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Class specific sparse representation for classification

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ABSTRACT

Motivated by the fact that the signals tend to have a representation biased towards their own classes, we propose a novel Sparse Representation-based Classifier (SRC) named Class Specific Sparse Representation-based Classifier (CSSRC), which incorporates the class information in the representation learning. Unlike the conventional SRC algorithms, CSSRC defines each class as a group and then impels these groups to compete for representing the test sample. To achieve such property, CSSRC imposes a L_1-norm constraint to the classes for compulsively selecting the most relevant classes and introduces a L_2-norm constraint to the samples belonging to the same class for making sure that all homogeneous samples can be sufficiently exploited for representation. Since CSSRC is a typical structure sparse representation issue, it can be efficiently solved by the convex optimization. Seven popular visual and audio signal databases are employed for evaluation. The results demonstrate its effectiveness in comparison with the state-of-the-art classifiers.

1. Introduction

It has been discovered in neural science [1] that the human vision system seeks a sparse representation for the incoming image using a few words in a feature vocabulary. This discovery boosts many computer vision and signal processing works that consider a visual or signal system as a regression model called Sparse Representation (SR) [2–8]. In SR, a L_1-norm constraint is introduced to the common regression model for compulsively selecting only a few of relevant measurements and ignoring the irrelevant ones by assigning their corresponding regression coefficients to zero. This endows SR with a strong discriminating power and a good robustness to noise. So, in recent years, more and more researchers apply SR for classification [2,3,9–11]. However, the time cost of SRC is expensive in comparison with other regression-based classifiers and the sparsity achieved by the L_1-norm constraint is too strong that leads to a higher reconstruction error. Zhang et al. [12–14] proposed a presentation algorithm called Collaborative Representation (CR) for addressing these issues and argued that even the irrelevant samples still have some contributions to the reconstruction of test sample. In other words, all the samples should collaboratively represent the test sample. In CR, a relatively mild L_2-norm constraint is leveraged to replace the L_1-norm constraint to achieve such property. Although the coefficients obtained by CR are not as sparse as the ones achieved by SR, the coefficients of the relevant samples still own greater magnitudes. Many works have already shown that such Collaborative Representation-based Classification (CRC) approaches can get a similar or even better performance. Moreover, SRC requires the overcomplete dictionary while CRC does not have such assumption.

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Although a lot of SR- and CR-based algorithms have been proposed for tackling different classification tasks, as far as we know, there are no SR- or CR-based classification methods that incorporate the class information during the representation learning previously. According to the compressed sensing [15–17], the input sample tends to have a representation biased towards their own class. In this short communication, we present a new sparse representation-based classification algorithm that can leverage the class information to incorporate the merits of both SRC and CRC for further improving their discriminating powers. We name our new SR algorithm Class Specific Sparse Representation (CSSR) and its corresponding classifier Class Specific Sparse Representation-based Classifier (CSSRC). In CSSR, the samples belonging to the same class are considered as a group and these groups will be in competition for representing the input sample. In other words, the sparsity exists among the classes while the samples in the same class work collaboratively to present the input homogenous sample. We impose a L_1-norm constraint to regression coefficients based on classes for achieving such sparsity and impose a L_2-norm constraint to regression coefficients of the homogenous samples for giving a smooth intra-class representation and avoiding the overfitting. Clearly, CSSR inherits the properties of both SR and CR and it is a typical structured sparse representation model which can be solved by the convex optimization. In order to better show the desirable behavior of CSSR, we visualize the learned coefficients of CSSR and its related approaches in Fig. 1. We evaluate CSSRC on seven popular visual and audio signal databases. The experimental results demonstrate that CSSRC gets a promising performance in comparison with the state-of-the-art classifiers.

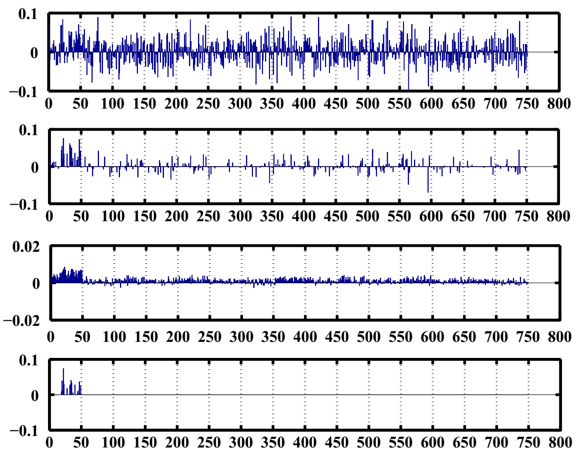

Fig. 1. The visualizations of the regression coefficients learned by Linear Regression (LR) [21], Sparse Representation (SR) [2], Collaborative Representation (CR) [12] and our proposed Class Specific Sparse Representation (CSSR) from top to bottom (50 samples per class for training in Scene15 database, each interval is corresponding to one class. The LR totally fails to highlight the relevant samples. The other three regression-based algorithms can highlight the relevant samples. However, some other inhomogeneous samples are also highlighted in the coefficients learned by SR or CR. With regard to the regression coefficients of CSSR, only the homogenous samples have been highlighted.)

2. Sparse representation and collaborative representation

In this section, we introduce Spare Representation (SR) and Collaborative Representation (CR) models, which are the related works of CSSR, and also define some basic notations. Let the $d \times n$-dimensional matrix X be the sample matrix, where d is the dimension of sample and n is the number of samples. The $d \times n_i$-dimensional matrix X_i is denoted as the sample matrix of class i, where n_i is the number of samples belonging to class i and $\sum_{i=1}^{C} n_i = n, i \in \{1, \dots, C\}$. C is the number of classes. Given a test sample y, the sparse representation model seeks to solve the following optimization problem:

$$\hat{a} = \arg\min_a \| a \|_0 \quad \text{s.t.} \quad \| y - Xa \| \le \epsilon, \tag{1}$$

where a is a n-dimensional column vector known as the regression coefficients (or representation coefficients), $\epsilon > 0$ is the noise level parameter, and $\| \cdot \|_0$ denotes the L_0-norm which counts the number of non-zero entries in a vector. However, problem (1) is NP-hard and is even difficult to be solved approximately [17]. Most of recent SR works tend to seek a close-form solution via relaxing the L_0-norm constraint to the L_1-norm constraint [2,3,15]. Consequently, the original problem (1) can be approximated by the relaxed one with high accuracy as follows:

$$\hat{a} = \arg\min_a \| a \|_1 \quad \text{s.t.} \quad \| y - Xa \| \le \epsilon, \tag{2}$$

which is a typical convex optimization problem. And the learned a should only have a few nonzero elements which are corresponding to the most relevant samples.

Zhang et al. [12] argued that the sparsity assumption of sparse representation is not necessary for distinguishing the samples and all the samples should give a contribution to the reconstruction of the test sample. Therefore, they presented the Collaborative Representation (CR) model by replacing the L_1-norm constraint with a L_2-norm constraint. The problem of CR can be formulated as follows:

$$\hat{a} = \arg\min_a \| a \|_2 \quad \text{s.t.} \quad \| y - Xa \| \le \epsilon. \tag{3}$$

This problem can be efficiently solved by regularized least squares. The L_2-norm constraint can not only avoid overfitting, but also enforce the model to sufficiently utilize all the samples for data representation.

3. Class specific sparse representation

Different to the other tasks, the classification task only requires the output of the best-match class for a test sample. Therefore, it is more meaningful to directly highlight the relevant classes instead of seeking the relevant samples like Sparse Representation (SR) and Collaborative Representation (CR). Naturally, a test sample tends to be well represented by its own class. Therefore, in our approach, we consider that only a few classes play the vital role in the representation of the test samples. The samples of such parsimoniously selected classes should be sufficiently utilized for representation. A L_1-norm constraint is imposed between the classes for achieving the sparsity among classes while a L_2-norm constraint is