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Group sparse representation based classification for multi-feature multimodal biometrics

Gaurav Goswami, Paritosh Mittal, Angshul Majumdar, Mayank Vatsa*, Richa Singh

IIIT-Delhi, India

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Multimodal biometrics technology consolidates information obtained from multiple sources at sensor level, feature level, match score level, and decision level. It is used to increase robustness and provide broader population coverage for *inclusion*. Due to the inherent challenges involved with feature-level fusion, combining multiple evidences is attempted at score, rank, or decision level where only a minimal amount of information is preserved. In this paper, we propose the Group Sparse Representation based Classifier (GSRC) which removes the requirement for a separate feature-level fusion mechanism and integrates multi-feature representation seamlessly into classification. The performance of the proposed algorithm is evaluated on two multimodal biometric datasets. Experimental results indicate that the proposed classifier succeeds in efficiently utilizing a multi-feature representation of input data to perform accurate biometric recognition.

1. Introduction

Biometrics research can be broadly classified into two categories: unimodal and multimodal. Multimodal biometrics is combining information from multiple unimodal biometric sources [1]. Researchers have shown that combining information can be beneficial when the quality or information content of one of the information sources is not sufficient for recognition. Multiple biometric information sources can be combined at different levels; namely, (a) sensor-level, (b) feature-level, (c) score-level, (d) rank-level, and (e) decision-level [1]. Fusion at each level has its advantages and limitations. For example, fusion at the sensor-level can preserve most of the information from each of the modalities however, sensor-level information may not be very discriminatory in nature [2]. While feature-level fusion does not suffer from noise to the same degree as in the case of sensor-level and also preserves much more information as compared to score-level, there exist various challenges in utilizing it. First, the relationships between different features are not always known. Second, some features are variable-length whereas others are fixed-length and therefore concatenation, which is a popular method of feature fusion [1], is not applicable in a large number of cases. Third, if these features do not reside in a commensurate space it is difficult for a classifier to determine reliable decision boundaries. Therefore, relatively less research has focused on feature-level fusion. A review of existing feature fusion algorithms in biometrics literature is presented in Table 1.

Multimodal biometrics can also be beneficial when the data is captured in an unconstrained environment and there are instances of missing information. While researchers have proposed several feature fusion algorithms, not all the algorithms can efficiently combine features in the presence of missing information. The performance of popularly used feature fusion algorithms such as concatenation and principal component analysis (PCA) is significantly affected due to missing information. It is our assertion that a well designed feature-level fusion algorithm which addresses the above mentioned challenges, can enhance the state-of-the-art in biometric recognition. Since the selection of the classifier is also critical towards performance and there are chances when the output of feature fusion algorithm is not suitable for the classifier, it may be optimal if the classifier can efficiently handle multiple features for every data point inherently. In such a manner, the requirement to have a compatible feature-level fusion and classification technique is removed and this process is integrated in the classification stage itself.

In this paper, we propose a multimodal multi-feature classifier termed as the Group Sparse Representation Classifier (GSRC), an extension of the existing Sparse Representation based Classification (SRC) [33], which handles a multimodal multiple feature representation for every data point and determines the class of test data by solving a group sparsity criterion. Fig. 1 presents

* Corresponding author.
E-mail addresses: gauravgs@iiitd.ac.in (G. Goswami), paritosh10059@iiitd.ac.in (P. Mittal), angshulm@iiitd.ac.in (A. Majumdar), mayank@iiitd.ac.in (M. Vatsa), rsingh@iiitd.ac.in (R. Singh).

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Table 1
A literature review of feature-level fusion in biometrics.

Authors	Algorithm	Modalities	Features
Kumar et al. [3]	Feature concatenation	Palmprint and hand-geometry	Standard deviations of combined directional maps of palmprints and measurements of hand lengths and widths [3]
Chang et al. [4]	Combining face and ear image	Face and ear	PCA [5]
Ross and Govindarajan [6]	Feature normalization, concatenation, and performance-oriented feature selection	Face and hand	PCA [5] and LDA (face) and 9-byte features [7] (hand)
Yao et al. [8]	Distance-based separability weighting strategy	Face and palmprint	Gabor PCA
Rattani et al. [9]	Adding key-point descriptor to minutiae features, concatenating, and dimensionality reduction	Face and fingerprint	SIFT (face) [10] and minutia features [11] (fingerprint)
Singh et al. [2]	Adaptive SVM based fused feature selection	Face	Amplitude and phase features using 2D log polar Gabor wavelet
Zhou et al. [12]	Concatenation followed by multiple discriminant analysis	Side face and gait	PCA
Carvalho and Rosa [13]	Fisher's criterion based feature selection	Footstep sounds	Gait frequency, spectral envelope, cepstral and mel-cepstral analysis and loudness
Matovski et al. [14]	Concatenation followed by feature reduction	Gait (multiple views)	Gait energy image and gait entropy image
Krishneswari and Arumugam [15]	Fusion of the low-level features (approximation images) of both modalities prior to high-level feature extraction	Palm-print and fingerprint	Discrete Cosine Transform [16]
Rathore et al. [17]	Feature template fusion using set union approach	Profile face and ear	SURF [18]
Lu et al. [19]	Multiview neighborhood repulsed metric learning	Face	Local Binary Patterns (LBP) [20], Linear Embedding [21], and SIFT [10]
Chai et al. [22]	Feature concatenation and linear discriminant analysis	Face	Gabor ordinal measures [22]
Yan et al. [23]	Discriminative multi-metric learning	Face	LBP [20], Spatial pyramid learning [24], and SIFT [10]
Chin et al. [25]	Feature concatenation	Fingerprint and palmprint	Bank of 2D Gabor filters
Goswami et al. [26]	Feature concatenation	Face (RGB-D)	Histogram of Oriented Gradients (HOG) [27] of depth/visual entropy and visual saliency
Odinaka et al. [28]	Concatenation before and after feature selection	Cardiovascular	Electrocardiogram [29] and laser Doppler vibrometry [30]
Huang et al. [31]	Biometric quality based piece-wise weighted concatenation	Face and ear	PCA
Huang et al. [32]	Feature concatenation	Face	PCA and LDA applied on top-level's wavelet sub-bands

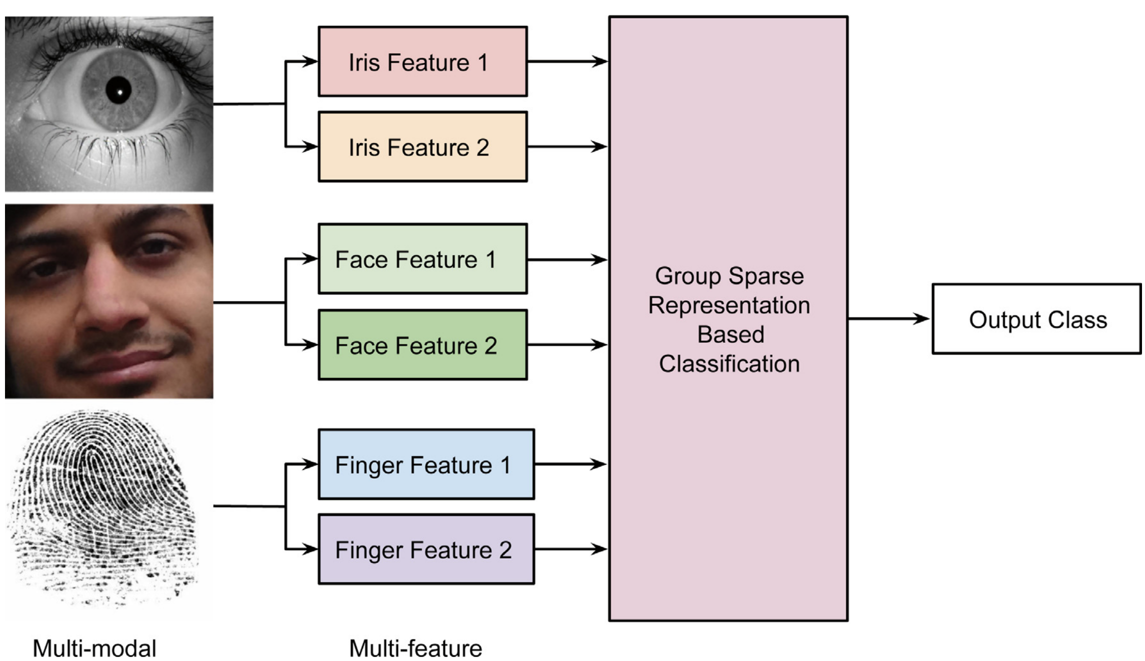

Fig. 1. A concept diagram of the proposed algorithm.

the outline of the proposed algorithm for a multimodal biometric recognition scenario. Face, iris, and fingerprint modalities of a person are encoded with multiple feature representations and matched using the proposed algorithm. By considering each feature source without the use of concatenation or feature reduction, the classification algorithm can utilize the different feature spaces