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ORIGINAL ARTICLE

Exploiting label consistency in structured sparse representation for classification

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Abstract

Sparse representation with adaptive dictionaries has emerged as a promising tool in computer vision and pattern analysis. While standard sparsity promoted by ℓ_0 or ℓ_1 regularization has been widely used, recent approaches seek for kinds of structured sparsity to improve the discriminability of sparse codes. For classification, label consistency is one useful concept regarding structured sparsity, which relates class labels to dictionary atoms for generating discriminative sparsity patterns. Motivated by the limitations of existing label-consistent regularization methods, in this paper, we investigate the exploitation of label consistency and propose an effective sparse coding approach. The proposed approach enforces the sparse approximation of a label consistency matrix by sparse code during dictionary learning, which encourages the supports of sparse codes to be consistent for intra-class signals and distinct for inter-class signals. Thus, the learned dictionary can induce discriminative sparsity patterns when used in sparse coding. Moreover, the proposed method is computationally efficient, as the label consistency regularization developed in our method brings very little additional computational cost in solving the related sparse coding problem. The effectiveness of the proposed method is demonstrated with several recognition tasks, and the experimental results show that our method is very competitive with some state-of-the-art approaches.

Keywords Sparse coding · Label consistency · Structured sparsity · Image classification

1 Introduction

In the last decade, sparse representation has shown its great advantages in discovering the underlying structures of high-dimensional data. With such advantages, sparse representation has become a promising tool in many recognition systems, e.g., face recognition, scene classification, object classification, action recognition; see, e.g., [2, 7, 9, 12, 25, 34, 41]. Given a set of input patterns, most existing sparse representation methods aim at finding a small number of *atoms* (i.e., representative patterns) whose linear combinations approximate those input patterns well.

More specifically, given a set of vectors $\{\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_P\} \subset \mathbb{R}^N$, sparse representation aims at determining a set of coefficient vectors $\{\boldsymbol{c}_1, \ldots, \boldsymbol{c}_P\} \subset \mathbb{R}^M$ with most elements close to zero, together with a set of atoms $\{\boldsymbol{d}_1, \boldsymbol{d}_2, \ldots, \boldsymbol{d}_M\} \subset \mathbb{R}^N$, so that each input vector $\boldsymbol{y}_j$ can be well approximated by the linear combination

$$\boldsymbol{y}_j \approx \sum_{m=1}^{M} \boldsymbol{c}_j(m)\boldsymbol{d}_m. \tag{1}$$

By stacking vectors as matrices, we can rewrite (1) in the matrix form as follows:

$$\boldsymbol{Y} \approx \boldsymbol{D}\boldsymbol{C}, \tag{2}$$

where $\boldsymbol{Y} = [\boldsymbol{y}_1, \ldots, \boldsymbol{y}_P] \in \mathbb{R}^{N \times P}$ denotes input signals, $\boldsymbol{D} = [\boldsymbol{d}_1, \ldots, \boldsymbol{d}_M] \in \mathbb{R}^{N \times M}$ contains the universal set of atoms and is called a *dictionary*, and $\boldsymbol{C} = [\boldsymbol{c}_1, \ldots, \boldsymbol{c}_P] \in \mathbb{R}^{M \times P}$ is often referred to the *sparse code* of input data. Basically speaking, sparse representation assumes data lies at some union of low-dimensional subspaces and represents the subspace of $\boldsymbol{y}_j$ by the span of the activated atoms.

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