Reliability Estimation for Multimodal Error Prediction and Fusion

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Abstract. This paper focuses on the estimation of reliability of unimodal and multimodal verification decisions produced by biometric systems. Reliability estimates have been demonstrated to be an elegant tool for incorporating quality measures into the process of estimating the probability of correctness of the decisions. In this paper we compare decision- and score-level schemes of multimodal fusion using reliability estimates obtained with two alternative methods. Further, we propose a method of estimating the reliability of multimodal decisions based on the unimodal reliability estimates. Using a standard benchmarking multimodal database we demonstrate that the score-level reliability-based fusion outperforms alternative approaches, and that the proposed estimates of multimodal decision reliability allow for an accurate prediction of errors committed by the fusion module.

1 Introduction

Reducing error rates of biometric authentication systems is a challenging enterprise. High-quality biometric signals are difficult to acquire, the behavioral characteristics of the users of biometric systems contribute to the intra-class variability of features, and the biometric traits are not stationary over time. As a result, classification errors are inevitable. Therefore it is necessary that next to the actual binary decision, the system produce an estimate of decision reliability. The reliability of a decision is the level of trust that one can have in its correctness [1, 2]. This level of trust, or *degree of belief* is given by a single event probability according to the subjective Bayesian interpretation [3]. Probabilistic output characterizes statistical classification methods that operate on Bayes' rule [4]. Any system that compares a sample to previously estimated probabilistic distributions of other samples' features is able to return a confidence measure [5] in terms of posterior probability. However, simple calculation of posterior probability does not allow an inclusion of quality measures, which have been demonstrated to supply identity-independent information that fosters improved robustness to adverse environments [6, 7, 1]. Also, appropriately trained neural networks can output scores that have been shown to be equivalent to posterior probabilities [8], but it is difficult to assign a probabilistic interpretation to the processes inside the network. An intuitive way for estimating decision reliability is based on analyzing the margins [9] - the absolute

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difference between the dichotomizer's accuracy in choosing one class over another observed on a development set. However, the use of margin-based confidence estimation does make use of signal quality measurements. In [1] a probabilistic method of computing reliability estimates allows for an easy incorporation of quality measures. The output of the estimate is in probabilistic terms. The reliability estimates have been applied to perform decision-level multimodal fusion (face and speech)[10]. The method of reliability estimation was based on Bayesian networks. A conceptually related method based on explicit distribution modeling with Gaussian Mixture Models (GMM) was demonstrated to accurately predict face verification errors [2]. The main difference between the two approaches is that the dependence relationships between the variables are not pre-defined during the GMM model construction, like it is in the case of Bayesian networks. Instead, those relationships are implicitly learned from the data in the training phase. In this paper we provide a comparison of the two alternative methods of reliability estimation using a benchmark multimodal biometric database BANCA [11]. The comparison includes also an alternative method of confidence estimation that has a probabilistic interpretation: margins [9].

In [10] the reliability estimates are applied to perform a fusion of unimodal decisions in a multimodal biometric verification scenario. In this paper we propose a score-level multimodal fusion scheme based on reliability estimates. We demonstrate that the proposed fusion scheme outperforms the decision gating method, for both BN- and GMM-based reliability estimators. We also show that the application of reliability estimators for multimodal fusion allows to achieve lower error rates than corresponding fusion schemes based on the alternative confidence measure. Since the discussed methods are probabilistic in nature, in this work we do not include comparisons with existing heuristic methods of integrating quality measures in the fusion process [6, 7].

Further, we propose a method of computing a multimodal reliability estimate using the unimodal reliability estimates. We show that thus obtained multimodal reliability estimate can be used to accurately predict multimodal classification errors in similar fashion as in the unimodal setting.

This paper is structured as follows: Section 2 defines the basic concepts of reliability and introduces the proposed schemes of multimodal fusion using reliability, as well as a scheme of fusion of reliability estimates. Section 3 gives the details of the criteria and experimental design for evaluation, Sections 4 and 5 contain the results of the reported experiments, with a discussion in Section 6. We conclude the paper in Section 7.

2 Reliability and Multimodal Fusion

2.1 Evidential Reliability

Reliability R of a classifier decision $D(x)$ for an observation x is defined as a conditional probability of the event ”the classifier made a correct decision”, given supporting evidence E [10]. Since reliability is estimated for each individual observation x, it can be considered as a function of $D(x)$:$R(D(x)) = P(D(x) = 1|E = e(x))$, where $D(x) = 1$ if the decision is correct and $D(x) = 0$, otherwise. An instance $e(x)$ of evidence E may consist of measures derived from the score, feature or signal levels in the classification process. In the experiments reported here, for both modalities the evidence vector was $e(x) = [S_m(x), qm_m(x)]$, where $S_m(x)$ and $qm_m(x)$ are normalized score and signal quality measure relevant to x. For details on reliability and evidence the reader is referred to $[1, 10, 2]$. Reliability estimation is a tool designed for the purpose of labeling decisions as reliable or unreliable for further processing. Labeling of decision $D(x)$ is performed by comparing the reliability estimate $R(D(x))$ to a *reliability threshold*, the minimal accepted value of the belief in the correctness of the decision $D(x)$. Without explicit labeling, the reliability estimates can be effectively used for multimodal fusion.

2.2 Multimodal Fusion

For each given decision $D(x)$, a matching score S_m and an associated reliability estimate R_m is available. We propose to perform multimodal fusion using the reliability measures, following the formula:

$$S_F = \frac{1}{n}\sum_{m=1}^{n} R_m S_m, \tag{1}$$

where n is the number of unimodal systems used (in our case $n = 2$) , R_m and S_m denote the respective reliability estimate and the unimodal classification output (score) for given modality m. In the case of *decision level fusion*, the output $S_m \equiv D$ is a binary decision: $S_m \equiv D \in -1, 1$. For *score-level fusion*, S_m is the normalized output of the classifier's discriminant function. Scores from different classifiers are often expressed in incompatible scales, therefore there is a need of normalization before performing the score-level fusion. In our work we used the *z*-normalization scheme [7]. In the case of decision-based fusion, the binarization of the scores eliminates the need for normalization. The decision based on the fused output is made by comparing the value of S_F to a threshold that minimizes the Half-Total Error Rate (HTER) [9] on a development dataset.

2.3 Fusion of Reliability Estimates

It is usually not possible to apply the reliability estimation scheme to directly estimate the reliability of multimodal decisions: this would require that the fused classifiers would make mistakes for the very same presentations. Since that is in general not the case, the number of models for all possible error configurations would grow geometrically with the number of classifiers involved. Training all these models would require amounts of available training data beyond what is usually available in reality. In this situation is is important to be able to derive multimodal reliability estimates from the unimodal estimates, which are not as data-demanding.

Out of all present unimodal scores, any and all can be correct, or wrong. Therefore the unimodal reliability estimates are combined into a multimodal estimate as follows:

$$R\left(D_F\right) = R\left(D_1 \cup D_2 \cup ... \cup D_n\right) \tag{2}$$

In the case of two fused modalities ($n = 2$), the multimodal reliability is expressed by

$$R\left(D_F\right) = R\left(D_1 \cup D_2\right) = R\left(D_1\right) + R\left(D_2\right) - R\left(D_1\right) \cdot R\left(D_2\right). \tag{3}$$

D_1 and D_2 are assumed to be independent, considering that they originate from different modalities. This is a simplifying assumption - dependencies between modalities may occur, and in this case the product $R(D_1) \cdot R(D_2)$ would have to be replaced by a more accurate estimate of $R(D_1 \cap D_2)$.

3 Experimental Design and Evaluation Criteria

3.1 Databases and Experimental Design

In our experiments we used face images and speech data from the BANCA database, English part. The BANCA database contains data collected from a pool of 52 individuals, 26 males and 26 females. For the details on the BANCA database and associated evaluation protocol the reader is referred to [11].

In the experiments presented in this paper we adhered strictly to the open-set protocol P, which involves training the classification models using 'clean' data recorded in the controlled conditions, and testing them in the controlled as well as deteriorated conditions. The protocol P defines that all database data are to be sub-divided into two datasets, g1 and g2. While data from one dataset is used for user model training and testing, the other dataset (a development set) may be used for parameter tuning. In accord with this directive, we use the development set to adjust the decision thresholds for the test set, but also to train the reliability estimation models.

The unimodal protocol P strictly defines the assignment of user data to the genuine access or impostor access pools. We respect this assignment and in order to do so we reduce the amount of client face data to one per access (as opposed to the available five) in order to match the amount of speech data at hand. in this way we maintain the compatibility with the P protocol and at the same time we overcome the problems related to the use of the chimerical databases [12]. In accordance with the BANCA gudelines, all error rates shown in Table 1 are reported separately for g1 and g2, and then their average is computed.

3.2 Unimodal Classifiers and Quality Measures

The face and speech data from the BANCA database consists of data collected in three different recording conditions: controlled, degraded and adverse. For each of the recording conditions, four independent recording sessions were organized, making a total of 12 sessions.

For face data, the faces in the images were cropped out and normalized geometrically (aligned eye positions) and photometrically (histogram normalization). The face verification was performed using the extracted DCTmod2 features and a Bayesian classifier with Gaussian Mixture Models (GMM) [13]. For each face image, a quality measure qm was derived by computing a correlation with the average face template [2]. The average face template was computed on the respective development dataset.

The BANCA database provides a large amount of speech data per user: 2 files per session (about 20 s each) x 2 microphones x 12 sessions. In our case, we used only the data from microphone 1.

The speaker verification system used is based on the Alize toolkit [14]. The Alize speech/pause detector is run to remove silence portions of the input speech signal before feature extraction. Features used are 12 MFCCs with delta and acceleration coefficients, and cepstral mean normalisation. A world model is trained from the pooled clean training data of all clients, using 200 diagonal covariance-matrix Gaussian components. Each client's model is then adapted (means only) with their own recordings using MAP adaptation. The quality measure used for speech is related to the signal-to-noise ratio, computed using energy-based voice activity detection [15].

3.3 Evaluation Criteria

The potential of each compared method to discard unreliable and therefore potentially erroneous decisions is evaluated according to the following criteria [2]:

- the accuracy of decisions labeled as reliable must be monotonically growing, and
- the number of discarded decisions must be kept at a minimum.

Since labeling the decisions as reliable or unreliable is a result of reliability-based decision thresholding, we analyze the properties of different reliability estimators as a function of the reliability threshold. Those properties are, in accordance with the criterion given above, accuracy of the classifier (in the terms of 1-HTER) after having discarded decisions labeled as unreliable, and the number of decisions labeled as reliable for the given reliability threshold value, relative to the total number of decisions. Since we wish these properties to be maximized simultaneously, we also analyze their product which we refer to as a 'Performance Measure' [2]. This property helps establish at which level of reliability the system achieves highest accuracy while keeping most decisions.

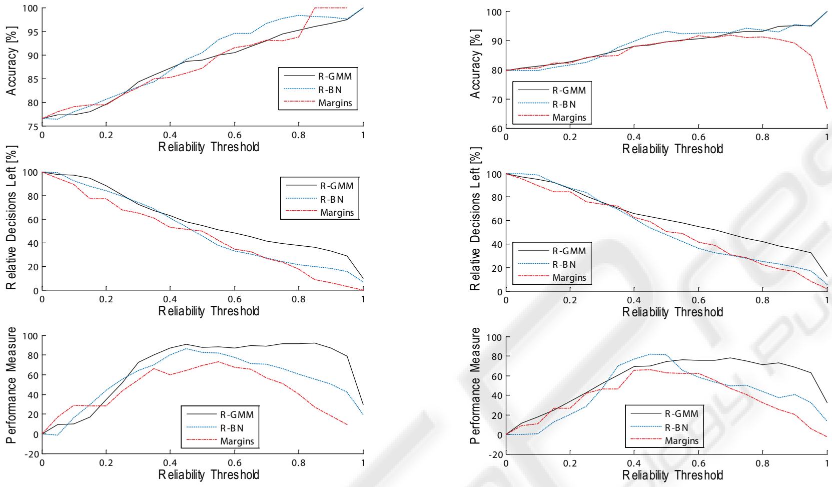
First, we evaluate the unimodal reliability estimates, then we apply them to multimodal fusion as discussed in Section 2. Finally, we perform a fusion of the reliability estimates and evaluate them in a similar fashion as it was the case with unimodal reliability estimates. In each case, we provide a comparison with the corresponding results obtained using the method of classifier confidence estimation based on the margins [9].

4 Unimodal Reliability - Experimental Evaluation

In this section we present the experimental results of reliability estimation for the unimodal classifiers operating on the face and speech modalities. For each modality, we consider following reliability estimators: explicit GMM-based reliability estimator R-GMM [2], Bayesian Network-based reliability estimator R-BN [1], confidence estimates derived from the margin information M [9].

4.1 Face Modality- Error Prediction

Figure 1 shows the properties of various reliability estimators applied to the classifier operating on the face modality, for datasets g1 and g2, in terms of accuracy gain (1-HTER), relative number of decisions remaining after reliability thresholding, and the relative performance measure.



(a) (b)

Fig. 1. Error prediction and decision reject/accuracy gain tradeoff, face, a.: dataset g1, b.: dataset g2.

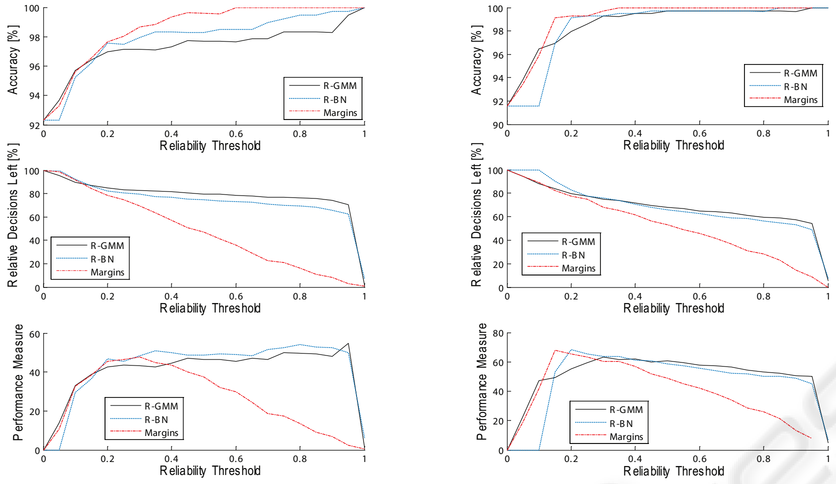
4.2 Speech Modality- Error Prediction

Figure 2 shows the properties of various reliability estimators applied to the classifier operating on the speech modality, for datasets g1 and g2, in terms of accuracy gain (1-HTER), relative number of decisions remaining after reliability thresholding, and the relative performance measure.

5 Multimodal Reliability - Experimental Evaluation

5.1 Multimodal Fusion

The results of the fusion experiments in terms of accuracy (1-HTER) are collected in Table 1. Next to the results of reliability and margin- based fusion, results of oracle fusion (disjunction of binary accuracies of unimodal classifiers), and mean rule fusion are presented for comparison.



(a) (b)

Fig. 2. Error prediction and decision reject/accuracy gain tradeoff, speech. a.: dataset g1, b.: dataset g2.

5.2 Error Prediction

The results presented in Table 1 show that score-based fusion schemes outperform their decision-based counterparts for fusion methods based on both reliability estimates and margins. Therefore, in further analysis of the reliability of decisions after fusion we take into account only score-based fusion results. In this section, we analyze how well different reliability estimates help predict recognition errors. We use the error prediction curves for this purpose. The fusion reliability estimates are obtained using Equation 3. The results are plotted in Figure 3(a) for the dataset g1 and (b) for the dataset g2, in terms of accuracy gain (1-HTER), relative number of decisions remaining after reliability thresholding, and the relative performance measure.

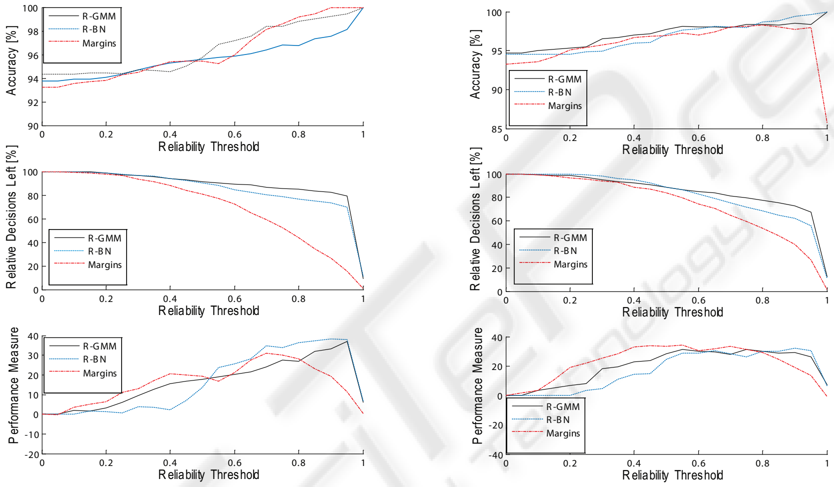
6 Discussion of the Experimental Results

6.1 Unimodal Reliability

The unimodal results for face show that all considered reliability measures can be used to predict classifier errors, and to discard unreliable decisions. While the properties of all reliability estimators are comparable for the face data, dataset g1, in the case of g2 the margin-derived confidence measure fails to provide adequate error prediction. This results shows that margin-based confidence measures are very sensitive to the dataset-dependent shifts in score distributions. Reliability estimators R-GMM and R-BN allowed to obtain error-free classification for both g1 and g2 dataset, by choosing the value of the reliability threshold equal or close to 1.

Table 1. Results of multimodal fusion experiments.

	Fusion method	g1	g2	average (g1+g2)/2
Unimodal systems	Face	0.754	0.782	0.768
	Speech	0.923	0.92	0.922
Reference fusion	Oracle	0.982	0.974	0.978
Decision-level fusion	Margins	0.904	0.911	0.908
	Reliability, R-GMM	0.932	0.943	0.938
	Reliability, R-BN	0.927	0.935	0.931
Score-level fusion	Margins, M	0.928	0.931	0.929
	Reliability, R-GMM	0.942	0.947	0.945
	Reliability, R-BN	0.941	0.938	0.938
	Mean rule	0.938	0.928	0.933



(a)

(b)

Fig. 3. Error prediction and decision reject/accuracy gain tradeoff, fusion. a.: dataset g1, b.: dataset g2.

6.2 Multimodal Fusion

The multimodal fusion results show that the application of reliability measures R-GMM and R-BN in fusion results in higher accuracy than using margin-based approach or mean/sum rule. We expect that for databases containing more degraded conditions (the speech degradation in the BANCA database in particular is not very pronounced), the difference would be more significant since the signal quality is explicitly taken into account. The score based fusion schemes proved to outperform decision-based algorithms using both margin and reliability estimates. This result can be explained by the fact that during a decision-based fusion information coming from a less reliable classifier is lost. The R-GMM reliability estimation scheme based on explicit GMM models granted best performance on the tested data. This result can be attributed to the difference in probabilistic modeling between R-GMM and R-BN methods, as discussed in Section 1.

6.3 Multimodal Reliability

For both datasets g1 and g2, the accuracy gains in terms of (1-HTER) for the R-GMM, R-BN and M reliability estimates were comparable. However, the application of margin-based estimates resulted in a dramatic decrease in the number of decisions considered reliable, for similar accuracy. This fact is reflected in the dropping shape of the corresponding curve in the performance plots for g1 and g2. The presented results show that R-GMM and R-BN methods are best suited for the estimation of reliability of multimodal fusion decisions, and that their performance meets the evaluation criteria defined in Section 3.3.

7 Conclusions

The lead idea of this work was to demonstrate that reliability measures can be effectively used for error prediction in uni- and multimodal biometric verification applications. The presented results show that reliability estimates allow for eliminating potentially erroneous decisions based on collected evidence. We have presented a method of performing probabilistic fusion of the multimodal reliability estimates. Proposed methods was proven to allow for accurate error prediction of multimodal decisions.

The results of the experimental evaluation suggest that both methods of reliability estimation based on the Bayesian networks R-BN, and on the explicit GMM modeling R-GMM, perform similarly in terms of their error prediction power. Insignificantly better results of R-GMM for fusion may hint at the exploitation of the intra-modal dependencies by the R-GMM method.

Margin-based confidence estimates proved to perform not as well as the reliability measures on the tasks of uni- and multimodal error prediction and multimodal fusion. This outcome can be explained by the fact that, unlike reliability estimates R-GMM and R-BN, margin-based confidence estimators do not allow for an inclusion of quality measures.

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