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Bin-based classifier fusion of iris and face biometrics

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ABSTRACT

Accuracy and usability are the two most important issues for a multibiometric system. Most of multibiometric systems are based on matching scores or features of multiple biometric traits. However, plenty of identity information is lost in the procedure of extracting scores or features from captured multimodal biometric data, and the loss of information stops accuracy and usability of the multibiometric system from reaching a higher level. It is believed that matching scores can recover some identity information, which has not been utilized in previous fusion work. This study proposes a framework of bin-based classifier method for the fusion of multibiometrics, to deal with this problem. The proposed method embeds matching scores into a higher-dimensional space by the bin-based classifier, and rich identity information, which is hidden in matching scores, is recovered in this new space. The recovered information is sufficient to distinguish impostors from genuine users more accurately. Therefore, the multibiometric systems which are based on such rich information, are able to achieve more accurate and reliable results. The ensemble learning method is then used to select the most powerful embedding spaces. Experimental results on the CASIA-Iris-Distance demonstrate the superiority of the proposed fusion framework.

1. Introduction

Multibiometrics offers a more accurate, secure and universal solution to personal identification than unimodal biometrics [1,2]. Multibiometrics can integrate complementary information extracted from multiple modalities to achieve superior performance, while single biometric modality systems continue to suffer from some shortcomings. One such shortcoming is that the said system is inherently affected by certain factors in surrounding conditions. For example, face recognition performance deteriorates dramatically if the illumination condition, pose or expression changes, and iris recognition is affected by the resolution of the device or the interaction between the user and device. Another shortcoming is that the information provided by single biometric modality is not rich enough to distinguish a user0 from similar ones. For example, face images of twins captured at a distance may lose distinctive information, and face recognition systems have difficulty in distinguishing one from the other. Some biometric modalities are also easily spoofed with a fake pattern, which is a serious problem of single biometric modality systems.

An intuitive solution to address these shortcomings is the fusion of multimodal biometrics. Experimental results suggest that the recognition performance of fused multimodal biometrics is always impressively better than that of any single biometric modality. One of the reasons is that the influence of noise on multimodal biometric systems is not so significant. Researchers have found that noisy conditions that affect one biometric modality may have no effect on other modalities. The fusion can also utilize the complementary evidences of multiple biometric traits, and the advantages of different biometrics. Fusion may also improve the recognition results depending on the correlation among modalities. Poh et al. [3] show that the higher the variance of base-experts and its covariance counterpart, the higher Equal Error Rate (EER) will be. Moreover, fusion can make complementary advantages of different biometrics. For instance, iris modality can provide an exact recognition result, but the modality is difficult in image acquisition; The face image is easy to capture, but the recognition performance is limited. The multimodal biometric system consisting of iris and face can solve this problem. In addition, the fusion system is easier to use and also provides more accurate performance. Given more biometric modalities existed in fusion systems, the difficulty of spoof-attacking all biometric modalities increases Table 1.

Most research on multibiometric fusion is based on matching scores and features of multiple biometric modalities, since score and feature contain rich identity information and are easy to access [2,7]. The fundamental framework of score level fusion was proposed by

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Table 1
Score level and feature level fusion methods of multibiometrics.

References	Fusion method	Fusion level
Kiltter [4]	Bayesian based fusion: sum rule, product rule.	Score level
Poh [5,6]	Quality-based fusion.	Score level
Nandakumar [7]	Likelihood ratio-based score fusion.	Score level
Terrades [8], and Ma[9,10]	Non-baysesian based fusion.	Score level
Wang [11]	Weighted sum rule.	Score level
Miao [12]	Robust linear programming based fusion.	Score level
Ross [13], and Chibelushi [14]	PCA, LDA	Feature level
Shekhar [15]	Joint sparse representation	Feature level

Kittler et al. [4]. In their framework, the conditional probabilities of matching scores should be calculated first. Based on the assumption of statistical independence of all the classifiers, the posterior probability was then obtained according to Bayesian theory. They also suggested many approximations to simplify the computation of the posterior probability, such as the sum rule and the product rule, which were used extensively and achieved robust fusion performance. Poh and Kittler [5,6] introduced the quality of acquired biometric data into the framework, and their quality-based biometric fusion achieved impressive performance. Another popular score level fusion method based on the likelihood ratio (LHR) test, was introduced by Nandakumar et al. to fuse multiple modalities based on the density estimation of matching scores, and got wide attention [16–19] and achieved good results. Without taking the assumption that all classifiers were statistically independent, a framework of non-Bayesian fusion was proposed [8–10]. They suggested various approximations to simplify the computation, and derived the weighted sum rule. Fakhar et al. [20] proposed a general framework of multibiometric identification system based on fusion at matching score level using fuzzy set theory. Liang et al. [21] combined the scores with an order-preserving fusion algorithm. Kim et al. [22] proposed an online learning network for the fusion of biometric scores, and achieved promising results in terms of fusion accuracy and computational cost. Wang et al. [11] used the weighted sum rule to fuse iris and face classifiers, which was similar to non-Bayesian fusion method, and the weight variables were derived from the performance of the classifiers. For the probability-based score fusion method, the conditional probabilities were derived from density estimation methods such as the Gaussian mixture model (GMM) [23] and the Parzen window [24]. However, in the fusion task, the number of samples, especially at the decision boundary, was usually small. A limited number of samples at the tails of the distribution was insufficient to describe the distribution of samples precisely, and therefore degraded the performance of the probability-based fusion. (However, as to an user-specific fusion system [25], the lack of data was not as a serious problem.) An increasing number of classifiers caused the curse of dimensionality especially in density estimation, and increased the difficulty of estimating the probability. To avoid the difficulties in density estimation, Miao et al. [12] directly used matching scores, and proposed a robust linear programming based classifier to fuse iris and face captured at a distance, which can relieve influence of noise. Although the score level fusion methods achieved great performance and were widely used in real-world applications, the amount of information contained in matching scores was limited, and restricted higher-level fusion performance.

In feature level, much essential work was proposed in various research fields. Chang Xu et al. proposed multi-view intact space learning and introduced various multi-view space learning methods to learn a shared subspace for multi-view examples in a robust approach [26,27]. Jun Yu et al. proposed a novel multimodal hypergraph learning-based sparse coding method, which can successfully explore the complementarity of different features through a group of weights [28]. In the feature level fusion of multibiometrics, Ross and Govindarajan [13], and Chibelushi [14] used principal component analysis (PCA) and linear discriminant analysis (LDA) to fuse the features of different biometric modalities. Shekhar et al. [15] used joint sparse representation to tune the representation of different features, and represented a probe sample using a sparse linear combination of gallery samples. This method was robust to occlusion and demonstrated outstanding performance. Mai et al. [29] proposed a feature fusion method that maximized the fused template discriminability and its entropy by reducing the bits dependency. Nagar et al. [30] also introduced a feature-level fusion framework that simultaneously protected multiple templates of a user as a single secure sketch. However, there existed various kinds of features such as the histograms of Local Binary Patterns (LBP) and Scale-invariant Feature Transform (SIFT), the binary templates of Ordinal Measures (OM) and Gabor, and so on, and the meaning and type of these features were usually different with each other, thus it was difficult for a multibiometric feature level fusion method to combine all types of features based on their meaning. What is more, feature templates may be not available due to commercial reasons, which stopped feature level fusion methods from being widely used in reality.

To overcome the shortcomings of the fusion methods mentioned above, Miao et al. [31] proposed a basic bin-based classifier for fusion, which can handle any kind of features and utilize identity information in features. An an improved work of [31], this paper proposes a framework of the bin-based classifier (BBC) fusion with three kinds of typical BBCs, continuous bin-based classifier (CBBC), dis-continuous bin-based classifier (DBBC) and pair-wise continuous bin-based classifier (PCBBC). And the fusion method in [31] can be treated as a special case of the DBBC. The proposed method separates heterogeneous feature templates into a number of patches, and the calculates matching scores among the corresponding patches. Therefore, it is appropriate for all types of features. The proposed method also can recover identity information from matching scores of these feature patches, and promote the fusion performance. In this work, three types of bin-based classifier are then proposed, and they recover detailed and distinctive information by embedding patch score into a higher dimensional space, as kernel methods do, so that the recovered information is sufficient for the recognition. A significant advantage of this work is that it can handle multiple features. The proposed method is also improved to be able to learn more distinctive and complex classifiers in the framework of the bin-based classifier, which cannot be achieved in [31]. The learned BBCs are combined based on ensemble learning methods, and complementarity of BBCs is well extracted in this way.

One of the two most significant contributions of this work is that a framework of bin-based classifier for score level fusion is proposed. The proposed method aims at recovering identity information lost in feature extraction and template matching phase, and hence promote the recognition performance after fusion with richer these evidences. The other one is that the recovered information is well combined by ensemble learning methods in this work, and complementary information is remained while redundance is reduced.

The remainder of this paper is organized as follows. Section 2 introduces the proposed BBCs. Section 3 illustrates how to fuse the BBCs by ensemble learning methods. Section 4 presents the experimental results on the CASIA-Iris-Distance database, as well as some further discussions. Finally, Section 5 summarizes the main results of this study and directions for future work.

2. Bin-based classifier

In this study, a novel fusion scheme called Bin-based Classifier (BBC) fusion, which explores and utilizes identity information hidden in matching scores, is proposed. The proposed method only utilizes

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