Information Sciences 269 (2014) 48–59

Contents lists available at ScienceDirect

Information Sciences

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

Unsupervised images segmentation via incremental dictionary learning based sparse representation

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ARTICLE INFO

Article history:
Received 4 January 2012
Received in revised form 3 January 2014
Accepted 15 January 2014
Available online 24 January 2014

Keywords:
Image segmentation
Dictionary learning and sparse representation based classifier
Incremental learning
Consistency-enhanced
Synthetic aperture radar

ABSTRACT

In this paper we propose a novel Dictionary Learning and Sparse Representation-based Classifier (DLSRC) for image segmentation. In DLSRC, instances-based learning is adopted to find representative dictionaries that can sparsely code various classes of prototype samples in images. Then an incremental version of DLSRC, IDLSRC, is advanced for incremental learning of accumulating knowledge obtained from labeled data. The unsupervised clustering algorithm provides initial labeled samples, and then the labels of candidate samples are incrementally predicted by defining a consistency-enhanced evaluation function. Some experiments are taken on both the artificial texture images and real Synthetic Aperture Radar (SAR) images, to investigate the performance of DLSRC and IDLSRC. Some aspects including (1) the comparison of DLSRC with the Sparse Representation based Classifier (SRC) and some unsupervised clustering approaches, (2) the comparison of IDLSRC with DLSRC, are tested, and the results prove the superiority of our proposed method to its counterparts.

1. Introduction

Modeling signals are fundamental for handling various processing tasks. The preceding decade has witnessed a growing interest in the sparse modeling of signals, whose goal is to model signals as a sparse linear combinations of some basis elements (or atoms) [3–5,24,16–28]. Recently sparse modeling has found fruitful applications in signal and image recovery, sampling, compression and more [7–11,13,16,18,20,21]. As a powerful and promising statistical modeling tool, sparse representation also provides useful tools for machine learning. In a very recent work [20], Sparse Representation based Classifier (SRC) is advanced by Wright for robust pattern classification, whose basic idea is that any sample can be represented as a linear combination of labeled prototype samples. That is, given sufficient labeled samples of multiple classes, any new sample will be approximately represented as the linear combination of them. If we cast a sparse assumption in synthesizing the sample, the representation coefficients will be remarkable for the class the new sample belongs to, while for the other classes, the coefficients are near to zero. Consequently the label of the new sample can be predicted from sparse coefficients. Nowadays SRC has proved to lead to state-of-the-art results in many pattern classification tasks [3,20].

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http://dx.doi.org/10.1016/j.ins.2014.01.023
0020-0255/

Different with discriminative and generative learning based classifiers, SRC is characteristic of very simple principle, robustness to noise, free of feature extraction, model selection and data distribution assumption. Although SRC has proved to be able to accurately classify various kinds of clustered data, it spends considerable time in predicting labels, when compared with traditional classifiers such as Neural Networks (NNs) and Support Vector Machines (SVMs). These traditional discriminative models often require a long training process, while the prediction is very fast as soon as model parameters are successfully tuned from instances. However, in SRC an NP-hard l_0-norm minimization problem needs to be solved when identifying each sample, which makes the label prediction very time-consuming. Although several algorithms have proved to be able to find sparse coefficients by replacing l_0-norm by l_1-norm [2,6,17] optimization, the classification is still of high complexity, especially when there are a large number of labeled samples. Another disadvantage of SRC is that it works in a supervised scenario and thus requires many training samples (or a large dictionary) to achieve accurate classification. However, it is unfeasible when only a few labeled samples are available, because the expert collaboration is expensive in labeling a large number of instances.

In this paper we address these two issues and propose a Dictionary Learning and Sparse Representation-based Classifier (DLSRC) and its incremental version, for accurate image segmentation without the requirement of labeled samples. In DLSRC, instances-based dictionary learning is adopted to find a dictionary that can well approximate many instances, i.e., the training set, and allows only a small number of non-zero coefficients for each approximation. Therefore, a more compact and representative dictionary is obtained to sparsely represent samples and replace the prototype samples in the original SRC, which makes an accurate and rapid classification of samples possible. Moreover, an unsupervised-clustering-cooperative scheme is proposed to initially select some "good" samples by defining a consistency-enhanced evaluation function of samples, and then the candidate samples are incrementally added and learned to obtain the final segmentation result. Because the dictionary is dynamically learned from incrementally labeled instances, we name it as the Incremental Dictionary Learning and Sparse Representation-based Classifier (IDLSRC) in the paper. Some experiments are taken on several artificial texture images and real Synthetic Aperture Radar (SAR) images to investigate the performance of our proposed DLSRC and IDLSRC. Some aspects including (1) the comparison of DLSRC with SRC and some clustering approaches; (2) the comparison of IDLSRC with DLSRC, are tested, and the results prove their superiority to other related segmentation approaches.

The contributions of the paper are as follows: (1) a dictionary learning and sparse representation based classifier is proposed for image segmentation, where dictionary learning technology is employed to achieve accurate classification of pixels, (2) an incremental version of DLSRC, IDLSRC, is advanced for incremental learning of accumulating knowledge obtained from data, to make full use of the middle segmentation result in DLSRC, (3) some experiments are taken on several artificial and real images to investigate the performance of DLSRC and IDLSRC.

The rest of this paper is structured as follows. Section 2 details the foundation of our work. The incremental image segmentation via IDLSRC is expounded in Section 3. In Section 4, some experiments are taken to compare the proposed method with other related segmentation ways. The conclusions are finally summarized in Section 5.

2. Dictionary Learning and Sparse Representation based Classifier (DLSRC)

In this section, the foundations of our proposed methods are illustrated, including the sparse representation, sparse representation based classifier, dictionary learning algorithm, and DLSRC.

2.1. Over-complete dictionary based sparse representation

Sparse representation aims at formulating signals using a few linear combinations drawn from a large candidate set that is called as "dictionary" with each element named as an "atom". Recent results indicate that over-complete dictionaries hope to achieve better approximation of signals [1,12]. Given a signal $\mathbf{x} \in R^n$ and an over-complete dictionary $\mathbf{D} \in R^{n\times k}$, $k > n$, a "sparse" approximation of $\mathbf{x}$ can be obtained through decomposing it by a series of linear combination of the columns (atoms) drawn from $\mathbf{D}$, which can be written as follows:

$$\mathbf{x} = \mathbf{D}\boldsymbol{\theta}, \quad \|\boldsymbol{\theta}\|_0 \ll k \tag{1}$$

Here $\|\boldsymbol{\theta}\|_0$ is defined as the l_0-norm of the coefficient vector $\boldsymbol{\theta} \in R^k$, and "sparse" means that only a few non-zero coefficients can be found in $\boldsymbol{\theta}$. Finding the sparse coefficient $\boldsymbol{\theta}$ of $\mathbf{x}$ can be reduced to the following optimization problem,

$$\begin{cases} \min\limits_{\boldsymbol{\theta}} \|\boldsymbol{\theta}\|_0 \\ s.t.\ \mathbf{x} = \mathbf{D}\boldsymbol{\theta} \end{cases} \tag{2}$$

which is typically NP-hard and non-convex, and can be solved by Matching Pursuit (MP) [12], Orthogonal Matching Pursuit (OMP) [15] algorithms. In practice, (2) is often changed to solving a convex l_1-norm optimization problem, and solved by Basis Pursuit (BP) [2] algorithm.