A Hybrid Fingerprint Multimatcher

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Abstract - *This paper focuses on extensive testing of multimatcher methods for obtaining a system that is comparable with the state-of-the-art commercial matchers. Through extensive testing, we propose an ensemble method that uses minutiae, correlation-based, and hybrid methods. To further improve our system, we conduct experiments with matchers that are also based on different enhancement techniques, combining matcher scores by sum rule. Our results are validated on all four FVC2004 DBs and on the easier FVC2002 DB2. Finally, we study the fusion among the proposed methods with the competitor systems in the FVC2004 competition. We find that our method improves the performance of the winner of FVC2004 competition. The MATLAB code for our experiments is freely available for downloading at bias.csr.unibo.it/nanni/Fconf.rar*.

Keywords: fingerprint identification; texture descriptors; minutiae; multimatcher ensemble

1 Introduction

Fingerprints are one of the most frequently used biometrics. As a result, fingerprint matching is an important area of research [1]. Fingerprint matching algorithms are generally classified into four categories: minutiae-based, correlation-based, image-based, and hybrid. Minutiae-based approaches search for the best alignment in a set of minutiae extracted from a fingerprint image and template [2]. Correlation-based approaches estimate the degree of similarity between a sample and a template by calculating the spatial correlation between corresponding pixels [3]. Image-based approaches extract features from the grey-level values of the fingerprint image, and then a distance metric or a classifier is used to make a matching decision [4]. Hybrid approaches align fingerprints using minutiae and estimate the degree of similarity between a sample and a template using an image-based method.

The focus of most research has been on exploring minutiae-based approaches. In general, these methods provide the best classification results [5]. Image-based and hybrid methods, however, are gaining in popularity primarily because they are able to handle low quality images [4], a common problem with real-world systems. Moreover, powerful methods for extracting relevant features from images, such as Local Phase Quantization (LBP) [6], have recently been developed. A recent work has shown that the fusion between image-based and minutiae-based methods outperforms the best stand-alone approaches [7].

The aim of this work is to improve the multimatcher approach for fingerprint recognition that we recently proposed in a preliminary work [8], which is based on the combination of different enhancement methods. The system described in this paper performs comparatively well to commercially available matchers on all four of the FVC2004 datasets as well as on the FVC2002 DB2 dataset.

This paper is organized as follows. In section 2 we describe the enhancement techniques, and in section 3 we discuss the fingerprint matching approaches that are examined and tested in this paper. In section 4 we report the experimental results obtained using the FVC2002 DBS and FVC2004 datasets. Finally, in section 5, we draw some conclusions and discuss directions for future research.

2 Enhancement approaches

A complete system for fingerprint verification is usually composed of two general steps: 1) a pre-processing step used to segment and to enhance the input image, and 2) a matching step based on feature extraction and distance evaluation and classification.

Below we list and briefly describe the enhancement approaches explored in this paper.

Chikkerur approach (C) [9]: this method uses Fourier analysis to estimate local ridge orientation and frequency information.

Hong approach (H) [10]: this method is based on Gabor filtering.

ROM approach (R): the ROM approach [11] uses a polynomial regression model. The approach first obtains the global orientation pattern in the fingerprint structure and then refines areas with singularities.

Yang (Y) [12]: this method is a two-step process that first enhances the image with a spatial ridge compensation filter and then subsequently enhances the image in the frequency domain. We have tested two versions: Y, which excludes the segmentation step in order to decide which part of the image belongs to the foreground and which to the background, and SY, which includes the segmentation step.

Combination approaches: In our experiments we also test some sequential combinations of the enhancement methods:

1) Hong + Yang (HY): the Hong's algorithm is applied first followed by the Yang method;
2) Chikkerur + Yang (CY): the Chikkerur's algorithm is applied first followed by Yang's approach.

A genetic approach for parameter optimization (GA): The GA[1] [13] is designed so that the chromosome is a bit string whose length is determined by the number of parameters in the enhancement method. Our selection strategy is cross generational. Assuming a population of size N, the offspring is $2N$. The GA then selects the best N individuals from the combined parent-offspring population. Uniform crossover is applied. In our experiments our population consists of 35 chromosomes. Each GA runs for 10 iterations. The objective function is based on the optimization of the quality of the input fingerprint according to the quality measure QM proposed in [7].

In the experimental section, we adopt this genetic approach to optimize the parameters of C. The resulting methods are named W when a global quality is considered, WR when the fingerprint is divided in four regions with only the average of the two regions with lowest quality used (thus avoiding considering the fitness function in regions with low information, e.g., straight ridges, which provide no information in matching).

3 Fingerprint matching systems

Below we describe the matchers used in our experiments. We divide them into three of the four categories given in [1]: minutiae-based, correlation-based, and hybrid. We exclude results from pure image-based methods because of their low performance in our experiments.

3.1 Minutiae-based matchers

We use the CUBS fingerprint toolbox[2] for extracting the minutiae and the method proposed by Tico [2] for matching. In [2] a descriptor is proposed that captures information in a region of the orientation field by surrounding a minutiae position $\mathbf{m}=[x, y]^T$ by L concentric rings. Each ring is comprised of 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. Because 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. We label this minutiae matcher TICO.

3.2 Correlation-based

Correlation-based approaches estimate the degree of similarity between two fingerprints by calculating the spatial correlation between corresponding pixels or local features [3]. In order to apply a correlation-based method, the fingerprints are first aligned using the minutiae-based alignment noted above for the TICO method. In this work we perform an image tessellation, with overlapping square regions of dimension 50×50 (*overlap*=50%), and we use the normalized 2-D cross-correlation for comparing two regions. We label this correlation-based matcher CORR.

3.3 Hybrid approaches

In the literature, hybrid methods generally refer to image-based approaches where the alignment is performed by considering the minutiae. In this work we propose three hybrid approaches.

The first approach is texture-based (TEX): the fingerprints are first aligned using the TICO approach, then each image is decomposed into overlapping square cells of dimension 50×50 (*overlap*=50%). We experimented with two descriptors: Local Phase Quantization (LPQ) [6] and Local Binary Pattern Histogram Fourier (HF) [14]. The matching value between two images is calculated by the City block distance function. The resulting methods are named TEXLPQ and TEXHF.

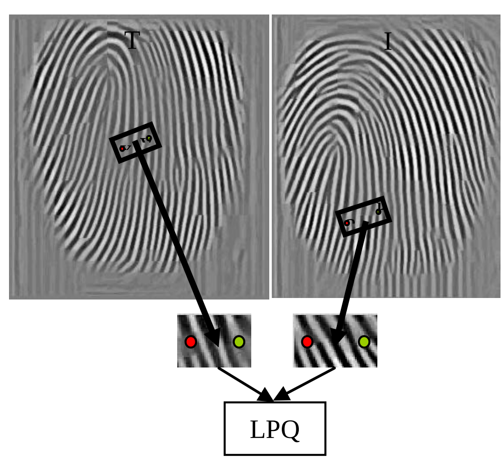

Figure 1. Edge based approach.

[1] It is implemented as in Gaot (Genetic Optimization Toolbox) Matlab Toolbox

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The second approach is orientation image-based (OR): the fingerprints are first aligned using the TICO approach, then the orientation image is calculated [1] and the orientation distance (minimal overlapping angle between two orientations) is calculated to perform the matching.

The third approach is edge-based (ED): for each couple of minutiae (x, y) of the template **T** that are mated with a couple of minutiae (a, b) of the input image **I,** we extract LPQ descriptors from the regions $a_{(x, y)}$ from **T** and $a_{(a, b)}$ from **I** (see Figure 1). The similarity between two images is the average similarity (City block distance) among all couples of regions. This method is our proposed variant of the approach described in [15].

4 Experimental results

We conducted experiments using all four datasets in the difficult FVC2004 benchmark database [16], as well as the easier FVC2002 DB2 (labeled below as 2002) [16]. All algorithms followed the FVC2004 testing protocol [16], where each system made the following two 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.

We report Equal Error Rate (EER) [1] as the performance measure. The label AV in the following tables is related to the average EER of the given approach in all the tested datasets.

In Table 1 (printed at the end of this paper due to size), we report the results of matching approaches coupled with the different enhancement methods (EM), which we listed above in section 2. To conserve space, we have reported only the EERs obtained with an overlap of 50%, since these outperform systems where there is no an overlap among the subwindows.

The most interesting conclusions extracted from the results reported in Table 1 are the following:

- C is the best enhancement method;
- It is very interesting to note that TEXLPQ, CORR, and OR outperform the minutiae-based method (TICO is, however, an older approach).
- Our proposed genetic enhancement algorithm improves the wavelet quality score of a given fingerprint image (e.g., the average value of the quality score after the enhancement by C is 5.55 while after W it is 6.57), but GA enhancement method does not improve performance. This is probably due to the fact that the fitness function guides the optimization process at improving the quality
- in regions of the fingerprint which are not central for the matching.

Y and SY are similar methods but produce different results. We tested the fusion by sum rule combining two TICO matchers: the first using the images enhanced by *Y*; the latter using the images enhanced by *SY*. The average EER obtained by their fusion is 8.57, which is better than both stand-alone approaches.

In Table 2 printed at the end of this paper, we report the results of the following multimatcher approaches:

- F2 is the sum rule between C+CORR (where C is the enhancement method and CORR is the matcher) and W+ TEXLPQ;
- F3 is the sum rule of C+CORR, W+ TEXLPQ and CS+TEXLPQ;
- F4 is the sum rule of C+CORR, W+ TEXLPQ, SY+TICO and CS+TEXLPQ.

The choice of the matchers to be fused was performed considering the average EER on the five dataset, among all the possible combinations of matchers. The sum rule simply sums the scores of all the methods in the ensemble, with the scores related to each descriptor are normalized to mean 0 and standard deviation 1.

It is interesting to note fusion F4, which obtains the best performance, contains 4 matchers, each of which is based on different enhancement approaches. This is further confirmation of the usefulness of combining different enhancement methods for improving performance. We want to stress that F4 outperforms our previous multimatcher system [7]. Using 16 matchers, not just the 4 in *F4*, the multimatcher system in [7] obtained the following EERs: 9.61% DB1, 4.26% DB2, 3.58% DB3, 2.94% DB4. For further comparison, in [17] the best EERs were obtained by coupling the complete NIST FIS2 matcher (the bozorth3 package) with different enhancement methods: 12.0% DB1, 8.2% DB2, 5.0% DB3, and 7.0% DB4. Our proposed multimatcher outperforms this free toolbox.

In Table 3 printed at the end of this paper, we report results combining our multimatcher with the best performing systems in the FVC2004 competition. Our aim in this experiment is to determine whether our multimatcher fused with the commercial state-of-the-art approaches (by sum rule) improves performance. The results in Table 3 demonstrate that our fusion method coupled with the FVC2004 competitors often improves their performance.

5 Conclusion and Discussion

In this paper we proposed a novel multimatcher approach that works well on the difficult FVC2004 databases and on the FVC2002 DB2 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, where each matcher is based on a different enhancement method.

Our aim was to propose a multimatcher approach that works well on all the FVC2004 datasets without a parameter tuning on each dataset. Our experimental section shows that we have succeeded in obtaining this goal. Our free MATLAB toolbox can be used to verify the results of our system. We also hope that our toolbox will serve as the foundation for further explorations by other researchers in the field. It is also interesting to note that when we combined our multimatcher with the competitor systems in FVC2004 competition, our fusion method often improved the results of these systems.

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

	EM	DB1	DB2	DB3	DB4	2002	AV
TICO	C	14.66	7.93	10.1	**7.81**	**2.57**	**8.61**
	H	17.67	24.98	9.32	11.69	3.98	13.52
	R	14.53	9.84	15.21	10.08	4.21	10.77
	Y	**13.65**	8.65	13.52	14.16	11.81	12.35
	SY	17.93	**7.28**	11.28	10.25	3.32	10.01
	CY	15.47	9.65	**8.27**	9.19	2.87	9.09
	HY	16.46	21.52	8.56	10.58	4.09	12.24
	W	16.61	10.11	9.22	9.34	3.64	9.78
	WR	16.86	10.60	10.60	9.82	3.38	10.25
	EM	DB1	DB2	DB3	DB4	2002	AV
TEXLPQ	C	11.38	5.1	4.84	**4.74**	2.19	**5.65**
	H	11.27	14.18	5.31	6.73	3.13	8.12
	R	12.19	5.96	8.73	5.64	3.02	7.10
	Y	11.75	5.28	7.14	8.28	5.82	7.65
	SY	15.21	**5.03**	6.44	6.67	2.55	7.18
	CY	11.32	5.94	4.9	5.91	**2.18**	6.05
	HY	**10.95**	12.71	4.86	6.54	2.87	7.58
	W	11.38	6.05	**4.42**	6.05	2.65	6.11
	WR	11.17	6.59	4.74	6.83	2.57	6.38
	EM	DB1	DB2	DB3	DB4	2002	AV
TEXHF	C	15.98	8.68	8.88	**9.95**	**5.47**	**9.79**
	H	17.8	20.21	8.96	11.71	7.27	13.19
	R	16.48	9.85	11.65	12.29	8.06	11.66
	Y	15.14	8.32	13	12.52	8.16	11.42
	SY	17.5	**7.93**	12.17	12.23	5.98	11.16
	CY	**15.08**	9.11	8.76	11.44	5.17	9.91
	HY	15.62	16.09	**8.48**	12.12	6.25	11.71
	W	15.20	8.79	8.61	11.46	6.16	10.04
	WR	15.43	9.42	8.66	12.06	5.94	10.30
	EM	DB1	DB2	DB3	DB4	2002	AV
CORR	C	12.72	**4.6**	6.49	**3.53**	1.47	**5.76**
	H	13.66	14.81	6.26	6.29	2.52	8.70
	R	15.32	8.66	12.76	5.74	3.22	9.14
	Y	12.69	5.53	8.52	6.83	5.62	7.83
	SY	24.14	5.2	8.18	5.45	2.1	9.01
	CY	**12.43**	5.88	5.88	4.51	**1.39**	6.01
	HY	12.5	11.89	**5.71**	5.52	2.39	7.60
	W	12.58	6.46	6.11	4.30	2.14	6.31
	WR	12.65	6.42	5.88	4.56	2.36	6.37
	EM	DB1	DB2	DB3	DB4	2002	AV
ED	C	18.44	12.61	**12.78**	**9.57**	7.65	12.21
	H	20.51	27.71	13.14	12.47	9.39	16.64
	R	**15.77**	10.69	15.90	10.27	**6.64**	**11.85**
	Y	17.78	**9.07**	19.81	13.49	11.31	14.29
	SY	18.19	9.83	18.55	13.09	8.02	13.53
	CY	17.06	13.77	15.73	11.42	7.59	13.11
	HY	18.93	23.72	15.68	13.26	7.84	15.88
	W[3]	---	---	---	---	---	---
	WR	---	---	---	---	---	---

[3] Due to computation time this enhancement is not coupled with ED

Table 1. Continued

	EM	DB1	DB2	DB3	DB4	2002	AV
OR	C	12.14	**6.93**	7.2	**7.51**	4.53	**7.66**
	H	11.93	15.73	7.36	8.95	5.39	9.87
	R	12.29	7.97	12.86	8.93	4.85	9.38
	Y	12.14	7.94	9.6	12.62	8.50	10.16
	SY	14.28	7	8.73	9.92	4.55	8.89
	CY	11.94	7.9	6.79	8.77	4.49	7.97
	HY	**11.72**	13.92	**6.76**	9.81	5.63	9.56
	W	11.85	7.85	6.94	8.16	4.36	7.83
	WR	11.95	8.32	7.08	8.87	**4.30**	8.10

Table 2. EERs obtained using fusion.

	DB1	DB2	DB3	DB4	2002	AV
F2	10.71	5.11	3.27	2.88	1.42	6.68
F3	9.80	4.40	3.09	2.88	1.31	4.30
F4	9.59	4.30	2.92	2.83	1.26	4.18

Table 3. Fusions among the best competitors of FVC2004 and our multimatcher *F4*.

	Stand-alone						Fusion between competitors and *F4*					
	P101	P047	P071	P004	P039	P097	P101	P047	P071	P004	P039	P097
DB1	2.72	1.97	4.37	4.10	7.17	3.38	2.60	2.22	4.46	4.09	7.00	4.94
DB2	3.56	3.49	2.58	2.78	1.58	3.22	2.42	2.99	2.45	2.29	1.62	3.22
DB3	1.19	1.18	1.63	1.88	1.78	4.16	1.03	1.18	1.56	1.33	1.44	2.45
DB4	0.79	1.76	0.60	1.00	1.07	1.75	0.63	1.58	0.60	0.95	0.89	1.60
AV	2.07	2.10	2.30	2.45	2.90	3.13	1.67	1.99	2.27	2.17	2.74	3.05