Weighted Integration of Neighbors Distance Ratio in Multi-biometric Fusion

Naser Damer, Alexander Nouak

Competence Center Identification and Biometrics
Fraunhofer Institute for Computer Graphics Research (IGD)
Darmstadt, Germany
naser.damer@igd.fraunhofer.de
alexander.nouak@igd.fraunhofer.de

Abstract: This work presents an approach to integrate biometric source weighting in the calculation of neighbors distance ratios to be used within a classification-based multi-biometric fusion process. The neighbors distance ratio represents the elevation of the top ranked identification match to the following ranks. Using biometric source weighing can help achieve more accurate initial identity ranking necessary for neighbors distance ratios. It also influences the effect of each biometric source on the ratios values. The proposed approach is developed and evaluated using the Biometric Scores Set BSSR1 database. The results are presented in the verification scenario as receiver operating curves (ROC). The achieved performance is compared to a number of baseline solutions and a satisfying and stable performance was achieved with a clear benefit of integrating the biometric source weights.

1 Introduction

Biometrics technology aims at identifying or verifying the identity of individuals based on their physical or behavior characteristics. Combining more than one biometric source is often performed to increase the accuracy, robustness and usability of biometrics [DOS13]. The different biometric sources can be based on different characteristics, captures, algorithms, sensors, or instances. Putting together the information provided by those 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 trade-off between performance and integrability.

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. Those 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. [CSN10] and extended later by Damer et al. [DON14a][DON14b].

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 imposter comparisons. Different types of classifiers were used to perform multi-biometric fusion, some of those are support vector machines (SVM) [SVN07][GV00][DO14], neural networks [Als10], and the likelihood ratio methods [NCDJ08].

A biometric system usually operates under one of two scenarios, verification or identification. Verification is the authentication of a claimed identity based on the captured biometric characteristics. Identification is assigning an identity to an unknown individual based on their biometric characteristics. Identification can operate as a closed-set identification where the user is known to be included in the biometric references set, or as an open-set identification where the user is not definitely included in the references set. In open-set identification, a verification final step is required to verify that the top ranked identification match is certainly the same captured subject and not an unenrolled subject.

Keeping the open-set identification scenario in mind, previous work by Damer et al. [DO14] tried to use the information provided by the ranked set of comparisons to perform more accurate verification of the top rank. The assumption was that a genuine top rank comparison has a lower distance ratio to its rank neighbors than that of an imposter comparison, this distance ratio was referred to as the neighbor distance ratio (NDR). Those information were integrated into a classification-based fusion approach using SVM.

This work proposes introducing information about the performance of the different biometric sources into the NDR calculation process. This will help in producing more accurate initial ranking and more informative NDR values as discussed later in Section 2. The performance information were included as biometric source weights calculated based on the Overlap Deviation Weighting (OLDW) [DON14a].

The proposed fusion technique is evaluated over the Biometric Scores Set BSSR1 - multimodal database [BSS]. A number of previously proposed base-line fusion approaches were evaluated including state-of-the-art combination rules and the use of SVM with and without consideration of the neighbor distance ratio. The proposed technique proved to outperform the base-line solution and the results are presented as Receiver Operating Characteristics (ROC) curves.

In Section 2 the proposed solution is discussed along with the evaluated base-line solutions. The experiment setup and the achieved results are then presented in Section 3. Finally, in Section 4, a conclusion of the work is drawn.

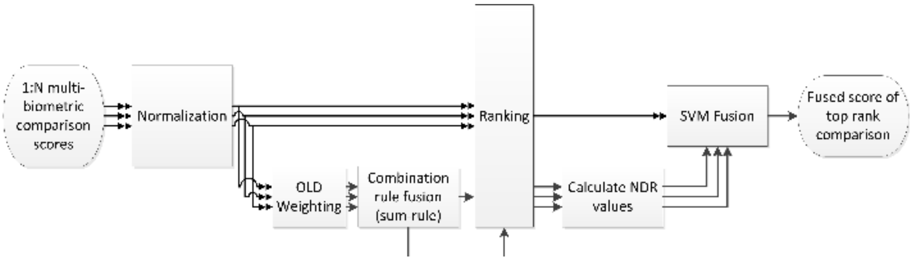

Figure 1: An overview of the proposed solution. The input scores of an 1:N comparison is weighted (OLDW) and fused by simple sum combination rule then ranked based on the resulted scores. The NDR values based on this ranking is concatenated with the original scores of the comparison to be verified. The concatenated vector is fed into the SVM to create a final fused score.

2 Methodology

2.1 Proposed solution

The assumption that builds the basis of the proposed solution in this work is anchored on the Neighbor Distance Ratio (NDR). Given a rank set of comparison scores that represents an 1:N comparison, NDR is defined as the ratio between one score in this set and a score of a higher rank (neighbor distance). NDR was previously used in the literature to match interest key point descriptors in images [MS05]. Looking into the NDR from the biometric prospective, the inverse ratio between a genuine similarity score and the next highest score (within a ranked 1:N comparison) is assumed to be lower than this ratio between an imposter score and the next highest score.

The contribution of this work is based on providing more accurate initial ranking to calculate NDR values. This is achieved by using OLD weighting [DON14a] approach to assign relative weights to different biometric sources to influence their effect on the overall initial ranking, and thus the accuracy of the NDR values. The weighted biometric scores also effects the values of the NDR as the initially fused scores are also fused by a weighted sum rule.

The proposed solution in this work aims at considering both, the scores absolute values and the relative distances to higher ranks in order to perform more accurate biometric verification. To achieve that, a classification-based fusion approach based on support vector machines (SVM) was used. In classification-based multi-biometric fusion, the fusion process is viewed as a binary classification problem that aims to separate between two classes, genuine and impostor.

Support vector machines [Vap95] is a statistical learning technique often used to learn binary classifiers, i.e. to learn how to separate two classes using information gained from known examples (training data). Classical learning techniques, such as Neural Networks

(NN), focused on minimizing the empirical error (error on the training set). This approach is commonly referred to as Empirical Risk Minimization (ERM). However, the SVM follows the Structural Risk Minimization (SRM) instead of the ERM approach. The SRM insures a high generalization performance as it tries to minimize the upper bound of the generalization error. In simple words, SVM tries to build a class-separation surface in the feature space that is optimized in a manner which considers generalized unknown data.

In order to map the input data space into a feature space where the data is linearly separable, SVM uses kernel functions. In general, those functions help in enhancing the discrimination power. In this work, the Radial Basis Function (RBF) is used as a kernel function as it proved to outperform linear kernels when dealing with low dimensional space [SZL+11], such as the problem dealt with in this work.

The feature vector considered for the SVM fusion process consisted of two concatenated Parts, the initial comparison scores of different sources N and the NDR values based on the initial weighted fusion. Here, three NDR values were considered, 2nd-rank-to-1st-rank, 3rd-rank-to-1st-rank, and the 3rd-rank-to-2nd-rank. This will result in a feature vector of size $N+3$. The SVM classifies the input feature vector and the resulting decision function value (the signed distance to the margin) is considered as the final fused score. An overall look on the proposed method is presented in Figure 1

2.2 Baseline solution

A number of baseline solutions are presented here to build a reference for the performance evaluation presented in the next Section 3. The first baseline solution aims at direct comparison by using the SVM based solution that integrates NDR values without weighted ranking [DO14]. The second baseline solution will be SVM based approach without using NDR information. Two other solutions utilized the widely used weighted-sum approach are also discussed, one utilizes the EER as a source performance measure while the second uses the Non-Confidence Width (NCW).

The baseline SVM based approach that integrates NDR values is similar to the proposed solution here, however it does not use weighted scores for initial ranking and NDR calculation. Instead it uses simple equal weight sum rule fusion. This approach will be referred to as SVM-NDR.

The conventional SVM baseline approach takes the biometric comparison scores of different sources $\{S_1, \ldots, S_n\}$ as a feature vector. The SVM is trained to classify this feature vector into genuine or impostor classes and reports the resulted decision function value as the fused score. The SVM used here also uses similar configuration to the proposed approach with RBF as a kernel function.

The two other baseline approaches are based on the weighted-sum combination rule that assigns each score value S_k with the weight of its source w_k to produce the fused score. The weights w_k are calculated from the training data of each biometric source. The fused score F by the weighted sum rule for N score sources is given as:

$$F = \sum_{k=1}^{N} w_k S_k, k = \{1, \ldots, N\} \tag{1}$$

The weights used here are based on either EER (equal error rate) or NCW (Non-Confidence Width Weight) values. The EER weighting (EERW) is based on the 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. [JNR05]. The EER is inversely proportional to the performance of the biometric source. Therefore, for a multi-biometric system that combines N biometric source, the EER weight for a biometric source k is given by:

$$w_k = \frac{\frac{1}{EER_k}}{\sum_{k=1}^{N} \frac{1}{EER_k}} \tag{2}$$

The Non-Confidence Width Weight (NCWW) was proposed by Chia et al. [CSN10] to weight biometric sources for score-level multi-biometric fusion. NCW corresponds to the width of the overlap area between the genuine and imposter scores distributions. Given that Max_k^I is the maximum imposter score and Min_k^G is the minimum genuine score, NCW is given by:

$$NCW_k = Max_k^I - Min_k^G \tag{3}$$

as the NCW is inversely proportional to the biometric source performance, the weights based on the NCW is given as:

$$w_k = \frac{\frac{1}{NCW_k}}{\sum_{k=1}^{N} \frac{1}{NCW_k}} \tag{4}$$

3 Experiments and Results

The database used to develop and evaluate the proposed solution is the Biometric Scores Set BSSR1 - multimodal database [BSS]. The database contains comparison scores for left and right fingerprints (Fli and Fri) and two face matchers (Fc and Fg). BSSR1 - multimodal database contains 517 genuine and $266,772$ impostor scores. The experiments here considered all possible pairs between finger and face matchers. 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.

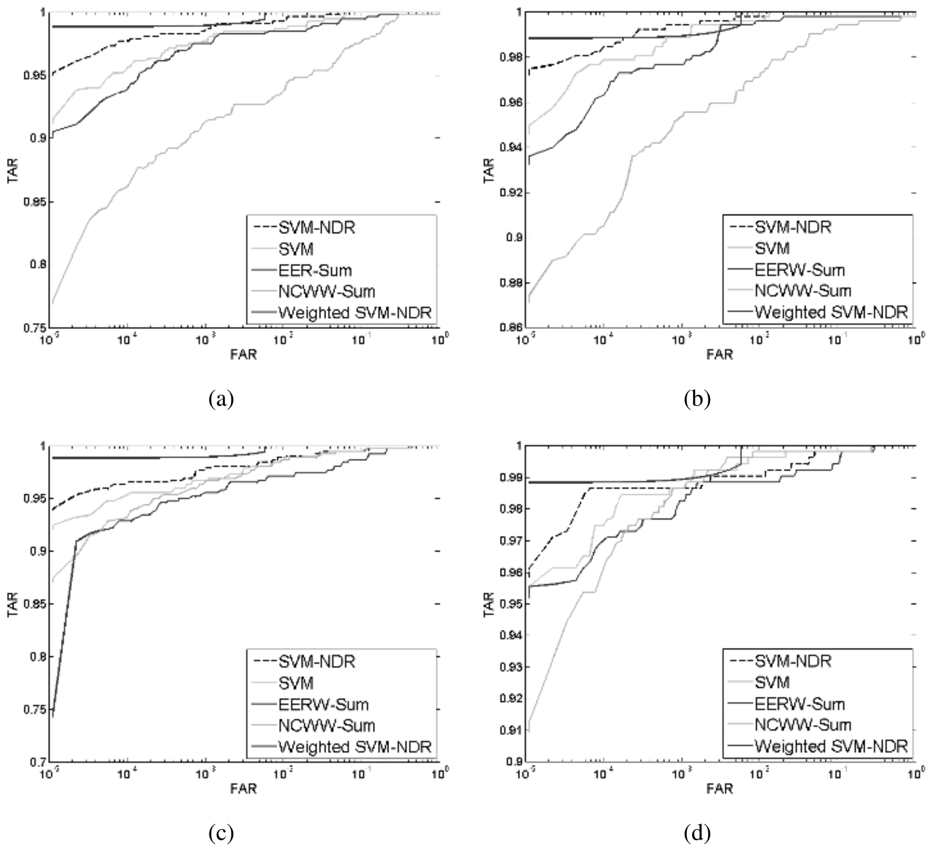

Figure 2: ROC curves achieved on the BSSR1 database: The rates shown here are for bi-modal combinations of face matchers (Fc and Fg) and finger matchers (Fli and Flr) in the BSSR1 database. a) Fc and Fli, b) Fg and Fli, c) Fc and Flr, d) Fg and Flr.

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:

$$S' = \frac{S - min\{S_k\}}{max\{S_k\} - min\{S_k\}} \tag{5}$$

Where $min\{S_k\}$ and $max\{S_k\}$ are the minimum and maximum value of scores existing in the training data of the corresponding biometric source. And S' is the normalized score.

To train and test the proposed approach, every possible open-set identification scenario that can occur in the database was simulated. To do that, the comparisons in the database were split into separated 1:N comparison sets. Each comparison of those sets were fused using the OLD weighted sum-rule fusion, then ranked according to the resulting fused scores. The three considered NDR values were calculated for each entry in the ranked comparison sets, except the last two ranks, as the second and third rank to those entries does not exist and thus the NDR values cannot be calculated. The resulted NDR values of each comparison are concatenated with the original scores of the comparison to create the final feature vector for that comparison. The resulted feature vectors are passed along with their genuine/imposter labels to train the SVM classifier in the training mode.

For evaluation, similar concatenated feature vectors are created from the testing data. Those features are evaluated by the trained SVM classifier to produce a final fused score from each comparison. The performance achieved by the proposed solution and the base line approaches is presented as ROC curves in Figure 2. Performance was presented for all possible bi-modal (two face and two fingerprint matchers). ROC curves plots the false acceptance rate (FAR) and the true acceptance rate (TAR) at different operational points (thresholds) and presents the tradeoff performance between the two error rates. Generally, for high secure biometric systems, the area to the left of the curve (low values of FAR) is of main interest. The results shown in Figure 2 shows the high performance of the proposed approach compared to the baseline solutions. This is clearer at lower FAR values.

4 Conclusion

This work focused on the process of multi-biometric score-level fusion. The fusion approach is based on including the neighbor distance ratios in a classification-based fusion framework. The proposed solution aimed at including biometric source weighting information in the NDR calculation process, this helped creating a more accurate initial ranking and influence the biometric sources effect on the NDR value. The evaluation was performed on the BSSR1 database and proved the superiority of the proposed solution compared to a number of baseline methods. The results clearly show the benefit of the initial biometric source weighting within an NDR-based biometric verification.

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