

An Adaptive Fusion Framework for Fault-Tolerant Multibiometrics

S. Chindaro, Z. Zhou, M.W.R. Ng, and F. Deravi

School of Engineering and Digital Arts, University of Kent, Canterbury, CT2 7NT,
United Kingdom

{S.Chindaro,Z.Zhou,F.Deravi}@kent.ac.uk

Abstract. The use of multiple biometrics will work with greater efficiency if all the systems are capable of acquiring biometrics of adequate quality and processing them successfully. However if one or more of the biometrics fails, then the system has to rely on fewer or one biometric. If the individual biometrics are set to use low thresholds, the system maybe vulnerable to falsely accepting impostors. The motivation behind the proposed method is to provide an adaptive fusion platform where the software system can identify failures in certain algorithms and if necessary adapt the current rule to ignore these algorithms and adjust operating points accordingly. Results from experiments carried out on a multi-algorithmic and multi-biometric 3D and 2D database are presented to show that adopting such a system will result in an improvement in efficiency and verification rate.

Keywords: Adaptive Fusion, Multibiometrics, Face Recognitions.

1 Introduction

Biometrics is an increasingly advancing field based on an automatically measurable, robust and distinctive physical characteristic or personal trait that can be used to identify an individual or verify the claimed identity of an individual. Automatic biometric-based systems have the potential of playing a major role in various applications in the areas of security, access control and surveillance. Even though a number of modalities have been tested and deployed in various applications with some success, there are limitations to each of them which are environment dependant (for example, lighting and pose for face, noise for voice recognition, and cleanliness of a finger in fingerprints etc). This has given rise to a growing interest in the use of multiple modalities [1]. Fusion of diverse modalities may result in systems which are more robust to changing conditions through integration of complementary information [1][2][3].

However, the use of multiple biometrics will work with greater efficiency if all the systems are capable of acquiring biometrics of adequate quality and processing them successfully with the correct configuration. However if one or more of the biometrics fails (fails to acquire or acquires an image of inadequate quality), then the system has to rely on fewer or one biometric. If both biometrics are set to use low thresholds, then the system has to adjust its configuration accordingly to avoid a false accept. Adaptive fusion is one solution to avoid such a scenario. The motivation behind the method is to provide an adaptive fusion platform where the software system can identify failures in certain algorithms or biometric modalities, and adapt the current rule to optimize the system performance.

This work is part of the European Project, ‘3D Face’ [4] whose aims are to (i) improve the performance of classical face recognition techniques by extending it to 3D, (ii) integrate privacy protection technology to safeguard the biometric information and (iii) deploy the secure face recognition system at airports for employee access control.

Even though there are several biometrics on the market today, the use of the face has gained prominence since the adoption of the ePassport by the ICAO as a standard for future passports [5]. The system adopted by the ICAO is mainly based on 2D face recognition. The disadvantages of developing an automatic authentication/verification system based on 2D include its sensitivity to changes in acquisition conditions such as lighting and the absence of liveness detection mechanisms [6] [7].

The integration of 3D models promises significant performance enhancements for border controls. By combining the geometry and texture-channel information of the face, 3D face recognition systems provide an improved robustness while processing variations in poses and problematic lighting conditions when taking the photo [6].

The work presented in this paper is based on fusion 2D and 3D facial biometrics in an adaptable fusion framework to optimize the system performance and improve efficiency, in addition to the robustness brought about by fusion. An experimental evaluation of the proposed system is presented and results are compared to non-adaptive systems. Results show that adopting such a system will result in an improvement in the verification rate. It also improves the efficiency of the system by reducing the number of rejections without compromising the security of the system.

In Section 2, the adaptive fusion framework is described. The experimental set-up which includes the database and the 3D and 2D face recognition algorithms used in these experiments are described in Section 3. Results and the analysis is presented in Section 4. Finally, the conclusions reached are presented in Section 5.

2 The Adaptive Fusion Framework

The use of multiple biometrics has seen a growing number of fusion frameworks being proposed using different modalities. There have been wide-ranging research in the fusion of various modalities such as speech and face, face and fingerprint [1] and more recently 2D and 3D face information [6][7]. In these investigations, the advantage of using fusion is not in dispute. However what is not clear is how these systems deal with failure to acquire images or to acquire images of adequate quality, or failure to process in one of the modalities is dealt with. Such systems have fixed thresholds and would be liable to falsely accepting users or reject users when one modality or algorithm fail (fails to acquire or process a particular biometric, for example) therefore reducing both accuracy and efficiency.

The motivation behind the method is to provide an adaptive fusion platform where the software system can identify failures in certain algorithms and if necessary adapt the current rule to ignore these algorithms and adjust thresholds accordingly. In the field, a configuration switch can be embedded in the software to adopt certain configurations according to the pattern of failure, with each configuration constituting of a pre-defined combinations and operational settings. This is depicted in Figure 1.

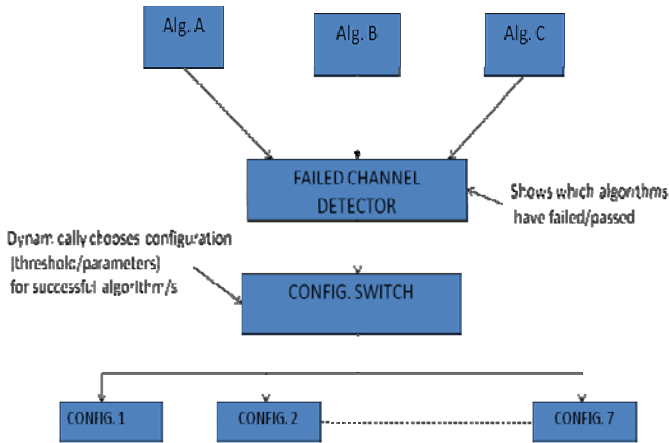


Fig. 1. An Adaptive fusion framework for multibiometrics

In the depicted system, the output of a set of different algorithms (Alg. A –C), which process different biometrics modalities indicates whether the acquisition and processing of the acquired biometric has been successful or not. Each algorithm outputs a code, say ‘1’ or ‘0’. The code produced is then interpreted by the configuration switch, which then chooses the optimum configuration settings to employ.

Testing of such a system in a laboratory setting is a challenge, if the aim is to produce ROC curves which show different operating points. This is because of the difference in the thresholds required for each configuration. You can therefore not adjust a uniform set of thresholds for the whole system, which makes the plotting of ROC curves impossible. However figures relating to the verification rate, FAR and FRR at certain predefined thresholds can be obtained. In the next section experiments carried out using 4 different 2D and 3D face recognition algorithms and 2 sets of combinations are described.

3 Experiments

3.1 Database and Test Scenarios

The experiments we carried out on a database collected by the 3D Face project [4]. One hundred subjects were used for this phase of testing; containing a total of 2200 images. 3D images and 2D images were obtained using the ViSense Scanner [8] developed within 3D Face.

The tests were designed to address three application scenarios created using 3 different masks for selecting the appropriate scores from the scores and decision matrices [2]. **Scenario 1 (S1)** tests the performance of the system. Only neutral expressions are considered that is, *Neutral vs Neutral*. **Scenario 2 (S2)** tests the realistic operational conditions, which takes into account the fact that expressions might differ during verification. It therefore tests the neutral expressions against other expressions (smiling and talking); that is, *Neutral vs. Expressions*. **Scenario 3 (S3)** tests the robustness of the system. It therefore compares neutral expressions against all other expressions and poses (see Figure 2); that is, *Neutral vs All*. Results in this paper are presented for this challenging scenario (S3).



Fig. 2. Poses and expressions: Images from left to right (top to bottom); frontal-neutral expression without glasses (only for individuals usually wearing glasses), frontal-neutral expression, frontal-smiling, frontal-talking, frontal-wearing a cap; head turned right, head turned left, head turned down, head turned up [2]

3.2 3D and 2D Face Recognition Algorithms

Four face recognition algorithms provided by three members of the consortium were utilized in the experiments. Three 2D and one 3D face recognition algorithm were utilized in the combinations. Brief descriptions of the algorithms are provided in this section. The names of the providers are withheld for commercial purposes; acronyms will be used.

A2D (2D Face recognition algorithm) –In this algorithm after normalization, face features are extracted by applying local image transforms at a set of predefined image locations. These features are then concatenated from these components to form a raw feature vector. A global transform is then applied to the raw feature vector to produce the final vector which is used for the matching step.

B2D (2D face recognition algorithm) – This 2D algorithm represent the facial geometry by means of a flexible grid which is adjusted to the specific facial pose and expression by adjusting the size, position, and internal distortion. A set of specific filter structures is assigned to each node of the graph and analyzes the local facial features. Approximately 2,000 characteristics are used to represent a face and an individual identity and are used for matching.

C2DHR (high resolution 2D face recognition algorithm) - This algorithm is based on a multi-resolution analysis of the skin texture. After normalization, several pre-processing steps are performed in order to emphasize the skin texture singularities (features) in the high informational zones of the face. These features are then associated with 2D template for the matching phase.

A3D (3D face recognition algorithm) - In this algorithm, firstly face localization, normalization and smoothing is performed. From the smoothed data, shape descriptors are determined which form the raw vectors. These are transformed by a global transform into templates maximizing the ratio of inter-person and intra-person variance. The similarity between two 3D faces is obtained by applying a simple function on their templates.

These four algorithms were used in two combination set-ups to evaluate the fusion framework. The experiments are described in the next section.

3.3 Adaptive and Non-adaptive Fusion

The following combinations were tested; *A2D-A3D-B2D* and *A2D-B2D-C2DHR*. These combinations were picked because the individual algorithms had significant failure to acquire rates. Two fusion methods were used, the Sum and Weighted-Sum. The weights for the Weighted Sum Method were calculated using the equal error rates for each algorithm obtained from a disjoint fusion training set.

Table 1. Possible output patterns for a 3-algorithm fusion combination and corresponding thresholds (F – fail, S = success)

Output Pattern	P1	P2	P3	P4	P5	P6	P7	P8
Alg1	F	F	F	S	F	S	F	S
Alg2	F	F	S	S	F	F	S	S
Alg3	F	F	F	F	S	S	S	S
Thresh.	R	T1	T2	T3	T4	T5	T6	T7

The target performance set for the 3D Face Project was an FAR = 0.0025 at an FRR = 0.025 [2]. Therefore the operating points (thresholds) for the fusion system were set at these targets. These operating points were obtained from a disjoint training set. For each possible output pattern (P1-P8) for the fusion set-up, corresponding thresholds (T1-T7) were obtained and stored as shown in Table 1. R’ means a complete rejection.

4 Results

In S3, the database had a total of 223 849 imposter scores and 3 287 genuine scores (a total of 22 7136). The confusion matrices in Tables 2-5 show the results obtained for the two different approaches; adaptive and non-adaptive fusion for the two different combinations and two fusion methods.

Table 2. Sum Result: A2D-A3D-B2D

Adaptive			Non-Adaptive		
	Gen	Imp		Gen	Imp
Gen	3131	156	Gen	3089	120
Imp	340	223509	Imp	340	217854

Table 3. Weighted Sum Result: A2D-A3D-B2D

Adaptive			Non-Adaptive		
	Gen	Imp		Gen	Imp
Gen	3123	164	Gen	3106	103
Imp	958	222891	Imp	958	217236

Table 4. Sum Result: A2D-B2D-C2DHR

Adaptive			Non-Adaptive		
	Gen	Imp		Gen	Imp
Gen	3173	114	Gen	3127	82
Imp	276	223573	Imp	276	217918

Table 5. Weighted Sum Result: A2D-B2D-C2DHR

Adaptive			Non-Adaptive		
	Gen	Imp		Gen	Imp
Gen	3199	88	Gen	3157	52
Imp	2252	221597	Imp	2252	215942

In these tables, the first row (Gen) indicates the number of genuine users accepted correctly (under the ‘Gen’ column) and those falsely rejected (under the ‘Imp’ column) respectively. The second row (Imp) illustrates the number of imposters falsely accepted by the system (under the ‘Gen’ column) and the number of imposters correctly rejected by the system (under the ‘Imp’ column).

In each case the number of genuine users rejected completely by the non-adaptive system is 78 (that is, for example in Table 2: $(3287 - (3089+120))$); which is a failure rate of 2.37%. This means in a large airport, processing for example 100 000 people per day, 2 370 are completely rejected. The number of imposters rejected by the system in each case is 5655 (that is, for example in Table 2: $223\ 849 - (340+217854)$) a failure rate of 2.53%.

The adaptive system in this case, processes all users. It increases the number of genuine users who successfully uses the system, who otherwise would have been rejected by the non-adaptive system. For example, of the 78 genuine users rejected by the non-adaptive system for A2D-A3D-B2D-Sum (Table 3), 42 are successfully processed (column A in Table 6), that is 54% (column B in Table 2) of these. In all cases, the 5655 imposters rejected by the non-adaptive are successfully processed (and correctly rejected). All the corresponding figures for the other combinations are given in Table 2. These figures are hugely significant in large scale implementations.

Table 6. Scale of rejected genuine users by non-adaptive system who are successfully processed by the adaptive system

	A	B
A2D-A3D-B2D-Sum	42	54%
A2D-A3D-B2D WSum	17	22%
A2D-A3D-B2D-Sum	50	64%
A2D-A3D-B2D WSum	42	54%

From these results it can be observed that using the adaptive system, the number of users accepted by the system is increased, therefore increasing the efficiency of the system. In this case all users are processed successfully by the adaptive system.

It can also be observed that despite the increase in the number of users being processed by the system in the adaptive framework, the number of imposters falsely accepted is not increased, therefore security is not compromised.

Table 7. The verification rates of the two systems

	Verification Rates	
	N-Adaptive	Adaptive
A2D-A3D-B2D-Sum	0.94	0.95
A2D-A3D-B2D WSum	0.94	0.95
A2D-A3D-B2D-Sum	0.95	0.97
A2D-A3D-B2D WSum	0.96	0.97

Table 7 shows the verification rates of the two systems. There is an increase in the verification rate in each case when using adaptive fusion (number of genuine users correctly accepted).

5 Conclusion

Multiple biometrics fusion can be efficient if all the biometrics are working correctly without failure. However if one or more of the biometrics fails, the system's accuracy and efficiency is compromised. Adaptive fusion is one solution to handle such a situation. From these experiments, the advantages of using the adaptive fusion approach has been shown to improve the performance of the 3D and 2D face recognition system in terms of verification rate and efficiency without compromising the security of the system (no increase in false acceptance) and presents a framework for utilising multi-biometric fusion in a more efficient way. Even though experimental results are presented for 2D and 3D facial biometrics fusion, the proposed system is generic and can be employed in any multi-biometric scenario.

Acknowledgments. The authors would like to acknowledge the support of 3D FACE, a European Integrated Project funded under the European Commission IST FP6 program contract number 026845.

References

1. Ross, A., Nandakumar, K., Jain, A.: Handbook of Multibiometrics. Int. Series on Biometrics. Springer, Heidelberg (2006)
2. Castro Neves, M., Chindaro, S., Ng, M., Zhou, Z., Deravi, F.: Performance Evaluation of Multibiometric Face Recognition Systems. In: Proceedings of the Special Interest Group on Biometrics and Electronic Signatures (BIOSIG 2008), Germany. Lecture Notes in Informatics (LNI), vol. P-137, pp. 47–58. Springer, Heidelberg (2008)
3. Veldhuis, R.N.J., Deravi, F., Tao, Q.: Multibiometrics for face recognition. *Datenschutz und Datensicherheit – DuD* 32(3), 204–214 (2008)
4. 3DFace, <http://www.3dface.org/home/welcome>

5. International Civil Aviation Organization Technical Advisory Group 15 Machine Readable Travel Documents/New Technologies Working Group, Biometrics Deployment of Machine Readable Travel Documents, Version 2.0 (May 2004)
6. Chang, K.I., Bowyer, K.W., Flynn, P.J.: Face recognition using 2D and 3D facial data. In: Proceedings of ACM Workshop on Multimodal User Authentication, pp. 25–32 (2003)
7. Cook, J., McCool, C., Chandran, V., Sridharan, S.: Combined 2D/3D Face Recognition Using Log-Gabor Templates. In: 2006 IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS 2006), p. 83 (2006)
8. Neugebauer, P.J.: Research on 3D Sensors - Minimizing the Environmental Impacting Factors. In: Workshop on Biometrics and eCards (2007)