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Learning discriminability-preserving histogram representation from unordered features for multibiometric feature-fused-template protection

Meng-Hui Lim, Sunny Verma, Guangcan Mai, Pong C. Yuen *

Department of Computer Science, Hong Kong Baptist University, Kowloon Tong, Kowloon, Hong Kong

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ABSTRACT

Multi-biometric feature-level fusion exploits feature information from more than one biometric source to improve recognition performance and template security. When ordered and unordered feature sets representing different biometric sources are involved, feature fusion becomes problematic. One way to mitigate this incompatibility problem is to transform the unordered extracted feature sets to ordered feature representation without sacrificing the discrimination power of the original features so that a feature fusion on ordered features can subsequently be applied. Existing unordered-to-ordered feature transformation methods are designed for three-dimensional minutiae point sets and are mostly not adaptable to high-dimensional feature input. This paper proposes a feature transformation scheme to learn a histogram representation from an unordered feature set. Our algorithm estimates the component-wise correspondences among the sample feature sets of each user and then learns a set of bins per user based on the distribution of the mutually-corresponding feature instances. Given the learnt bins, the histogram representation of a sample can be generated by concatenating the normalized frequency of unordered features falling into histogram bins. Experimental results on seven unimodal and three bi-modal biometric databases show that our feature transformation scheme is able to preserve the discrimination power of the original features more promisingly than state-of-the-art transformation schemes.

1. Introduction

Multi-biometric recognition uses more than one biometric modality, algorithm or/and sensor to achieve recognition [31]. Not only multi-biometric recognition could offer higher recognition accuracy than the conventional single-biometric recognition, it also provides larger population coverage and higher system security against spoof attacks [23,32].

In multi-biometric recognition, information of multiple biometric sources can be fused at the feature level, forming a composite feature set for each individual. As this fusion approach exploits information at the level where most discriminability is preserved, it often produces better accuracy performance than fusion at other levels [37,40].

Biometric templates are typically stored in a protected form to prevent irrevocable compromise of biometrics [29]. When fusion is applied at the feature level, features are fused prior to protection so that a more informative multi-biometric secret can be derived for template protection. This allows one to achieve stronger security when a template protection scheme such as fuzzy commitment, fuzzy vault or fuzzy extractor is applied. Compared to other fusion approaches that protect unimodal templates individually, the protected feature-fused template is more difficult to break than the multiple individually-protected templates [19,23].

A feature set extracted from each biometric source for feature fusion can be ordered or unordered based on the characteristic of the set elements [16]. An ordered feature set is a feature vector or matrix containing ordered elements. Examples include a subspace-projected feature vector, a histogram feature vector and a transformed feature matrix. An unordered feature set contains non-ordered elements such as a fingerprint minutiae point set and facial point descriptor set.

As feature extractors are usually developed specifically for a biometric source, the features extracted from different biometric sources could be incompatible. This poses a great challenge when

* Corresponding author.
E-mail addresses: menghuilim@comp.hkbu.edu.hk (M.-H. Lim), sunnyverma.iitd@gmail.com (S. Verma), csgcmai@comp.hkbu.edu.hk (G. Mai), pcyuen@comp.hkbu.edu.hk (P.C. Yuen).

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incompatible features need to be fused. Most biometric feature fusion schemes avoid fusing incompatible features (ordered with unordered features) together. For instance, Chin et al. [6] extract ordered Gabor features from both fingerprint and palmprint modalities for fusion; Rattani et al. [30] fuse unordered Scale Invariant Feature Transform (SIFT)-based face features with unordered fingerprint minutiae points through concatenation; Huang et al. [11] extract ordered EigenFace and EigenEar features using Principal Component Analysis (PCA) for fusion; Xing et al. [36] extract ordered features from face and gait modalities via coupled projections for fusion.

Although one could select feature extractors to obtain only either ordered or unordered feature sets from distinct biometric sources for feature fusion, the optimal fusion performance can rarely be achieved. This is due to that state-of-the-art feature sets of these biometric sources may not necessary be of the same type. For instance, a state-of-the-art fingerprint representation to date is the unordered Minutia Cylinder Code (MCC) [5] and a state-of-the-art face representation is the ordered Monogenic Binary Code [38]. These two representations are incompatible in their present form and therefore cannot be fused at the feature level.

To obtain accuracy optimality in feature fusion, flexibility to adopt any type of features for fusion is important. To realize this, one can either (1) propose a fusion method that works effectively on heterogeneous feature sets; or (2) propose a transformation that converts heterogeneous feature sets into homogeneous features for fusion, such that there should not be any significant degradation in discrimination power in the converted feature sets. This paper focuses on the latter, so that a feature fusion technique that operates on multiple ordered feature sets, such as serial concatenation [11] or feature selection [23], can be applied, as shown in Fig. 1.

To propose a feasible unordered-to-ordered transformation approach, a few challenges need to be tackled:

1.1. Feature alignment problem

The correspondence of unordered feature elements between the query and enroled samples, which is important for similarity assessment, is unknown. These element-wise correspondences are typically sought during matching via a brute force comparison over the alignment possibilities followed by a best match selection [5,8]. However, when ordered feature-based fusion is concerned, the alignment of transformed unordered feature elements is needed during fusion. This implies that the above-mentioned strategy cannot be applied because the correspondence of unordered features between query and enroled samples has to be determined before matching. Hence, to transform an unordered feature set into an ordered set appropriately, a criterion is to ensure a clear correspondence of each transformed feature among different acquisitions so that fusion and similarity assessment can be carried out semantically.

1.2. Variable set cardinality problem

Unordered feature set such as the fingerprint minutiae set can have an uncertain number of feature elements in every acquisition. The variability in the number of minutia extracted in different acquisitions is mainly caused by missing or spurious feature points extracted due to noise introduced during acquisition. To enable fusion of the transformed feature set with other ordered feature sets, a criterion is to ensure that the transformed feature set always has a fixed size disregarding the variable number of feature elements in different acquisition.

Although there have been several methods [1,10,22,24,33–35,37] developed to address these challenges, a major limitation is that these unordered-to-ordered feature transformation methods are designed specifically for three-dimensional minutiae points and are mostly not applicable to high-dimensional feature points. Most of these methods rely on operations/processes that are easy to apply in two or three-dimensional space but are difficult to apply in high-dimensional space. Instances of these operations/processes include identification of clockwise orientation [34] and Fourier transform [24,37].

The extraction of a histogram feature representation from an unordered set is a popular approach [1,10,33] because histogram features are inherently aligned and are of a fixed length. A histogram feature can be extracted by counting feature points that fall within a specific interval known as bin. To extract a discriminative histogram feature representation, the main objective is to minimize intra-class variation and maximize inter-class variation. To achieve this objective, instances of the same feature element need to be enclosed within the same bin; while the average difference in the number of features between a genuine user and an imposter user in each bin has to be maximized.

In this paper, we explore a new perspective on deriving a discriminative histogram feature representation. Different from existing histogram-based methods that adopt a heuristic approach in constructing the histogram bins, we design a feature transformation scheme to learn a discriminative histogram representation from an unordered feature set without significantly deteriorating the discrimination power of the original unordered features. Our transformation scheme consists of two stages, as shown in Fig. 2. The first stage addresses the feature alignment problem by estimating the group correspondence for every unique feature that appears in the training set. The second stage addresses the variable set cardinality problem by learning a set of bins for each genuine user according to how the genuine and imposter link structures are distributed in the high-dimensional feature space. By ordering the bins, an ordered histogram representation can be extracted for each sample by counting the unordered feature elements that fall into these bins.

In summary, our contribution is two-fold:

1) We propose a learning-based feature transformation method to transform an unordered feature set into a histogram feature representation for the application of ordered feature fusion.
2) We propose a discriminative measure for histogram representation, which is useful in guiding the learning of bins for deriving a discriminative representation for the target genuine user.

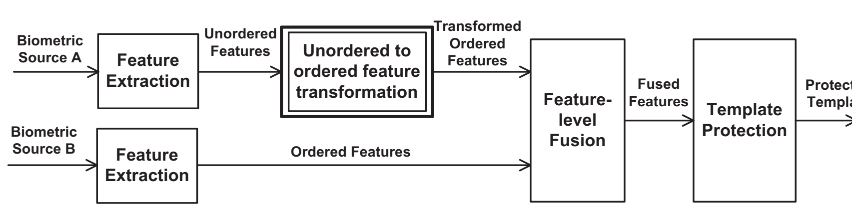

Fig. 1. A typical approach of transforming unordered feature set into ordered set for multi-biometric feature fusion.