Trust the Biometric Mainstream: Multi-biometric Fusion and Score Coherence

Naser Damer[1], Chadi Izzou Rhaibani[1], Andreas Braun[1], Arjan Kuijper[12]
[1]Fraunhofer Institute for Computer Graphics Research IGD
Darmstadt, Germany
[2]Mathematical and Applied Visual Computing group, Technische Universität Darmstadt
Darmstadt, Germany
Email:{naser.damer, chadi.izzou.rhaibani, andreas.braun, arjan.kuijper}@igd.fraunhofer.de

***Abstract*—Multi-biometrics aims at building more accurate unified biometric decisions based on the information provided by multiple biometric sources. Information fusion is used to optimize the process of creating this unified decision. In previous works dealing with score-level multi-biometric fusion, the scores of different biometric sources belonging to the comparison of interest are used to create the fused score. This is usually achieved by assigning static weights for the different biometric sources with more advanced solutions considering supplementary dynamic information like sample quality and neighbours distance ratio. This work proposes embedding score coherence information in the fusion process. This is based on our assumption that a minority of biometric sources, which points out towards a different decision than the majority, might have faulty conclusions and should be given relatively smaller role in the final decision. The evaluation was performed on the BioSecure multi-modal biometric database with different levels of simulated noise. The proposed solution incorporates, and was compared to, three baseline static weighting approaches. The enhanced performance induced by including the coherence information within a dynamic weighting scheme in comparison to the baseline solution was shown by the reduction of the equal error rate by 45% to 85% over the different test scenarios and proved to maintain high performance when dealing with noisy data.**

I. Introduction

Biometric technology aims at identifying or verifying the identity of individuals based on their physical or behavioural characteristics. Combining more than one biometric source is often performed to increase the accuracy, robustness and usability of biometrics. The different biometric sources can be based on different characteristics, captures, algorithms, sensors, or instances. Putting together the information provided by these sources and creating a unified biometric decision is referred to as multi-biometric fusion.

The fusion process can be applied on different levels such as the data, feature, score, or rank level. Higher levels such as score and rank provide a more flexible and integrable solution. Data and feature fusion levels provide more information but affect the integrability and may be hard to achieve in certain multi-biometric combinations. In this work, the score-level fusion will be considered as it provides a fair tradeoff between performance and integrability.

This work proposes the use of the multi-biometrics scores coherence as a supplementary source of information in the fusion process. This is based on the assumption that if most of the biometric sources point out to a certain decision (mainstream), the smaller number of sources pointing elsewhere might be misinformed (e.g. due to noisy captures) and thus should play a smaller role in the final decision. A coherence measure is defined and integrated in the fusion process as a dynamic weight along with a conventional static source weighting approach.

The proposed fusion technique is evaluated on the BioSecure multi-modal biometric database [1]. Different versions of the database were created by adding blur noise to a certain percentage of the raw data, to create a more realistic scenario. The proposed inclusion of coherence information proved to reduce the equal error rates by more than 45% in comparison to the baseline solution in all evaluation settings. More importantly, in the scenarios where noisy data is involved, including the coherence information limited the effect of noise on the overall performance.

The next section contains a short overview of related works motivating and leading to the presented approach. In Section III, the proposed solution is discussed along with the evaluated baseline solution. The experiment setup and the achieved results are then presented in Sections IV and V. Finally, in Section VI, a conclusion of the work is drawn.

II. Related work

Score-level biometric fusion techniques can be categorized into two main groups, combination-based and classification-based fusion. Combination-based fusion consists of simple operations performed on the normalized scores of different biometric sources. These operations produce a combined score that is used to build a biometric decision. One of the most used combination rules is the weighted sum rule, where each biometric source is assigned a relative weight that optimizes the source effect on the final fused decision. The weights are related to the performance metrics of the biometric sources, a comparative study of biometric source weighting is presented by Chia et al. [2] and later extended by Damer et al. [3].

Classification-based fusion views the biometric scores of a certain comparison as a feature vector. A classifier is trained to classify those vectors optimally into genuine or impostor comparisons. Different types of classifiers were used to perform multi-biometric fusion, some of those are support

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vector machines (SVM) [4][5][6], neural networks [7], and the likelihood ratio methods [8].

More advanced approaches of multi-biometric fusion considered dynamic weights that adapt to the comparison set in hand. Hui et al. proposed a dynamic weighting approach for multi-biometric fuzzy-logic based fusion [9]. The dynamic weights took into account the variations during data acquisition (e.g. lighting, noise and user-device interactions). Other works applied dynamic weights based on capture quality and scenario on a feature level fusion process [10][11].

Conventionally, score-level multi-biometric fusion exclusively uses the biometric comparison scores provided by the fused biometric sources and general information about those sources (e.g. weights). Previous works extended this concept to include additional supplementary information. Sample quality information related to each biometric comparison was integrated into the fusion process, resulting in accuracy gain [12][13][14], but requires analysing the raw data. Another source of supplementary information is the relative relation between different comparisons. This was previously fused with the comparison scores in the form of neighbour distance ratios with performance boost seen especially in scenarios such as biometric duplicate enrolment checks [6]. However, this requires 1:N comparisons, where N is the number of enrolled identities. In the following sections, this work proposes to include information related to comparison scores coherence within the fusion process.

III. Methodology

The score-level multi-biometric fusion approach presented in this work aims at integrating supplementary information based on the coherence of the fused scores. The coherence here points out the level of agreement of one score with all the other fused scores. The basic assumption is that, in a group of decision makers (multi-biometric sources) giving an opinion (score) on a certain topic (multi-biometric comparison), the mainstream opinion (opinion pointed out by the majority of decision makers) have a higher probability of being correct. Odd (outlier) decision, made by a relatively small number of decision makers, has a higher probability of being misinformed or misanalysed decision (e.g. noisy capture, poor preprocessing).

Within this scheme, a biometric score that has a higher level of agreement (coherence) with the other scores, in the same multi-biometric comparison, will be appointed a relatively higher weight and thus have more influence on the final decision. This is coupled with a static weight that points out the general quality of each biometric source.

The rest of this section will introduce the used coherence measure, the baseline static weights that will also be coupled with the coherence based dynamic weight, and how both weights are integrated with the scores to result in the fused score.

A. Coherence

The coherence measure for a certain score should point out the agreement of this score with all other scores in the same multi-biometric comparison. Based on this, a simple coherence measure was defined as the inverse of the average distance of the concerned score to all other scores in the multi-biometric comparison. Given that all scores are properly normalized, the coherence measure of the score $S_{k,l}$ (belonging to the source k out of K sources) in a multi-biometric comparison noted by l, is given as:

$$Coh(S_{k,l}) = \frac{K-1}{\epsilon + \sum_{i \neq k} |S_{k,l} - S_{i,l}|}, \tag{1}$$

where ϵ is a small positive number to avoid zero denominator (here, $\epsilon = 0.01$).

A score with a higher coherence value points out a higher probability for a score to be of the mainstream decision of the multi-biometric sources, and thus, should be given a relatively higher weight. This results in the coherence based dynamic weight given as:

$$w_{k,l}(Coh_{k,l}) = \frac{Coh_{k,l}}{\sum_{i=1}^{i=K} Coh_{i,l}}. \tag{2}$$

B. Static weights

To influence the general accuracy of each biometric source in the multi-biometric fusion process, static weights are used to weight the biometric scores. The static weights are constant for each biometric source (hence, static). In this work, the static weighting is used as a baseline solution to measure the effect of adding the coherence information into the fusion process. They are also used to influence this information along with the coherence based dynamic weights as will be shown later. Three different types of static weights are used, namely the equal error rate weighting (EERW), the D-Prime weighting (DPW), and the Fisher discriminant ratio weighting (FDRW).

The EERW is based on the equal error rate (EER) value which is the common value of the false acceptance rate (FAR) and the false rejection rate (FRR) at the operational point where both FAR and FRR are equal. EER weighting was used to linearly combine biometric scores in the work of Jain et al. [15]. The EER is inverse proportional to the performance of the biometric source. Therefore, for a multi-biometric system that combines K biometric sources, the EER weight for a biometric source k is given by

$$w_k(EER_k) = \frac{\frac{1}{EER_k}}{\sum_{i=1}^{K} \frac{1}{EER_i}}. \tag{3}$$

The DPW is based on the D-Prime that is used to measure the separation between the genuine and the imposter scores [16]. High separation indicates a higher performance of the biometric source. Given that σ_k^G and σ_k^I are the genuine scores and imposter scores standard deviations and μ_k^G and μ_k^I are their mean values, the D-prime is given by

$$d'_k = \frac{\mu_k^G - \mu_k^I}{\sqrt{(\sigma_k^G)^2 + (\sigma_k^I)^2}}, \tag{4}$$

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and it is directly proportional to the performance of the biometric source and thus the weight can be calculated as:

$$w_k(d'_k) = \frac{d'_k}{\sum_{i=1}^{K} d'_i}. \quad (5)$$

The third static weight considered in this work is the FDRW. The Fisher Discriminant Ratio (FDR) as described by Lorena and Carvalho [17] and used by Poh et al. [18] measures the separability of classes, here genuine and imposter scores. The higher the separability, the higher is the biometric source performance. The FDR and the corresponding weights are given as:

$$FDR_k = \frac{(\mu_k^G - \mu_k^I)^2}{(\sigma_k^G)^2 + (\sigma_k^I)^2}, \quad (6)$$

$$w_k(FDR_k) = \frac{FDR_k}{\sum_{i=1}^{K} FDR_i}. \quad (7)$$

C. Fusion

To capture both the general performance of each biometric source and the individual certainty represented by the coherence, a combined weight was proposed as follows:

$$w_{k,l}(Coh_{k,l}, St_k) = \beta w_{k,l}(Coh_{k,l}) + (1-\beta) w_k(St_k). \quad (8)$$

Here, β is a constant between zero and one [0,1]. β controls the relative effect of the dynamic and static weights. Different values of β are evaluated to optimize the trade-off between both types of weights. St is the static weight that can be EERW, DPW, or FDRW.

The fused score based on the dynamic weighting is given by

$$F = \sum_{i=1}^{K} w_{k,l}(Coh_{k,l}, St_k) S_{k,l}, \quad (9)$$

where $S_{k,l}$ is a score of the biometric source k of the comparison l and $w_{k,l}$ is its corresponding dynamic weight as in Equation 8.

IV. Experimental Setup

A. Database

The database used to develop and evaluate the proposed solution is the BioSecure multi-modal biometric database [1]. This database was acquired within the framework of the European BioSecure Network of Excellence. This work utilize three biometric sources out of the DS2 part of the BioSecure database, the face (webcam, no flash) and both the left and right middle fingers captured by an optical sensor. This data was collected on a desktop PC environment in seven different European institutions and totalled in 210 subjects over two sessions.

1) Noise: to simulate a more realistic scenario, the raw captures of both fingers and face images were subjected to bluring using an averaging filter of the size *m x m*. The blurring was performed on the second session data, considered as probe in this work. While the data of session 1 was considered as reference data and was not subjected to additional noise. The noise was applied by randomly selecting the filter dimension *m* to be one of $\{7, 9, 11, 13\}$.

Each probe sample of the three biometric sources was compared to each reference sample resulting in a similarity score. This was done using the original (noise-free) data and the data with induced noise. This resulted in a noise-free and a noise-induced scores databases. To create a realistic scenario, a certain percentage of the noise-free score database was randomly replaced by scores from the noise-induced score database. This resulted in the four score databases used in this work with 0%, 2.5%, 7.5%, and 15% of their scores originating from the noise-induced probes.

2) Comparators: the following methods were used to measure the comparison score between pairs of face images and pairs of fingerprint scans:

Face comparison: to calculate a similarity scores between face captures, the OpenFace implementation was used [19]. OpenFace is a Python and Torch implementation based on the work of Schroff et al. [20]. This solution utilises a deep neural network to build a 128-dimensional unit hypersphere face representing.

Fingerprint comparison: fingerprint comparison used the NIST Biometric Image Software (NBIS) implementation [21]. This implementation utilised the MINDTCT algorithm [21] to locate all minutiae in a fingerprint scan, assigning to each minutia point its location, orientation, type, and quality. BOZORTH3 algorithm [21] is used to perform the comparison by using the minutiae detected by MINDTCT to determine if two fingerprints are from the same person and same finger.

B. Experiments

The goal of our experiments is to show the effect of embedding coherence information in the multi-biometric score-level fusion process. This effect is also important in the more realistic scenario where some of the captured data is noisy. To achieve that, the proposed solution and the base line solutions are tested on four different database settings. As described in Section IV-A, the databases always included noise-free reference data and a certain percentage of noise-induced probe data. The four resulting score databases contains a portion of scores originated from noisy probe data of the percentage 0%, 2.5%, 7.5%, and 15%.

To evaluate the statistical performance of the proposed solutions, the database was split into three equal-sized partitions. Experiments were performed on all possible fold combinations where one partition is used as an evaluation set and the other two are used as a development set. All the reported results are the averaged results of the three evaluation/development combinations.

Min-max normalization was used to bring comparison scores produced by different biometric sources to a comparable range. Min-max normalized score is given as

$$S = \frac{S' - min\{S'_k\}}{max\{S'_k\} - min\{S'_k\}}, \quad (10)$$

where $min\{S'_k\}$ and $max\{S'_k\}$ are the minimum and maximum value of pre-normalization scores existing in the training data of the corresponding biometric source, and S is the normalized score.

The evaluation was performed on each of the four score databases using the three different static weights EERW, FDRW, and DPW. As in Eq. 8, β was used to control the relative effect of each of the dynamic coherence weight and the static weight. A β value of zero presented the baseline solution were only the static weight is in effect. The fusion included the three biometric sources (face and two fingerprints) under a verification scenario.

V. Results

The achieved results under different experiment settings are presented as receiver operating characteristic (ROC) curves and EER values. The EER is the common value of the false acceptance rate (FAR) and false rejection rate (FRR) at the operational point (decision threshold) where both rates are equal. The EER value provides a general and comparable measure of the evaluation performance, lower EER values correspond to higher performance. ROC curves plot the false acceptance rate (FAR) and the true acceptance rate (TAR) at different operational points (thresholds) and presents the trade-off performance between the two rates. In contrast to EER values, ROC curves provides a wider insight into the verification performance at all possible operational points. This might be of interest for a user focused on a relatively low FAR or FRR rate for a specific application.

The EER values achieved under different experiment settings are presented in Table I. The positive effect of including coherence information becomes apparent when comparing the baseline approaches ($\beta = 0$) at different noisy data percentages. When no noisy data was involved, EER was reduced by 48% when combined with EERW and 82% when combined with FDRW, both at $\beta = 0.85$ and in comparison with the baseline pure static weighting ($\beta = 0$). At a noisy data percentage of 15%, the EER reduction was 63% and 81% for the EERW and FDRW based solution respectively (comparison between $\beta = 0$ and $\beta = 0.85$). It must be noticed that although the effect of the noise is clear in the baseline static weight solutions, the achieved error rates when including coherence information is only slightly effected by noise.

To put the presented values in prospective, the single source EER value for the face source is 2.0% in the 0% noise-induced data and 4.3% in the 15% noise-induced data. The EER values for the left middle fingerprint source are 3.3% and 4.6% respectively.

The ROC curves in Figure 1 show the effect of including the coherence information at different operation points. The curves are a comparison of the EERW based solution at the baseline $\beta = 0$ and the presented coherence based solution at $\beta = 0.85$. The improvement in the performance at very low FAR is clear on noise-free data. More importantly, the performance of the coherence based solution on the noise-induced data almost matches that of the noise-free data. On the other hand, the negative effect of the more realistic noise-induced data on the performance of the baseline solutions is noticeable. Similar behaviours also appears for the FDRW and DPW based solutions.

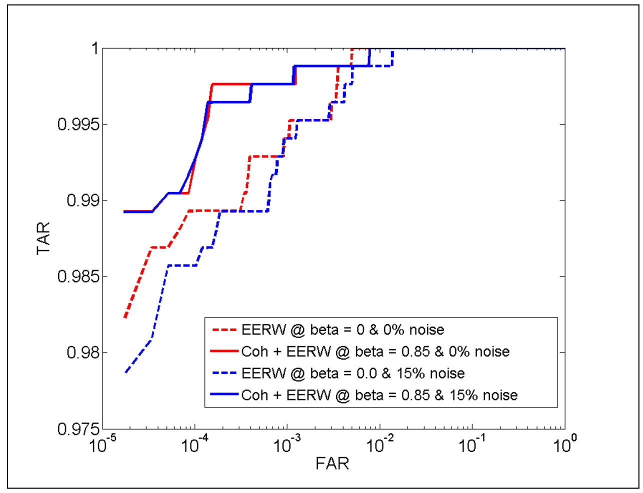

Fig. 1: ROC curves showing the performance of the proposed solution and the baseline using the EERW as static weight under different percentages of noisy data.

VI. Conclusion

This work proposed the use of score coherence information in multi-biometric score-level fusion. This was based on the assumption that the minority of decision makers (biometric sources) pointing out a different decision than the majority, might have faulty conclusions and should be given a relatively smaller role in the final fused decision. This was incorporated in a dynamic weighting approach that also considers static weights. The approach was evaluated on a database with different level of induced noise and was compared to three baseline static weight solutions. Including the coherence information proved to largely enhance the biometric performance, especially in the more realistic scenario where some of the captured data could be slightly noisy.

Acknowledgement

This work was supported by the German Federal Ministry of Education and Research (BMBF) as well as by the Hessen State Ministry for Higher Education, Research and the Arts (HMWK) within CRISP.

	EERW Percentage of noisy data				DPW Percentage of noisy data				FDRW Percentage of noisy data			
β	0.00%	2.50%	7.50%	15.00%	0.00%	2.50%	7.50%	15.00%	0.00%	2.50%	7.50%	15.00%
0	0.2349	0.2349	0.3546	0.3454	0.2535	0.253	0.3709	0.358	0.6691	0.6694	0.795	0.7197
0.05	0.2307	0.2307	0.3491	0.3391	0.2473	0.247	0.3643	0.3574	0.5861	0.5861	0.6971	0.6837
0.1	0.2218	0.2218	0.3414	0.3343	0.2381	0.2375	0.3589	0.3543	0.4971	0.4968	0.4991	0.4087
0.15	0.2143	0.2141	0.3371	0.3331	0.2318	0.2315	0.3506	0.348	0.4553	0.4544	0.4851	0.384
0.2	0.2103	0.2098	0.33	0.2684	0.1686	0.1683	0.2865	0.3431	0.3703	0.3697	0.4728	0.38
0.25	0.1439	0.1434	0.2639	0.2596	0.1625	0.1623	0.2816	0.334	0.2776	0.277	0.3903	0.3643
0.3	0.1402	0.1402	0.2618	0.2621	0.1514	0.1508	0.2681	0.332	0.2598	0.2596	0.378	0.3609
0.35	0.1365	0.1362	0.2613	0.2581	0.1437	0.1437	0.2699	0.2664	0.2435	0.243	0.3663	0.3557
0.4	0.1316	0.1316	0.259	0.2553	0.1425	0.1434	0.2598	0.2604	0.2398	0.2361	0.3586	0.3514
0.45	0.1328	0.1331	0.2455	0.2418	0.1394	0.1394	0.2581	0.2547	0.2318	0.2315	0.3494	0.3437
0.5	0.1331	0.1319	0.2338	0.2309	0.1334	0.1331	0.243	0.2395	0.2195	0.2192	0.338	0.3348
0.55	0.1265	0.1299	0.2238	0.2232	0.1322	0.1311	0.2292	0.2264	0.2066	0.2109	0.3288	0.271
0.6	0.1282	0.1273	0.1574	0.1551	0.1305	0.1294	0.2206	0.2189	0.1422	0.1431	0.2533	0.255
0.65	0.1276	0.1268	0.15	0.1465	0.1276	0.1268	0.1505	0.1477	0.1328	0.1328	0.2307	0.2378
0.7	**0.1219**	**0.1213**	0.1411	0.1402	**0.1236**	0.1276	0.1457	0.1439	0.1302	0.1296	0.2189	0.2204
0.75	**0.1242**	**0.1236**	0.1336	0.1334	**0.1228**	**0.1222**	0.1334	0.1379	**0.1245**	0.1305	0.1522	0.1497
0.8	0.1262	0.1253	0.1322	0.1314	**0.1248**	**0.1239**	**0.1311**	0.1296	**0.1251**	**0.1242**	0.1431	0.1405
0.85	**0.1219**	**0.1211**	**0.1259**	**0.1294**	**0.1216**	**0.1208**	**0.1314**	**0.1294**	**0.1216**	**0.1208**	**0.1348**	**0.1359**
0.9	**0.1251**	**0.1242**	**0.1268**	**0.1245**	**0.1248**	**0.1239**	**0.1265**	**0.1253**	**0.1219**	**0.1211**	**0.1256**	**0.1296**
0.95	0.1262	0.1256	**0.1294**	**0.1253**	0.1259	0.1253	**0.1291**	**0.1248**	0.1256	**0.1251**	**0.1282**	**0.1245**
1	0.1268	0.1265	**0.1314**	**0.1242**	0.1268	0.1265	0.1314	**0.1242**	0.1268	0.1265	**0.1314**	**0.1242**

TABLE I: The achieved EER values (in percentage) for the different baseline solutions and with different levels of the proposed score coherence influence (β) under different percentage of noise-induced data. The lowest range of error rates per experiment setting (column) are in bold.

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ISBN 978-0-9928626-7-1 © EURASIP 2017