

Optimal Decision Fusion for Verification of Face Sequences

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Abstract

Face sequence contains more information of the user than a single face image. In this paper, optimal decision fusion is proposed to verify the face sequences, based on the original verification system for a single face image. We show by experiments that optimal decision fusion is a simple but effective approach, and that the performance of the original verification system can be significantly boosted by introducing face sequences and applying optimal decision fusion on them.

1 Introduction

Nowadays biometric verification is widely used in various security applications such as secure access to a transaction or a network, and identity check at an airport. The larger context of our work is biometric authentication as a link between a user and a private PN (personal network), via an intermediate MPD (mobile personal device) [3]. The PN is shown in Fig. 1.

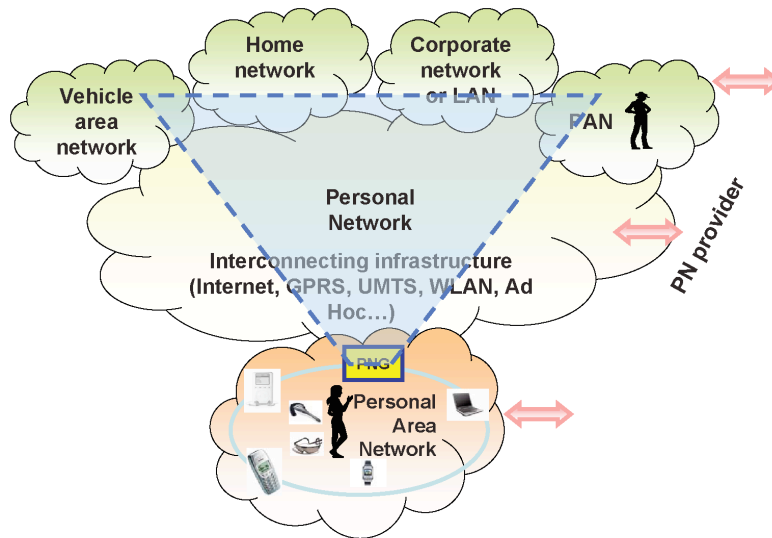


Figure 1: The PN in which face verification is a secure link between the user and the network.

To achieve high security for the PN, it is specially demanded, among other requirements, that the authentication should be done not only at logon time, but also ongoing, in order to prevent the scenario that a MPD is taken away by the impostors after logged in by the user. For this reason, face sequences are taken as the biometric input. Face sequences, as multiple inputs to a classifier, enable us to fusion the multiple outputs of the original classifier into a more robust and reliable decision.

Fusion of the classifiers can be at feature level, matching score level, and decision level. In the literature fusion at matching score level is more frequently discussed [1] [2]. In this paper, however, we will show that fusion at decision level by the AND rule and OR rule can be applied in a optimal way such that it always gives an improvement in terms of error rates over the classifiers that are fused. Here optimal is taken in Neyman-Pearson sense [4]: at a given false-reject rate α , the decision-fused classifier has a false-reject rate β that is minimal and never larger than the false-reject rates of the classifiers that are fused at the same α . We will give both theoretical analysis and experiment results on the optimal decision fusion by AND and OR rule.

This paper is organized as follows. In Section 1 the theory of optimal decision fusion is introduced, and in Section 2 the optimal decision fusion for face sequence is discussed as a special case. In Section 3 the results of optimal decision fusion on face sequences are presented. Section 4 gives the conclusions.

2 Optimal Decision Fusion Theory

Suppose we have multiple binary decisions and assume that the decisions are statistically independent. (Note that this independency may arise from independent classifiers, or independent samples.) We will discuss the optimal decision fusion by AND rule, and the optimal decision fusion fusion by OR rule can be similarly done.

Each decision D_i is characterized by the two error probabilities: the first is the probability of a false accept, the false-accept rate (FAR), α_i , and the second is the probability of a false reject, the false-reject rate (FRR), β_i . To analyze the AND rule it is more convenient to work with the detection probability or detection rate $p_{d,i} = 1 - \beta_i$. It is assumed that $p_{d,i}$ is a known function of α_i , $p_{d,i}(\alpha_i)$, known as the ROC (Receiver Operating Characteristic). In practice, the ROC has to be derived empirically. After application of the AND rule to decisions D_i , $i = 1, \dots, N$, we have, under the important assumption that all decisions are statistically independent, that

$$\alpha = \prod_{i=1}^N \alpha_i, \quad p_d(\alpha) = \prod_{i=1}^N p_{d,i}(\alpha_i) \quad (1)$$

with α the false-accept rate and p_d the detection rate of the fused decision, respectively. Optimal AND rule fusion can be formally defined by finding

$$\hat{p}_d(\alpha) = \arg \max_{\alpha = \prod_{i=1}^N \alpha_i} \prod_{i=1}^N p_{d,i}(\alpha_i) \quad (2)$$

It is easily proved that the optimized detection rate $\hat{p}_d(\alpha)$ is never smaller than any of the $p_{d,i}$'s at the same FAR α

$$\hat{p}_d(\alpha) \geq p_{d,i}(\alpha) \quad i = 1, \dots, N \quad (3)$$

Because, by definition

$$\begin{aligned}\hat{p}_d(\alpha) &= \arg \max_{\alpha = \prod_{i=1}^N \alpha_i} \prod_{i=1}^N p_{d,i}(\alpha_i) \\ &\geq \prod_{j=1}^N p_{d,j}(\alpha_j) \Big|_{\prod_{i=1}^N \alpha_i = \alpha}\end{aligned}\quad (4)$$

As it holds for any classifier that, $p_{d,i}(1) = 1$, (3) readily follows by setting $\alpha_j = \alpha$ and $\alpha_i = 1, i \neq j$.

By solving the optimization problem in (2), the operation points for every component classifiers are obtained, hence the fused classifier which yields the optimal performance in the Neyman-Pearson sense [4]. Because in real situations, the ROCs, i.e. $\hat{p}_d(\alpha)$, are characterized by a set of discrete operation points rather than analytically, the optimization in (2) must be solved in a numerical way. In [5] the problem is reformulated in a logarithmic domain as an unconstrained Lagrange optimization problem.

3 Optimal Decision Fusion on Face Sequences

In this section we will discuss the optimal decision fusion on face sequences as a special case as presented in Section 1. In this case, we use the original classifier, but applied to subsequent face images, and then fuse the multiple outcome decisions. For simplicity, we will analyze fusion on two decisions. Fusion on three or more decisions can be done in a similar manner.

Because the classifiers are identical, we have that $p_{d,1} = p_{d,2} = p_d$ and the optimization problem can be formulated to

$$p_{\text{fusion}}(x; \alpha) = p_d(x) \cdot p_d\left(\frac{\alpha}{x}\right) \quad (5)$$

$$\hat{p}_{\text{fusion}}(\alpha) = \arg \max_{\alpha \leq x \leq 1} \{p_{\text{fusion}}(x; \alpha)\} \quad (6)$$

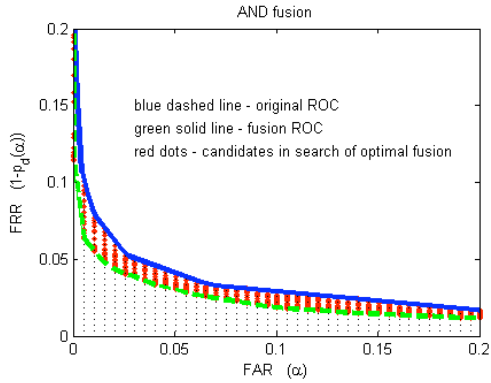
where x is a changing variable in the search process, and $\hat{p}_{\text{fusion}}(\alpha)$ is the detection rate at α under optimal AND fusion.

The optimum can be found by looking for the stationary point where the derivative of (5) w.r.t x is zero. As this derivative can be written

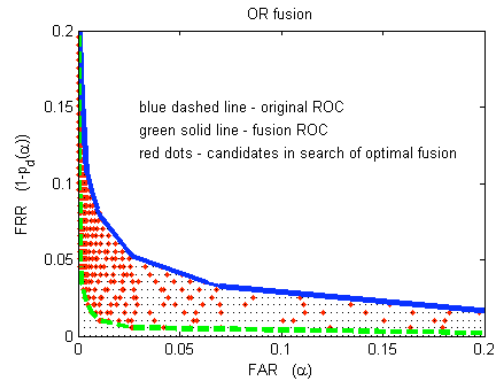
$$p'_{\text{fusion}}(x; \alpha) = p'_d(x)p_d\left(\frac{\alpha}{x}\right) - \frac{\alpha}{x^2}p_d(x)p'_d\left(\frac{\alpha}{x}\right) \quad (7)$$

Obviously when $x = \sqrt{\alpha}$, i.e. $\alpha_1 = \alpha_2 = \sqrt{\alpha}$, the derivative reaches zero. However, for some ROCs and for some α , this stationary point corresponds to a minimum, then the optimum is found at the border, either $\alpha_1 = 1$ or $\alpha_2 = 1$, which means only one of the two ROCs is taken. The former case happens more often in practice.

Fig. 2 and Fig. 3 shows the results of optimal decision fusion by AND and OR rule. Significant improvement on the ROC can be observed. It can be further seen that AND rule is more suitable for the type of ROC in Fig. 3, while OR rule is more suitable for the type of ROC in Fig. 2. In Fig. 3 (b), we show the case when only one of the two ROCs is taken.

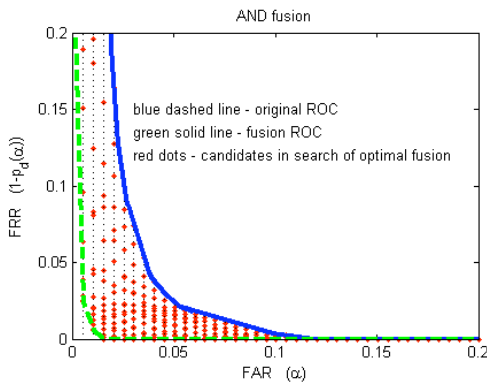


(a) Optimal AND fusion

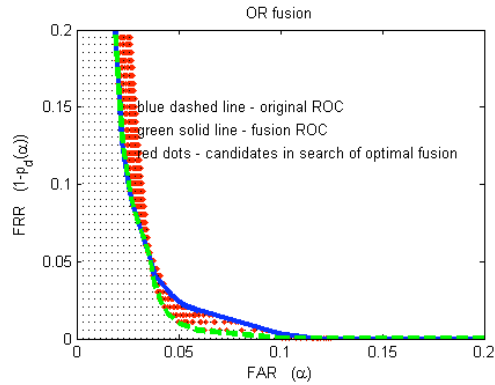


(b) Optimal OR fusion

Figure 2: Optimal decision fusion on ROC, example 1



(a) Optimal AND fusion



(b) Optimal OR fusion

Figure 3: Optimal decision fusion on ROC, example 2



(a) Session 1

(b) Session 2

Figure 4: Different sessions of the user data

4 Experiments and Results

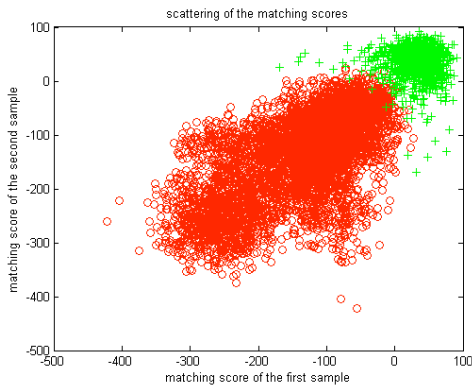
Face sequences are used as the biometrics in our face verification system. It is important that the classifier, which was trained during the enrollment session, can generalize to the face sequences collected independently under different situations. Therefore we collected multiple sessions of the user data under different illuminations for the testing purpose. In each session, the face images are collected with a frequency of 5 frames per second. Examples of the cross session data are shown by Fig. 4.

The testing procedure is as follows. Firstly, the classifier is trained on the one session. Secondly, the classifier is tested on the second session, with a ROC obtained, which represents the component classifier in the decision fusion. The optimal decision fusion by AND rule and OR rule is then made on the ROC. Finally, the optimal decision fusion scheme is tested on multiple inputs from the second session, with each component classifier working on its optimal operation points.

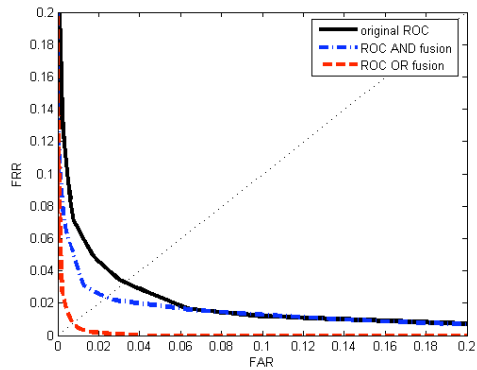
As assumed in (1), the two input face frames are statistically independent. This assumption can be satisfied when the time interval between the two subsequent frames are relatively long, for example 30 seconds. Fig. 5 shows the results of optimal decision fusion on the two frames with a time interval of 30 seconds. In this figure, we show both the scattering of the matching scores, and the three ROCs: original, AND-fused, OR-fused. In Fig. 5 (a), the circles \circ represent the matching scores of the impostor data, and the cross $+$ represent the matching scores of the user testing data. In Fig. 5 (b), the solid line represents the original ROC, the dash-dot line represents the ROC after optimal AND fusion, and the dashed line represents the ROC after optimal OR fusion.

When the time interval between the two subsequent frames becomes shorter, for example 1 second, the assumption in (1) is less true. But as long as some independency exists which spread the matching score in the two dimensional matching score space, optimal decision fusion by AND and OR rule could still be advantageous, as is shown in Fig. 6.

In both Fig. 5 and Fig. 6, improvement by optimal decision fusion, especially by OR fusion, can be clearly seen. The improvements can be explained by the scatter plot in (a), where the original classifier only works in a one dimensional space, and the fused classifiers work in a two dimensional space, which provides more space for separation. Even when the two dimensions are not fully independent, as Fig. 6 shows, the optimal decision fusion still improves the performance of the original classifier, reducing the



(a) Scatter plot of matching scores

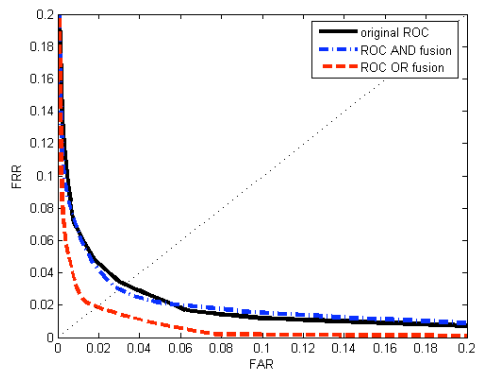


(b) Comparison of the ROCs

Figure 5: Experiment results with samples chosen at a long time interval of 30 seconds



(a) Scatter plot of the matching scores



(b) Comparison of the ROCs

Figure 6: Experiment results with samples chosen at a short time interval of 1 second

EER to half of the original value. We can expect that optimal decision fusion on three or more images will yield even better results.

5 Conclusions

In this paper, optimal decision fusion is proposed to solve the verification of the face sequence, using optimal decision fusion by AND or OR rule. Both the optimal decision fusion theory and experiment results on a real face verification system are given. The improvements brought by optimal decision fusion is significant. This implies that without changing the original classifier, we can very easily boost the performance of a face verification system by introducing face sequences and applying optimal decision fusion on the face sequences.

References

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