Engineering Applications of Artificial Intelligence 72 (2018) 241–252

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

An interactively constrained discriminative dictionary learning algorithm for image classification

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ARTICLE INFO

Keywords:
Dictionary learning
Sparse coding
Image classification

ABSTRACT

Researches demonstrate that profiles (row vectors of coding coefficient matrix) can be used to select and update atoms. However, the profiles are seldom used to construct discriminative terms in dictionary learning. In this paper, we propose an interactively constrained discriminative dictionary learning (IC-DDL) algorithm for image classification. First, we give a Lemma of the relation between the profiles and atoms. That is, similar profiles can lead to the corresponding atoms which are also similar, and vice verse. Then, we construct a profile constrained term by using the profiles and Laplacian graph of the atoms. Third, we explore the atoms and the Laplacian graph of the profiles to construct an atom constrained term. By alternatively and interactively updating the profiles and atoms, the two proposed constrained terms not only can inherit the structure information of the training samples, but also preserve the structure information of the atoms and profiles simultaneously. Moreover, the atom constrained model also can minimize the incoherence of the atoms. Experiment results demonstrate that the IC-DDL algorithm can achieve better performance than some state-of-the-art dictionary learning algorithms on the six image databases.

1. Introduction

Sparse representation has achieved excellent performance in many domains (Wright et al., 2009; Wang and Guo, 2017; Banerjee and Chatterjee, 2017). However, researches demonstrate that dictionary learning model usually has a better signal reconstruction and classification performance than directly utilizes original training samples (Zhu and Shao, 2014; Huang et al., 2017; Chen and Su, 2017). Therefore, many dictionary learning algorithms have been proposed for classification tasks (Shu et al., 2018; Vu and Monga, 2017; Wang et al., 2017; Akhtar et al., 2016; Banerjee and Chatterjee, 2016).

In the sparse coding and dictionary learning models, the locality information is more essential than the sparsity (Yu et al., 2009). Therefore, many dictionary learning algorithms have been proposed by using the locality information of the training samples to construct the discriminative terms (Wang et al., 2010; Zheng et al., 2011; Haghiri et al., 2015; Liu et al., 2015). However, since the training samples often include noise and outliers in practical applications, they may not obtain the true locality information of the training samples. Moreover, the locality information of the coding coefficients and atoms is also ignored. Then, they may degrade the discriminative ability of the learned dictionary. Recently, the profiles (row vectors of coding coefficient matrix) have been used to select and update atoms, and to design the discriminative terms in the dictionary learning algorithms (Lu et al., 2014a; Sadeghi et al., 2014; Li and Zhang 2016; Li et al., 2017). Especially, in Li et al. (2017), Li et al. proposed a locality constrained and label embedding dictionary learning (LCLE-DL) by using the profiles and atoms to inherit the locality characteristics of the training samples. However, the LCLE-DL algorithm ignored the structure information of the coding coefficients and the incoherence characteristics of the atoms. Although discriminative terms based on the coding coefficients (column vectors of coding coefficient matrix) have been well studied, how to use the profiles to construct discriminative terms for enhancing discrimination of the learned dictionary is still in its infant stage.

To this end, we propose an interactively constrained discriminative dictionary learning (IC-DDL) algorithm by using the profiles and atoms. The IC-DDL algorithm not only can preserve the locality information of the coding coefficients and the atoms, but also inherits the locality information of the training samples. The basic idea of IC-DDL is

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https://doi.org/10.1016/j.engappai.2018.04.006
Received 25 August 2017; Received in revised form 30 March 2018; Accepted 8 April 2018
Available online 8 May 2018
0952-1976/

illustrated in Fig. 1. We first use the K-SVD algorithm to initialize a dictionary, which can inherit the geometric structure of the training samples (Aharon et al., 2006; Zhu and Lafferty, 2005; Shaban et al., 2013). Then, we construct a Laplacian graph of the atoms, and use the profiles to measure the similarity of the corresponding atoms. In this way, we can construct the profile constraint term by using the profiles and the learned Laplacian graph of the atoms. The profile constraint term not only inherits the locality information of the training samples, but also preserves the locality information of the atoms immediately surrounding them. Similarly, we construct an atom constraint term by using the atoms and the learned Laplacian graph of the profiles. The atom constraint term not only can preserve the locality information of the coding coefficients, but also can minimize the incoherence of the atoms. Since there is a one-to-one correspondence between the profile and atom, the atom constrained and profile constrained terms can be alternatively and interactively updated in dictionary learning. Moreover, since the data is more likely to reside on a low-dimensional sub-manifold embedded in the high-dimensional ambient space, the geometrical information of the data is important for discrimination (Zheng et al., 2011). Therefore, by preserving the locality characteristics of the atoms and coding coefficients, the discriminative ability of the learned dictionary can be improved in the proposed IC-DDL algorithm.

In the testing stage, we use the orthogonal matching pursuit (OMP) (Tropp and Gilbert, 2007) algorithm to calculate the sparse representation coefficients with the learned dictionary. And then, we explore the coding coefficients and the label of the training samples to calculate a classifier parameter. By combining the classifier parameter and sparse representation coefficients, we can obtain the label of the testing samples.

The main contributions of this work are summarized as follows:

(1) A lemma about the relation between the profiles and atoms is given, that is, similar profiles can lead to the corresponding atoms which are also similar, and vice verse. The relation between the profiles and atoms can provide a new insight to design discriminative terms.

(2) The atom constrained term is constructed by using the Laplacian graph of the profiles and atoms. It not only can preserve the locality information of the coding coefficients, but also minimizes the incoherence of the atoms. Both of them are important for enhancing the discrimination ability of the learned dictionary.

(3) The two constrained terms are constructed by using the profiles and atoms, which can be adaptively and interactively updated in dictionary learning. In this way, the discriminative information can be mutual transformed between the atom constrained and profile constrained terms.

The rest of this paper is organized as follows. The related works are presented in Section 2. The definition of the profiles is given in Section 3. Section 4 introduces the proposed dictionary learning algorithm. Section 5 presents the optimization of the proposed algorithm. Relationships between the proposed algorithm and comparison algorithms are discussed in Section 6. The experimental results and analysis are included in Section 7. Some conclusions are drawn in Section 8.

2. Related work

For discriminative dictionary learning algorithms, the label information usually plays an important role for improving classification performance. Therefore, the labels of the training samples or/and atoms are usually used to construct the discriminative terms. In Zhang and Li (2010), in order to utilize the label information of the training samples, Zhang et al. proposed the D-KSVD algorithm by constructing the classification error term and learning the linear classifier simultaneously. Furthermore, the label consistence K-SVD dictionary learning algorithm (LC-KSVD) is proposed, which explored both the label information of the atoms and training samples to design the discriminative terms (Jiang et al., 2013). In Zhang et al. (2016), based on the LC-KSVD algorithm, Zhang et al. imposed the embedding learning on the dictionary learning model to enhance the discrimination ability of the coding coefficients. Moreover, in Cai et al. (2014), Cai et al. explored the labels of the training samples to construct an adaptive weighted model to constrain the coding coefficients, and presented a support vector guided dictionary learning (SVGDL) algorithm for classification. However, those algorithms all ignore the incoherent properties of the atoms, and it may enhance the redundancy of the learned dictionary. In Yang et al. (2014), Yang et al. proposed a discrimination dictionary learning algorithm by simultaneously using the Fisher criterion of the coding coefficients and imposing the self-incoherent constraints on each dictionary. In Wang and Kong (2014), Wang and Kong also used the incoherence characteristics of the atoms to construct the discriminative term. However, the above algorithms all ignored the locality information of the training samples, and it may degrade the discrimination of the learned dictionary. The reason is that the locality information is more essential than the sparsity in sparse coding and dictionary learning (Yu et al., 2009).

In Wang et al. (2010), in order to exploit the locality information, Wang et al. explored the distances between the atoms and the training samples to constrain the coding coefficients. In Liu et al. (2015), Liu et al. proposed a kernel collaborative representation classification algorithm by using the locality-constrained dictionary. Although the structure properties can be preserved by an ensemble of the representative points in the above algorithms, the structure information immediately surrounding the representative points is discarded. In order to address this problem, in Li et al. (2015), Li et al. proposed the locality-constrained affine subspace coding by using an ensemble of subspaces attached to the representative points. In Lu et al. (2014b), Lu et al. designed the ACDL algorithm by using the k-means clusters method and the manifold learning method. However, in the ACDL algorithm, the structure information of the atoms and coding coefficients are constructed by directing utilizing the training samples, which is the structure information of the training samples in essence. Moreover, the ACDL algorithm also ignored the geometric structure of the atoms immediately surrounding them, it played an important role in sparse coding and dictionary learning (Li et al., 2015). Recently, in Li et al. (2017), Li et al. proposed the LCLE-DL algorithm by using the profiles and the atoms. The LCLE-DL algorithm not only can inherit the structure information of the training samples, but preserve the structure information of the atoms immediately surrounding them. However, the LCLE-DL algorithm ignored the structure information of the coding coefficients and the incoherence characteristics of the atoms. In order to address this problem, we propose an interactively constrained discriminative dictionary learning algorithm by using the profiles and atoms. The IC-DDL algorithm not only can inherit the structure information of the training samples, but also preserve the geometric structure of the atoms and coding coefficients. Moreover, The IC-DDL algorithm also can minimize the incoherence of the leaned dictionary. All of them are benefit to improve the discriminative ability of the learned dictionary. Therefore, the IC-DDL algorithm can achieve better performance than some discriminative dictionary learning algorithms on the four face databases and two image databases.

3. Definition of the profiles

In general, the basic framework of dictionary learning is as follows.

$$\min_{\boldsymbol{D},\boldsymbol{X}} \|\boldsymbol{Y}-\boldsymbol{D}\boldsymbol{X}\|_2^2+\varepsilon f(\boldsymbol{X}) \tag{1}$$

where $\boldsymbol{Y}=\left[\boldsymbol{y}_1,\boldsymbol{y}_2,\ldots,\boldsymbol{y}_n\right]\in\Re^{m\times n}$ is the training sample set and $\boldsymbol{y}_i$ is the ith training sample. $\boldsymbol{D}=\left[\boldsymbol{d}_1,\boldsymbol{d}_2,\ldots,\boldsymbol{d}_s\right]\in\Re^{m\times s}$ is the learned dictionary and $\boldsymbol{d}_i$ is the ith atom. $\boldsymbol{X}=\left[\boldsymbol{x}_1,\boldsymbol{x}_2,\ldots,\boldsymbol{x}_n\right]\in\Re^{s\times n}$ is the coding coefficients and $\boldsymbol{x}_i=\left[x_{1i},x_{2i},\ldots,x_{si}\right]^T$ is the coding coefficient vector of training sample $\boldsymbol{y}_i$. ε is the regularization parameter and $f(.)$ is the sparsity function of the coding coefficients. In ideal conditions, Eq. (1) can be rewritten as follows (Lu et al., 2014a).