Sparse Discrimination based Multiset Canonical Correlation Analysis for Multi-Feature Fusion and Recognition

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Canonical correlation analysis (CCA) [3] is a powerful tool for finding the correlation between two sets of multidimensional variables. It investigates the linear correlations between two sets of random variables and linearly projects two sets of random variables into a lower-dimensional space in which they are maximally correlated. However, most of CCA-based methods are not efficient for multiple (more than two) feature representations classification tasks [5]. As a generalized extension of CCA, multiset canonical correlation analysis (MCCA) [6, 7] was proposed to solve this problem. In recent years, with the development of sparse representation [1, 2, 4, 9], sparse representation based classification (SRC) has been proved to be robust for feature selection and efficient in handling occlusion and corruption. Sparsity preserving projections (SPP) [8] aims to preserve the sparse reconstructive relationship of the data. Extensive experiments on some common datasets show that the projections obtained by SPP are invariant to rotations, rescalings and translations of the data.

However, MCCA usually fails to discover the intrinsic sparse reconstructive relationship and discriminating structure of multiple data spaces in real-world applications. In this paper, by taking discriminative information of within-class and between-class sparse reconstruction into account, we propose a novel algorithm, called sparse discrimination based multiset canonical correlations (SDBMCCs), to explicitly consider both discriminative structure and sparse reconstructive relationship in multiple representation data. In addition to maximizing between-set cumulative correlations, SDBMCC minimizes within-class sparse reconstructive distances and maximizes between-class sparse reconstructive distances, simultaneously. The feasibility and effectiveness of the proposed method is verified on four popular databases (CMU PIE, ETH-80, AR and Extended Yale-B) with promising results.

We characterize the within-class and between-class scatter matrices, i.e., minimizing the average within-class distance and maximizing the average between-class distance, simultaneously. Given m feature sets \(X(i) = \{X(i)_{1}, X(i)_{2}, \ldots, X(i)_{n}\} \in \mathbb{R}^{m \times n}\) extracted from n samples of c classes. Let \(\Phi: \mathbb{R}^{m} \rightarrow \mathbb{R}^{m}\) be the characteristic function that selects the coefficients of \(s(i)_{j}\) associated with the same class of the sample \(X(i)_{j}\). We can construct the model of SDBMCC as follows:

\[
\text{max} J(\alpha) = \sum_{i=1}^{m} \sum_{j=1}^{n} (\alpha^{T} X(i)_{j} \Phi(s(i)_{j}) - \tau[\vec{\alpha}_{j}^{T} - (1 - \eta) J(j)])
\]

subject to \(\sum_{j=1}^{n} \alpha^{T} X(i)_{j} \Phi(s(i)_{j}) = 1\).

Similarly to the within-class scatter, let \(\Psi: \mathbb{R}^{m} \rightarrow \mathbb{R}^{m}\) be the characteristic function that selects the coefficients of \(s(i)_{j}\) associated with the different classes of the sample \(X(i)_{j}\). We can construct the total between-class scatter for all m feature sets as follows:

\[
J_b = \sum_{i=1}^{m} J_b(i) = \sum_{i=1}^{m} \alpha^{T} X(i) \Phi(s(i)) X(i)^{T} \alpha(i)
\]

where \(S(i) = [I - \Phi(S(i))][I - \Phi(S(i))]^{T}\).

Then we can construct the total within-class scatter for all m feature sets as follows:

\[
J_w = \sum_{i=1}^{m} J_w(i) = \sum_{i=1}^{m} \alpha^{T} X(i) \Phi(s(i)) X(i)^{T} \alpha(i)
\]

Obviously, minimizing the total within-class scatter \(J_w\) can lead to a better sparse reconstructive relationship of the samples belonging to the same class.