When Fingerprints Are Combined with Iris - A Case Study: FVC2004 and CASIA

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Abstract

This paper presents novel studies on fusion strategies for personal identification using fingerprint and iris biometrics. The purpose of our paper is to investigate whether the integration of iris and fingerprint biometrics can achieve performance that may not be possible using a single biometric technology. Moreover we are interested in evaluating the correlation among the best state of art algorithms for fingerprint verification presented at FVC2004. We show that the fusion among some competitors of FVC2004 permits a drastically reduction of the performance. Particularly interesting is the result obtained by combining the competitors of FVC2004 and an IRIS matcher in terms of EER (the most used parameter in the evaluation of real identification systems), significantly lower than for other approaches. This indicates that the intrinsic error of the system is very low and tends to 0 for some of the tests carried out. The results of this paper confirm that a multimodal biometric can overcome some of the limitations of a single biometric resulting in a substantial performance improvement.

Keywords: Classifier combination, fingerprint recognition, machine learning

1 Introduction

Establishing the identity of a person is a task of increasing importance in various areas in the modern society, as entrance control in buildings and restricted areas, authentication in day-to-day affairs like dealing with the post office, and detection of a suspect in a particular crime in the field of criminal investigation. Biometrics, which measures a physiological or behavioral characteristic of a person, such as voice, face, fingerprints, iris, etc, provides an effective way to solve the problems that the traditional methods such as password and IC cards have faced. Biometric systems that rely on the evidence of a single source of information for authentication (e.g., single fingerprint or face) are often affected by a variety of practical problems such as noisy data (due to a dirty sensor or an environment poorly illuminated), large intra-class variations (i.e. several facial poses), non-universality, spoof attacks, and unacceptable error rates. Multiple biometrics [15] can help to solve several practical problems: thus improving the recognition performance, increasing population coverage (i.e. to those not having a legible fingerprint) and providing anti-spoofing measures by making it difficult for an intruder to spoof multiple biometric traits simultaneously. There has been a substantial amount of work done on the multimodal fusion approaches: the key is the combination of the various biometric characteristics at the feature extraction, match score, or decision level [15]. Feature level fusion (also known as pre-classification fusion) combines feature vectors at the representation level to provide higher dimensional data points; match score level fusion and decision level fusion (post-classification fusion) combine the individual scores from multiple classifiers and the accept or reject decisions of each biometric system, respectively. Two sound theoretical frameworks for combining classifiers with application to biometric verification are described in [1] and [9]. Both of them concluded that the weighted average is a good way of combining the similarity scores provided by the different experts (under some mild assumptions that may not hold in practice). Machine learning approaches have also been applied for combining biometric classifiers [5].

Although there has been much research on combining different biometrics for a variety of purposes, however, not much work has focused on the combination of fingerprint and iris, which are two of the characteristics that can reach the best recognition performance for high security applications. In this paper we examine a scenario for integrating fingerprint and iris biometric by comparing different fusion strategies on several recognition methods: mean rule, linear support vector machines, radial-basis-function support vector machines and Dempster-Shafer [21] are compared. As concerns the recognition methods we select a well know approach for iris recognition which grants good performance and is easy to implement and we make experiments in combining this approach with several fingerprint recognition methods presented at the FVC2004 fingerprint competition. The aim of this work is not only to show how a multimodal system can outperform a single biometric, but also to demonstrate that since the correlation among different biometrics is very low, good improvements can be reached simply combining a medium level fingerprint system with the iris recognition system.

The rest of this paper is organized as follows: Section 2 gives a brief overview of the fingerprint and iris recognition systems used in our experiments. Section 3 introduces some fusion algorithms adopted for combining biometrics. Section 4 presents the experimental results. Finally, Section 5 concludes the paper.

2 Identity Verification by Unimodal Systems

2.1 Iris Verification

Automated iris recognition is receiving increased attention among other biometrics for noninvasive verification and identification of people. First of all, that is because of its high reliability (the probability of finding two people with identical iris pattern is almost zero); in addition compared to fingerprint or face, the iris is well protected from the environment (behind the cornea and the eyelid) and stable over time (neither subject to aging nor to variability in appearance). Like the fingerprint and the face, the iris can be acquired by a noninvasive device; moreover, differently to the other two biometric characteristics, the iris is relatively insensitive to angle of illumination, changes in viewing angle and distortions, thus it is more suitable for the creation of a size-invariant representation that makes possible an automated recognition with high degree of accuracy, based on currently available machine vision technologies.

One of the most well known systems for iris recognition is based on phase code using Gabor filters and has been developed in the first 90s by Daugman [4] and patented by IriScan Inc. Other works proposed later are the following: Wildes [19] proposed a system based on Laplacian pyramid constructed with four different resolution levels for representing iris texture and used the normalized correlation as similarity measure; Boles et al. [2] used zero-crossing representation of 1-D wavelet transform for feature extraction; Sanchez-Reillo et al. [16] used Gabor filters as feature extractor and a statistical matcher; finally Ma et al. [13] adopted texture analysis methods to capture the iris details.

In general, the process of iris recognition can be divided into four steps:

1) Localization of the iris

2) Normalization of the iris to a fixed size

3) Feature Extraction

4) Matching

In this work we use a publicly available library for iris recognition [11] written in MATLAB. The localization step consists of an automatic segmentation system based on the Hough transform as proposed by [20]; the extracted iris region is normalized into a fixed rectangular block by remapping each point within the iris region to a pair of polar coordinates according to the rubber sheet model developed by Daugman [4]; as concerns feature extraction and matching, the phase data from 1D Log-Gabor filters are extracted and quantized to four levels as proposed in [4] and the Hamming distance is employed for matching [4].

2.2 Fingerprint Recognition

Reliable and accurate fingerprint recognition is a challenging pattern recognition problem, requiring algorithms robust in many contexts. FVC competitions [6, 12] attempted to establish the first common benchmark, allowing companies and academic institutions to unambiguously compare performance and track improvements in their fingerprint recognition algorithms. In this work we suppose to have the methods of the participants to FVC2004 and we select in our experiments the approaches that give the best performance on the test DBs, or those that are most uncorrelated. In FVC2004 two different categories (Open and Light) were admitted, where the light category was intended for algorithms characterized by low computing needs, limited memory usage and small template size. In this work we do not consider these limitations, therefore we take algorithms from the Open category.

The correlation among different algorithms is a measure of their similarity in making errors: a strong correlation means that they made similar errors (i.e. they found particularly difficult almost the same fingerprint pairs); a low correlation indicates that they made different errors. In order to evaluate correlation between two or more approaches we measure the EER (equal error rate) of the selected approaches combined using the mean rule as fusion strategy. Selecting the most uncorrelated methods among all FVC2004 participants by minimizing such a value is a very time consuming problem if performed by exhaustive search, so we adopt a suboptimal search method: the sequential floating search method, proposed by Pudil et al. [17] which performs sequential forward search with provision for backtracking. According to the comparative study made by Jain and Zongker [8], this is probably the most effective known suboptimal method for performing the minimization of the proposed objective function.

Since participants to FVC2004 maintain secrets the details of their algorithms, it is not possible to give an accurate method description as made for iris, however a high-level structured description of the algorithms is available, which can help in classifying method among minutiae-based, correlation-based, and ridge feature-based approaches [6]. The information available for the FVC2004

Table 1: Some information about the FVC2004 competitors involved in our experiments

ID	Organization	Country	Type
P039	Jan Lunter	France	Independent
P047	Sonda Ltd.	Russia	Industry
P071	Inst. of Aut., The Chinese Academy of Sciences	China	Academ
P075	Ariel Unanue	Argentina	Independent
P101	Bioscrypt Inc.	Canada	Industry

competitors involved in our experiments are reported in Table 1, while a high-level description of the algorithms is in Table 6.

We suppose to use the following configurations for multimodal fusion:

- The best FVC2004 competitor (which resulted [6] to be P101, a correlation-based approach which exploits the ridge pattern of the fingerprint, proposed Bioscrypt Inc.)
- A middle-ranking competitor (we selected P075, a minutiae based approach proposed by an independent competitor)
- The three most uncorrelated FVC2004 competitors (P101, P39, P47)
- The three FVC2004 competitors which resulted to be most uncorrelated with IRIS (P101, P47, P71)

In the last two configurations we fix to three the number of fingerprint competitors, since such a value is, in our opinion, the best trade-off between complexity and performance, as shown in Figure 1 in Section 4.

3 Fusion Algorithms

Two sound theoretical frameworks for combining classifiers with application to biometric verification are described in [1] and [9]. Both of them concluded that the weighted average is a good way of combining the similarity scores provided by the different experts (under some mild assumptions that may not hold in practice). Machine Learning approaches have also been applied for combining biometric classifiers [9]. In Machine Learning approaches the matchers' output is treated as a feature vector: then any known classifiers can be trained to determine the separation bound between impostor and genuine users.

In this work we examine a scenario for integrating fingerprint and iris biometric by comparing different fusion strategies: the mean rule (MEAN) to combine similarity scores and three Machine Learning approaches: linear support vector machines (LSVM), radial-basis-function support vector machines (RSVM) and the Dempster-Shafer model (DS) [21] are compared.

The mean rule is a simple aggregation method that needs not train beforehand and only combines the output of classifiers. SVM [18] is primarily a dichotomy classifier. The optimization criterion is the width of the margin between the classes, i.e., the empty area around the decision boundary defined by the distance to the nearest training samples. These patterns, called the support vectors, finally define the classification function. The support vector machines use optimization methods to maximize the gap between the classes. A SVM with a large margin separating two classes has a small VC dimension, which yields a good generalization performance. The computational complexity of the training procedure (a quadratic minimization problem) is one of the drawbacks of SVMs. A number of classifiers can be trained using different kernels (linear, polynomial, radial basis function, and sigmoid) for SVMs.

The Dempster-Shafer theory, also known as the theory of belief functions, is a generalization of the Bayesian theory of subjective probability. In the Dempster-Shafer frame, the best representation of support is a belief function rather than a Bayesian mass distribution. The theory embraces the familiar idea of assigning numbers between 0 and 1 to indicate the degree of support but, instead of focusing on how this numbers are determined, it concerns the combination of degrees of belief. Here, we use the algorithm proposed by [10].

4 Experimental Results

4.1 Databases

We conducted our experiments on 4 databases that contains 100 persons and for each person 7 fingerprint samples and 7 iris samples. The databases have been constructed by joining one of the four DBs of fingerprints constituting the FVC2004 benchmark [6] and the CASIA Iris Image Database [7]. Three different scanners and the SFinGE synthetic generator [3] were used to collect fingerprints for the FVC2004 benchmark: the size of each database is 100 fingers, with 8 impressions per finger (800 impressions). It is important to underline that FVC2004 is a very difficult benchmark with many intraclass variations derived by large skin distortion, which is a well-known difficulty in fingerprint recognition; in fact the accuracy of the top algorithms of this competition is sensibly lower than in the previous one (FVC2002). CASIA Iris Image Database includes 756 iris images from 108 eyes: for each eye, 7 images are captured in two sessions. Obviously, the FVC2004 database does not come with corresponding iris, so to each fingerprint, we assign an arbitrary (but fixed) iris. Moreover, the number of individual is fixed to 100 and we use only the first 7 fingerprint for each person, since CASIA has only 7 iris images.

For each database, we use a 2-cross fold validation for the training of the three Machine Learning combination

Table 2: Equal error rate obtained by a multimodal fusion of the iris method with the best FVC2004 competitor

	IRIS	P101	MEAN	RSVM	LSVM	DS
Db1	3.2	1.74	0.47	0.45	0.47	0.5
Db2		1.26	0.28	0.2	0.27	0.21
Db3		0.8	0.088	0.11	0.11	0.03
Db4		0.58	0.044	0.02	0.05	0.045
Average	3.2	1.095	0.2205	**0.195**	0.225	0.196

Table 3: Equal error rate obtained by a multimodal fusion of the iris method with "P075" FVC2004 competitor

	IRIS	P101	P075	MEAN	RSVM	LSVM	DS
Db1	3.2	1.74	5.61	2.86	1.72	1.89	2.82
Db2		1.26	5.09	2.88	1.66	1.68	2.89
Db3		0.8	1.84	0.48	0.58	0.63	0.53
Db4		0.58	5.98	0.044	0.02	0.05	0.045
Average	3.2	1.095	4.63	1.9025	**1.3725**	1.4475	1.912

approaches: in the first fold we use the first 50 individuals as training (and the last 50 as testing), in the second fold we use the last 50 individuals as training (and the first 50 as testing).

4.2 Performance Indicators

Each algorithm was tested using the FVC2004 testing protocol, by performing, for each database, the following matching attempts:

- *genuine recognition attempts*: the template of each impression (fingerprint or iris) is matched against the remaining impressions of the same finger or iris, but avoiding symmetric matches (i.e. if the template of impression j was matched against impression k, template k was not matched against impression j);

- *impostor recognition attempts*: the template of the first impression was matched against the first impressions of the remaining fingers or iris, but avoiding symmetric matches.

Then, for each database, a total of 600 enrollment attempts are performed (the enrollment of the last impression of any finger does not need to be performed) and a total of 2100 genuine matching attempts and 4950 impostor matching attempts. If an enrollment failure occurs, we set to 0 the score in order to have in any case an input value for the fusion step.

Please note that Fingerprint Verification Competition FVC2004 focuses on performance evaluation of fingerprint verification systems (not identification), therefore the performance indicator adopted in this work is the Equal Error Rate (EER). ERR is the error rate where the frequency of fraudulent accesses (FAR) and is the frequency of rejections of people who should be correctly verified (FRR) assume the same value; it can be adopted as a unique measure for characterizing the security level of a biometric system.

4.3 Experiments

In the following tables the ERR obtained by several multimodal fusion methods on our four databases are reported (the last row contains the average value). The first two columns are replicated in each table to enhance readability and always refer to stand-alone matchers: the IRIS method and the best FVC competitor (the EER obtained by IRIS is the same, since the 4 DBs do not differ by the iris images). In Table 2, the ERR obtained by a multimodal fusion of the iris method with the best FVC2004 competitor (P101) is reported.

Please note that the EER here reported for the iris method is considerably higher than that obtained using the suggested [7] "CASIA protocol" (0.45). In fact, the "CASIA protocol" is quite different: for each eye, three images are collected in a first session and used for training, the remaining four are used for testing. In Table 3, the ERR obtained by a multimodal fusion of the iris method a with "P075" FVC2004 competitor is reported.

Based on the above results and analysis, we can draw some conclusions: the goal of our experiment is to compare the performance of different combination methods in the context of combining fingerprint and iris recognition system. As Table 2 shows, the performance of the best (nominated by FVC2004) fingerprint recognition system can be greatly improved by a fusion with an iris system. Moreover also a middle-ranking fingerprint method is enough to obtain acceptable performance if coupled with an iris system; such multimodal system gains an EER comparable to the best single fingerprint recognition system (see Table 3).

Table 4: Equal error rate obtained by a multimodal fusion of the iris method with the three most uncorrelated FVC2004 competitors

	IRIS	P101	MEANfvc	MEAN	RSVM	LSVM	DS
Db1	3.2	1.74	0.88	0.43	0.28	0.24	0.41
Db2		1.26	0.9	0.19	0.01	0.02	0.04
Db3		0.8	0.21	0.044	0	0	0.01
Db4		0.58	0.47	0.098	0	0	0.044
Average	3.2	1.095	0.615	0.19	0.0725	**0.065**	0.125

Table 5: Equal error rate obtained by a multimodal fusion of the iris method with the three FVC2004 competitors which resulted to be most uncorrelated with IRIS

	IRIS	P101	MEANfvc	MEAN	RSVM	LSVM	DS
Db1	3.2	1.74	1.21	0.23	0.25	0.24	0.27
Db2		1.26	0.97	0.14	0.044	0.02	0.065
Db3		0.8	0.28	0	0	0	0
Db4		0.58	0.43	0.088	0	0	0.02
Average	3.2	1.095	0.7725	0.1145	0.0735	**0.065**	0.089

In Table 4, the ERR obtained by a multimodal fusion of the iris method with the three most uncorrelated FVC2004 competitors (P101, P39, P47) is reported. In this paper, we use the mean rule as a criterion to find the most uncorrelated methods: we select the methods which minimize the average EER on our 4 test DBs. The third column refers to a unimodal fusion of the three fingerprint methods (without IRIS), adopting the mean rule (MEANfvc). This simple aggregation method already gives a better result compared with the single best biometric systems; however the fusion with another biometrics like iris (columns 4-8) significantly further improves the results.

In Table 5, the ERR obtained by a multimodal fusion of the iris method with the three FVC2004 competitors which resulted to be most uncorrelated with IRIS (P101, P47, P71) is reported. It is interesting to note that these competitors are exactly the three best competitors of FVC2004 [6].

According to Table ?? and Table 5 we can find that the two SVM methods are better than the simple mean rule and the Dempster-Shafer method. Moreover these combinations showed, at the same time, good performance, low performance variance and good generalizing abilities among datasets of fingerprints, which have been collected by different type of sensors (optical for DB1 and DB2, Thermal-sweeping for DB3, while DB4 is synthetic). Particularly interesting is the result obtained by the multimodal fusion in terms of EER: this indicates that the intrinsic error of the system is very low and tends to 0 for some of the tests carried out (see Table 4 and Table 5).

In Figure 1, we plot the average (on our 4 DBs) ERR obtained by two different combinations as a function of the number of FVC competitors involved (each set k refers to the best k competitors of FVC2004):

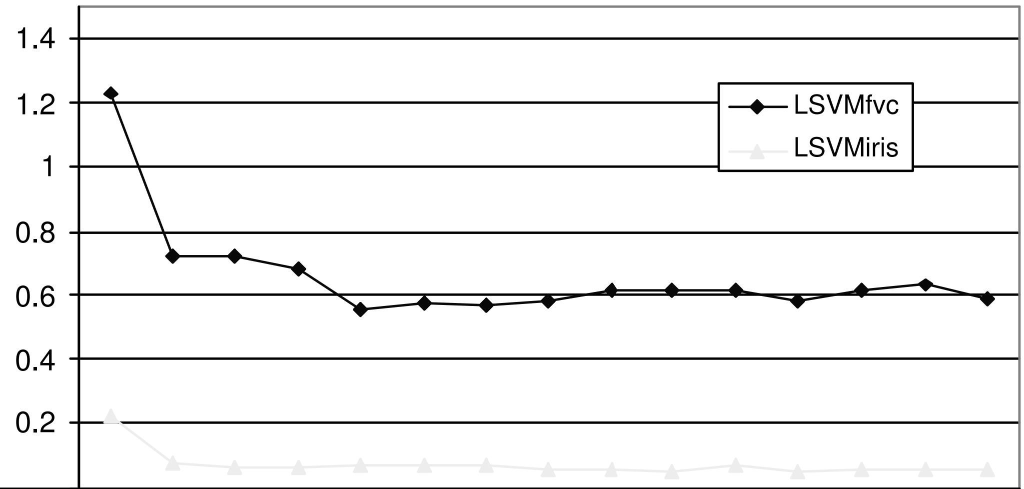
- LSVMfvc: fusion of the best k competitors of FVC2004 by LSVM
- LSVMiris: fusion of the best k competitors and iris by LSVM

These results suggest that, as stated in Subsection 2.1, the choice of three fingerprint methods grants the best trade-off between complexity and performance; in fact, a value higher than three does not allow to gain a significant increasing in performance. Moreover, it is evident that using iris the results considerably improve to values that are not reachable using only fingerprints: the EER is close to 0 independently by the number of competitors.

In Table 6 an high-level description of the algorithms of FVC2004 considered in this paper is given (the complete table is in [21]). Analyzing various individual cases, best combinations are usually obtained when combining systems that are based on heterogeneous matching strategies, such minutia-based with ridge-based and/or correlation-based.

In Table 7 the average comparison time of the algorithms of FVC2004 used in this paper is given (the complete table is in [14]). The comparison time of the iris matcher is about 3 seconds (Matlab code). Of course, the matchers may work in parallel, in any case, a comparison time of about 6 seconds may be considered acceptable for a real-time application.

The multimodal biometric has been well explored from the scientific community, but in our opinion the results here presented are an important validation of the results yet obtained in the literature because we tested the really state-of-the-art (academic and industrial) in fingerprint verification and the state-of-the-art of Iris Matching. Moreover, this work represents an interesting analysis of



k	1	2	3	4	5	6	7	8	9	10	12	18	24	30	36
LSVMfvc	1.23	0.73	0.73	0.688	0.56	0.579	0.568	0.582	0.615	0.615	0.615	0.585	0.615	0.637	0.59
LSVMiris	0.225	0.076	0.065	0.067	0.072	0.072	0.072	0.059	0.059	0.054	0.073	0.054	0.059	0.062	0.062

Figure 1: Equal error rate obtained by the LSVMfvc and LSVMiris methods as a function of the number of fingerprint competitors k

the systems presented in FVC2004 since, surprisingly, our experiments show that the error correlation between the best performing algorithms of FVC2004 is very low. That is, different algorithms tend to make different errors. This indicates that there is still much potential for algorithmic improvement. Finally, we prove that simply combining algorithms allows EER to be markedly reduced.

Table 7: Average comparison time (on a Athlon 1600+ (1,41 GHz)) on each database of the algorithms from 5 participants to FVC2004

	Average comparison time (seconds)				
	DB1	*DB2*	*DB3*	*DB4*	**Avg**
P039	1.32	0.83	1.09	1.53	**1.19**
P047	1.87	2.18	2.30	1.93	**2.07**
P071	0.77	0.57	0.81	0.53	**0.67**
P075	0.44	0.30	0.68	0.29	**0.43**
P101	3.19	0.81	0.85	1.06	**1.48**

5 Conclusions

Fusion of multiple biometrics has recently gained more interests with an increasing emphasis on security. In this paper, we have tested a fusion strategy for personal identification using fingerprint and iris biometrics. The results of this paper suggest that a multimodal integration of iris and fingerprints can offer substantial performance gain that may not be possible with a single biometric indicator alone. Moreover a fusion of fingerprint and iris can be easily applied with low costs to some applications without requiring the acquisition of the best commercial products. Experimental results obtained from a large fingerprint database (FVC2004 and CASIA) show that the fusion leads to a substantial improvement in the overall performance. Surprisingly, correlation between best performing algorithms is very low, that is, algorithms tend to make different errors: this indicated there is still much room for improvements.

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Table 6: An example of accumulated values of curve codes

	Participant	P039	P047	P071	P075	P101
Preprocessing	*Segmentation*	√	√		√	√(*only on DB1*)
	Enhancement	√		√	√	√
Alignment	*Before matching, During matching*	D	D	D	B	BD
	Displacement, Rotation, Scale, Non-linear	N	DRSN	N	DR	DRS
Features	*Minutiae*	√	√	√	√	
	Singular points		√	√		√
	Ridges		√	√		√
	Ridge counts		√	√		√
	Orientation field	√	√	√		√
	Local ridge frequency	√	√			√
	Texture measures		√			
	Raw/Enh. image parts		√	√		√
Comparison	*Minutiae (global)*	√	√			
	Minutiae (local)		√	√	√	
	Ridge pattern (geometry)			√		√
	Ridge pattern (texture)		√			
	Correlation			√		√

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