including the variable quality of acquired fingerprints, distortions and degradations in the fingerprints themselves (due to cuts, bruises, and calluses), impersonation, and fraud detection. It is very difficult to extract characteristic features in the fingerprint that offer the most relevant and secure information.

In general, fingerprint systems can be classified into three categories based on the type of features and methods used in classification. The first category is based on extracting minutiae points (points where ridges end or are split into two ridges) from fingerprint images. Minutia-based systems match prints by seeking out the best alignment among two sets of minutiae [29]. The second category is correlation-based. This approach estimates the degree of similarity between a sample and a template by calculating the spatial correlation between corresponding pixels, without using specific features [1]. The third category is image-based. This approach extracts local or global texture features from the fingerprint pattern and uses a distance metric or a classifier to make a matching decision [9].

Minutiae-based approaches have been widely studied and are used in many commercial fingerprint matching systems. Minutia-based methods are oftentimes favored because they are analogous to the way forensic experts compare fingerprints. As a result, minutia-based methods have legal standing in many countries. Machine learning systems that use minutiae are evaluated based on the accuracy of the minutiae extracted and on the efficacy of a point pattern matching model. Spurious and missing minutiae are common problems in low quality fingerprints and can introduce errors in minutiae correspondence. Thanks to their high level of uniqueness and practicality in comparison with other types of fingerprint features (e.g., ridge orientation and skin pores) approaches based on minutiae typically provide the best classification results [9] [24].

Correlation and image-based methods are gaining in popularity. Correlation-based matching involves superimposing two fingerprint images and then calculating a pixel-wise correlation for different displacements and rotations [8] [11]. Correlation-based methods provide good classification rates but require accurate alignment.

Image-based approaches use powerful methods for extracting relevant features from images, such as Local Binary Patterns (LBP) [21] [20] [27] [10] and Gabor filters [23], both widely used in texture recognition. The advantage of using texture features is that they can be represented as fixed length vectors that can be used for indexing purposes (e.g., multidimensional index [7]) or as couples in some protection strategy, such as in Biohashing [12] [18]. The recognition performance of image-based approaches, however, is not comparable with minutiae-based methods, but recent experiments have demonstrated that the fusion of image-based and minutiae-based methods outperforms the best stand-alone approaches [15] [24].

Another drawback of image-based systems is the need for precise alignment among images. Both core alignment and minutiae alignment have been proposed in the literature [15] [18]. In core alignment, each fingerprint is aligned to a template by considering a reference point, called the core point. FingerCode [9] and its variants [25] [28] [31] use Gabor filters or other texture descriptors in the area around the core point. Unfortunately, it is very hard to find a reliable reference point in low quality images. In minutiae alignment [24] [2], a fingerprint is aligned to a template considering its minutiae sets [19] [19] [18]. Minutiae alignment is more robust than core alignment [24] but requires a reliable minutiae extraction method. Two excellent recent methods based on minutiae alignment use, in the one case, LBP combined with Gabor descriptors [20] and, in the other case, local Gabor filters extracted starting from the minutiae localizations and orientations [2].

In this paper, we start with the well-defined literature on hybrid/multimatcher approaches for fingerprint authentication by proposing a system that performs comparatively well to other systems but that is also able to be linked with biohashing for secure biometric verification. The good performance of the proposed method is validated using several benchmark datasets: all four FVC2004 datasets and DB2 of FVC2002. An additional experiment shows that the fusion between our approach and the competitor systems of the FVC2004 competition outperforms the winner of FVC2004.

Since the main problem in fingerprint authentication is the alignment of the two fingerprints to be compared, we have modified the well-known TICO method [29] by changing the descriptors used for describing the area around the minutiae. We combine different TICO-based approaches (each based on a different minutiae descriptor and a different preprocessing method) for minimizing the number of erroneously aligned couples of fingerprints. Moreover, different descriptors are extracted from the image after the alignment step. Each descriptor is then used to build a different texture-based matcher, and the matchers are combined by sum rule. We highlight the fact that our proposed system can be coupled with a Biohashing technique [5], since both the descriptors used for describing the area around the minutiae in the TICO approach and the texture features used for matching are fixed-length vectors. Finally, we want to stress that our proposed approach is not a heavily parameterized system in need of fine-tuning for each dataset. It works out of the box. In all reported results, we used the same parameters across all five datasets.

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 report the experimental results obtained using the FVC2004 and FVC2002 datasets. Finally, in section 4, we draw some conclusions and mention directions for future research.

2. FINGERPRINT MATCHING SYSTEM

A complete system for fingerprint verification is usually broadly composed of the following three steps: 1) an enhancement step used to improve the quality of the input image; 2) a feature extraction step; and 3) a matching step based on a distance evaluation and/or classification method. In this section, we explain the steps of our fingerprint matching system, designed according to the structure depicted in figure 1.

Our algorithm can be broken down into the following steps:

STEP 1: ENHANCEMENT. The fingerprint image is enhanced by the approach proposed by Chikkerur et al. [4]: it is based on the Fourier analysis for estimating the local ridge orientation and the frequency information.

STEP 2: MINUTIAE EXTRACTION. In this work we perform minutiae extraction with the main aim of aligning the image, since we do not use a pure minutiae-based matcher. The minutiae are extracted using the CUBS toolbox [4].

STEP 3: PREPROCESSING (WAVELET IMAGE TRANSFORMATION). Each image is projected onto a transformed space by two-level wavelet decomposition [16]. This step is motivated by [13], where performance was boosted in an image-based fingerprint matcher by designing an ensemble of matchers based on the perturbation of the preprocessing step (i.e., by performing different image transformations, with each used to train a different matcher). In this work we use such a method to choose the Haar wavelet decompositions (horizontal and vertical details at the first level of decomposition are used). An example of Haar wavelet decomposition is shown in figure 2.

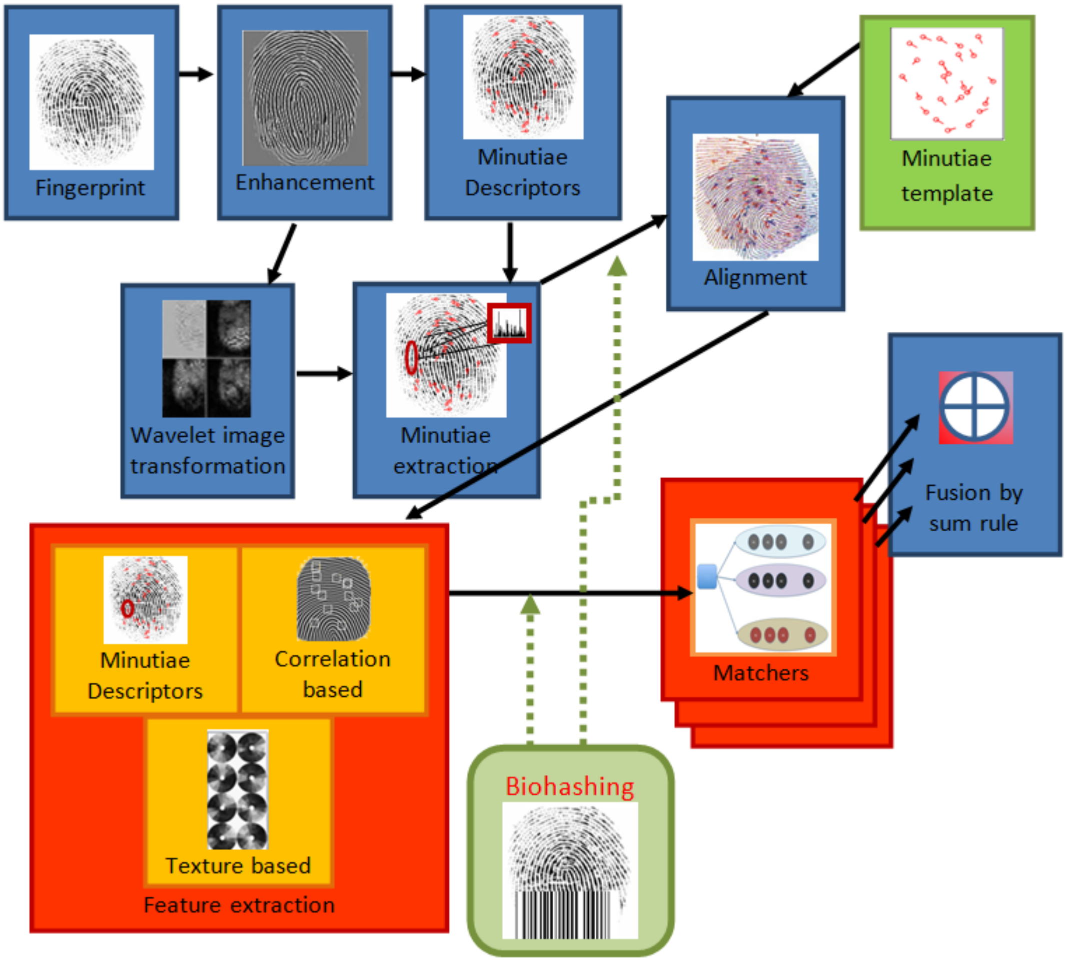

Figure 1. Schema of the proposed approach.

STEP 4: MINUTIAE DESCRIPTORS. According to the original idea proposed in [29] (the TICO approach), we extract local descriptors from a small region around each minutia: this additional information is used to improve the alignment procedure. The descriptor proposed in [29] captures information in a region of the fingerprint by surrounding a minutia position by concentric rings, and using the minutia direction as the reference point for ordering the rings in a counterclockwise direction. In this way, the descriptor becomes invariant to rotation and translation. Differently from [29], we have tested several texture based descriptors for describing the area around the minutia. In our final system, we have combined different minutiae descriptors for minimizing the number of erroneously aligned couples: the original TICO descriptors (TD), LBP [21], with two different radii, and histogram of gradients [18]. These four matchers (one for each descriptor) are combined by weighted sum rule, where the weight of TD is 3 and the weight of the other three matchers is one.

STEP 5: FINGERPRINT ALIGNMENT. A minutiae-based matcher is used in our system to evaluate the best roto-translational movement for aligning the input fingerprint to the template. In this work the matcher is a modified version of [29], designed to deal with the texture descriptors used in *STEP 4*.

STEP 6: FEATURE EXTRACTION AND MATCHING. Our system is a composition of matchers from different categories, divided according to the taxonomy proposed in [15], namely, into correlation-based, image-based, and minutiae-based matchers. A detailed description of these three matchers is provided separately below.

STEP 7: BIOHASHING (OPTIONAL). Biohashing is an encryption technique for providing more secure fingerprint authentication [17]. BioHashing and its variants can be considered a feature transformation that calculates a vector of bits, commonly called the BioHash code, from a biometric feature vector and a Hash key, or seed. In this work, we use BioHashing both in the minutiae descriptors (*STEP 4*) and in the texture descriptors (*STEP 6*), both of which are fixed-length vectors. The correlation-based matcher cannot be coupled with the Biohashing module, since it requires the gray-level image. Using Biohashing, a biometric descriptor is reduced to a bit vector of size m, and compared to the template by the Hamming Distance. In this work, we use the improved algorithm for generating the BioHash code [17].

Figure 2. On the left an enhanced fingerprint, on the right its one-level decomposition by Haar wavelet (the selected bands are highlighted).

STEP 8: FUSION. The scores from different matchers (*STEP 6*) are combined using the sum rule, i.e., by summing the scores of a pool of classifiers that belong to an ensemble for the final score. It is important to note that before fusion, the scores are normalized to a mean of 0 and a standard deviation of 1.

In the remainder of this section, we describe the three types of matchers used in *STEP 6*.

2.1 Correlation-based matchers (COR)

COR estimates the degree of similarity between two fingerprints by calculating the spatial correlation between corresponding pixels [1]; therefore, to be accurate, alignment is important. In this work we propose a "local" correlation-based matcher, which, instead of calculating a global correlation, performs an image tessellation in overlapping square regions of dimension 50×50 (*overlap*=50%). We use the normalized 2-D cross-correlation for comparing two regions.

To reduce the computation time, we use only the alignment obtained considering TD and LBP with (R=3, P=24) (see section 2.3, below). We thus have six correlation matchers: two different alignments and three different preprocessing methods of the image (original image; Haar wavelet, first level of decomposition, horizontal details coefficients; and Haar wavelet, first level of decomposition, vertical details coefficients). These matchers are combined by the weighted sum rule. The weight of TD coupled with original image is two; otherwise, the weight is always one.

2.2 Texture-based matchers (TEX)

TEX is a matcher that exploits the information in the fingerprint pattern. In this work we test several texture descriptors to represent the image patterns, but only report the results obtained by the best approaches: two descriptors based on Local Phase Quantization (LPQ) [22], obtained by varying the method used for local frequency estimation (STFT with uniform window and Gaussian derivative quadrature filter pair), extracted from the image filtered by Gabor filters.

In TEX, first, the image is decomposed into overlapping square cells of dimension 50×50 (overlap=50%). Each cell is then resized to dimension of 25×25 (to reduce the computation time) and convolved, as in [18], with a bank of 2 Gabor filters at different scales and orientations (i.e., the two LPQ descriptors are extracted from two different filtered images). Before the convolution, each subwindow is normalized using the method as in [18]. The two Gabor filters are 1) scale σ=2, angle θ = 90°, fixing the frequency to ν=1/3 and 2) scale σ=1, angle θ = 135°, fixing the frequency to ν=1/3.

The matching value between two fingerprints (previously aligned) is calculated separately for each descriptor, and the two distances are combined by sum rule according to the City block distance function, which calculates the distance between descriptors x_r and x as follows

$$dist_{\mathrm{CB}}(x_r, x_s) = \sum_{j=1}^{\mathrm{n}} |x_r(j) - x_s(j)| \qquad \boldsymbol{EQ}: \mathbf{1}.$$

In all TEX experiments, we use three descriptors: 1) LPQ (STFT with uniform window) extracted from the original image; 2) LPQ (STFT with uniform window) extracted from the Gabor filtered image (angle $\theta = 135°$); and 3) LPQ (Gaussian derivative quadrature filter pair) extracted from the Gabor filtered image (angle $\theta = 90°$).

To reduce computation time, we use only the alignment obtained considering TD and LBP with (R=3, P=24) (see section 2.3 below). Thus, we have eighteen TEX matchers: two with different alignments, three with different preprocessing methods of the image (original image; Haar wavelet, first level of decomposition, horizontal details coefficients; and Haar wavelet, first level of decomposition, vertical details coefficients), and three different descriptors. These matchers are combined by weighted sum rule. The weight of TD, coupled with original image, is two; otherwise, the weight is always one.

2.3 Minutiae-based matchers (MIN)

In this work we do not use a pure minutiae-based matcher, but rather a matcher based on descriptors that capture information in the region of the fingerprint surrounding a minutiae position with concentric rings (as described in *STEP 4*). The matching score returned by the MIN matcher is the average distance among each couple of mated minutiae obtained in the alignment step. The distance between each couple of minutiae is evaluated according to the selected descriptor. The minutiae descriptors are the original TICO descriptors [29], LBP [21], with different radii, and the histogram of gradients (HOG) [18].

LBP is a powerful texture descriptor based on the occurrence histogram of the LBP operator. The LBP operator is rotation invariant and evaluates the binary difference between the gray value of a pixel $\mathbf{x}$ and the gray values of P neighboring pixels on a circle of radius R around $\mathbf{x}$. The final descriptors are obtained with (R=2, P=16) and (R=3, P=24).

For HOG, each image in our experiments is divided into a grid with 3 rows and 3 columns (9 cells total). The orientation and magnitude of each pixel is calculated. The absolute orientation is divided into 9 equally sized bins, which results in a 9-bin histogram per each of the 9 cells.

3. EXPERIMENTAL RESULTS

In order to evaluate the proposed system, several experiments have been carried out on the most used benchmarks for fingerprint recognition: the four databases of FVC2004 [14], considered very difficult, and the easier FVC2002 DB2 (named “2002” in the tables below). All the experiments follow the well-known FVC testing protocol [14], which include the following matching attempts:

1. Genuine recognition attempts, where the template of each impression is matched against the remaining impressions of the same user;
2. Impostor recognition attempts, where the template of the first impression is matched against the first impressions of the remaining fingers.

The system performance is measured according to the Equal Error Rate (EER) [15] performance indicator. In the following tables, the label **AV** is related to the average EER of the given approach in all the tested datasets.

The first experiment evaluates the performance of a minutiae-based system, which can be considered a baseline for results. In Table 1 the performance of some matchers obtained by varying steps *3* and *4* are compared, i.e., a simple minutiae-based matcher is coupled with different wavelet preprocessing approaches and/or descriptors.

The following approaches are compared in Table 1:

- *TICO* is the original method proposed in [29]. This is a system where *STEP 4* is performed using the original TICO descriptors, and *STEP 3* is not performed;
- *MINw* is an ensemble of minutiae-based matchers, each evaluated starting from a different preprocessing method (*STEP 3*) of the image [13] (original image; Haar wavelet, first level of decomposition, horizontal details coefficients; and Haar wavelet, first level of decomposition, vertical details coefficients) combined by sum rule. This is a system where the *STEP 4* is performed using the original TICO descriptors;
- *MINm* is an ensemble of minutiae-based matchers (as described in section 2.3), with each based on a different minutiae descriptor (without the preprocessing step), combined by sum rule. This is a system where *STEP 3* is not performed;
- *MINmw* is an ensemble of minutiae-based matchers with different preprocessing steps. This is a system where both *STEP 3* and *STEP 4* are performed, as described in section 2.

	DB1	**DB2**	**DB3**	**DB4**	**2002**	**AV**
TICO	14.66	7.93	10.10	7.81	2.57	8.61
MINm	13.62	7.78	8.24	6.24	2.45	7.68
MINw	12.60	7.24	8.74	7.03	2.20	7.46
MINmw	12.45	7.11	7.32	5.98	2.10	6.99

Table 1. EERs obtained by different minutia based's approaches.

From the results reported in table 1, it is clear that combining different minutiae-based matchers provides a performance improvement with respect to the stand-alone approach. In our opinion, this is due to the fact that the use of an ensemble of alignments (*STEP 3* and *STEP 4*) improves the quality of the alignment.

The second experiment is aimed at evaluating the performance of the other two matchers described in sections 2.1 (COR) and 2.2 (TEX), coupled with different wavelet alignments:

- *{COR, TEX}*, the matchers based on a stand-alone alignment by the original TICO approach;
- *{CORmw, TEXmw}*, ensemble of matchers where alignment is performed as in *MINmw* and as described in section 2.

	DB1	**DB2**	**DB3**	**DB4**	**2002**	**AV**
COR	12.72	4.60	6.49	3.53	1.47	5.76
CORmw	11.81	4.89	6.42	2.77	1.63	5.50
TEX	10.89	4.75	4.86	4.49	2.40	5.48
TEXmw	10.06	5.07	4.56	4.42	2.38	5.29

Table 2. EERs obtained using different matchers and their version based on different alignments.

The results in table 2 show that using an ensemble of alignments (*STEP 3* and *STEP 4*) with these two matchers does not provide the same gain as was the case with the minutiae-based matcher. This could be due to the fact that the wavelet selection optimized the minutiae-matcher and thus could be descriptor dependent.

The third experiment is aimed at evaluating our complete system, as described in section 2, and comparing it with two other approaches.

In table 3 we report the performance of the following systems:

- *MCT* is the system proposed in this paper, that is a the combination by the sum rule among *MINmw*, *CORmw*, and *TEXmw*;
- *HFM* is the system proposed in [3] based on a combination of different enhancement techniques and matchers;
- *LFE,* a minutiae-based matcher recently proposed in [5] obtained by coupling the complete NIST FIS2 matcher (the bozorth3 package) with different enhancement methods;
- *ENH* combines the ideas in this paper with [3], i.e., the creation of a multimatcher based on the variation of the enhancement step. The multimatcher tested in this work is the fusion by the sum rule of *MINmw*, *Chikkerur approach*+TEX, *ROM approach*+*MIN*, *Yang approach* (with the segmentation step)+*MIN*. See [3] for a detailed description of the enhancement procedures. Their MATLAB code is available in the toolbox for this paper.

	DB1	**DB2**	**DB3**	**DB4**	**2002**	**AV**
MCT	9.60	4.31	4.40	2.64	1.63	4.51
ENH	8.84	3.92	3.49	2.31	1.10	3.93
HFM [3]	9.59	4.30	2.92	2.83	1.26	4.18
LFE [5]	12.00	8.20	5.00	7.00	---	---

Table 3. Comparison among different free approaches.

The multimatcher approach proposed in [3] obtains a lower EER with respect to *MCT*, but the use of different enhancement techniques requires higher computational cost. The idea of our approach gains a performance improvement if coupled with different enhancement methods (*ENH*) and obtains a lower EER, but at the cost of higher complexity. In [5], the best EERs were obtained by coupling the complete NIST FIS2 matcher (the bozorth3 package) with different enhancement methods. The NIST matcher is very old but still very widely used by researchers as a baseline method, primarily because it is freely available. Our proposed multimatcher (*MCT*) outperforms these free toolboxes.

The fourth experiment, reported in Table 5, gives the EER obtained by combining our multimatcher (ENH) with the best performing systems in the FVC2004 competition (according to the average EER in the four datasets), with the aim of determining whether the fusion of *ENH* with commercial state-of-the-art approaches improves performance. The results in Table 5 demonstrate that coupling *ENH* with the FVC2004 competitors often improves performance.

	DB1	DB2	DB3	DB4	AV
P101	2.72	3.56	1.19	0.79	2.07
P101+ENH	2.53	1.96	0.89	0.58	1.49
P047	1.97	3.49	1.18	1.76	2.1
P047+ENH	2.45	2.77	1.21	1.38	1.95
P071	4.37	2.58	1.63	0.6	2.3
P071+ENH	4.6	2.49	1.42	0.63	2.28
P004	4.1	2.78	1.88	1	2.45
P004+ENH	4.1	2.17	1.31	0.89	2.11
P039	7.17	1.58	1.78	1.07	2.9
P039+ENH	6.9	1.6	1.19	0.91	2.65

Table 5. Fusions among the best competitors of FVC2004 and *ENH*.

3.1 Biohashing

The fifth experiment is addressed at evaluating BioHashing applied to the novel feature vector based on texture-based features. Because the BioHashing approach requires a fixed length feature vector, it cannot be applied so easily to minutiae-based methods. In the experiments reported in Table 6, the performance is obtained by improving the BioHashing matcher in [17] related to 1) the worst test case when an “impostor” always steals the hash key and 2) the best case when the key is not stolen (the original method in [17] is also reported for comparison). As can easily be seen, in the best and most probable case when the hash key is not stolen, the BioHashing approach gives excellent results, even on the difficult FVC2004 datasets.

	DB1	DB2	DB3	DB4	2002	AV
MCT	9.60	4.31	4.40	2.64	1.63	4.51
Worst	12.20	5.68	5.12	2.95	2.24	5.63
Best	3.25	0.45	0.52	0	0	0.84

Table 6. EER obtained by BioHashing matcher in the two testing protocol.

4. CONCLUSION AND DISCUSSION

One of the main problems in fingerprint identification is to align the two fingerprints that should be compared. To obtain at least one good alignment, given a couple of low quality fingerprints, we propose some variants of the widely used TICO method of changing the descriptor used for describing the area around the minutiae by performing a wavelet-base preprocessing step. After the alignment, several matchers of different types are fused: some correlation-based, some texture-based, and some minutiae-based. Moreover, since our alignment method is based on texture features describing the appearance of the fingerprint pattern in a broad region around the minutia, we couple it with Biohashing to obtain a more secure fingerprint authentication approach.

Our experiments show that the proposed multimatcher approach works well on all the FVC2004 datasets as well as the FVC2002-DB2 dataset without parameter fine tuning for each dataset. Our results show a significant improvement over the baseline TICO matching algorithm. Results are superior to those reported by several academic systems, and our system is nearly comparable to the commercial competitors of FVC2004.

The application of the Biohashing procedure to our approach provides secure storage and transmission of biometric data. In particular, we highlight the fact that the minutiae-based alignment needs only the position of the minutiae, not the type, for the fingerprint image around the minutiae to be secured by Biohashing. Similarly the matching procedure is secured by Biohashing. Thus, the only information that can be stolen is the position and angle of the minutiae, which has been proven to be insufficient to synthetically reconstruct a fingerprint that can spoof a texture-based system [18].

Our MATLAB toolbox is freely available and can be used to verify or compare the results of our system. We also hope that it will serve as the foundation for further explorations in the field.

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