Optik 140 (2017) 216–222

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Original research article

Differentiated representation and applications to face recognition

Xuansheng Wang [a,*], Yan Chen [b]

[a] School of Software Engineering, Shenzhen Institute of Information Technology, Shenzhen, 518000, China
[b] Shenzhen Sunwin Intelligent Corporation, Shenzhen, 518000, China

ARTICLE INFO

Article history:
Received 14 June 2016
Received in revised form 5 April 2017
Accepted 14 April 2017

Keywords:
Differentiated representation
Sparse representation
Face recognition

ABSTRACT

Sparse representation has received much attention. Sparse representation usually first determines and uses a linear combination of all training samples that can well approximate to the test sample and then assigns the test sample to the class whose training samples obtains the minimal class-residual. In this paper, we propose an idea to make all training samples of different classes represent a test sample in a more competitive way, which is more useful to distinguish the class most similar to the test sample from the other classes. Based on this idea, we design a novel method, differentiated representation method, which uses a mathematically tractable means to make representation coefficients on a test sample generated from a class quite unsuitable for other classes. We propose a new classification procedure for the designed method. Applications on face recognition and object classification demonstrate that differentiated representation is very promising. It outperforms original sparse representation methods, collaborative representation and linear regression classification.

1. Introduction

In recent years sparse representation is one of methods that have attracted the most attention of researchers in fields of pattern recognition and machine learning [1–3]. Researchers are very impressed by its notable performance in various problems. It seems that sparse representation is very suitable to explore similarity between high-dimensional data. For example, it is reviewed as a breakthrough of face recognition owing to its surprising accuracy [4]. We also see that sparse representation performs very well in other image classification problems, video analysis, denoising, image super-resolution and video tracking [5–11].

In the past, various sparse representation methods have been proposed. From the viewpoint of 'materials' to represent test samples, previous sparse representation methods can be categorized as original sample based and dictionary based methods. Original sample based methods directly construct sparse representation of a test sample in terms of all training samples. In this paper we focus on original sample based methods, which are relatively mathematically tractable and computationally very efficient. Differing from original sample based methods, dictionary based methods first obtain a dictionary via all original samples and exploits the dictionary to produce sparse representation of test samples. Besides the original sparse representation method proposed in [1,2] is an original sample based method, linear regression classification (LRC) [12] and

* Corresponding author.
E-mail addresses: wxs111111@163.com (X. Wang), 673764341@qq.com (Y. Chen).

http://dx.doi.org/10.1016/j.ijleo.2017.04.055

the methods proposed in [13] all belong to this kind. The methods proposed in [14–16] are examples of dictionary based methods.

We can also roughly group previous sparse representation methods as two kinds, holistic and local representation methods. Holistic representation methods obtain an approximate representation of a test sample via all training samples of all classes. In contrast, local representation methods use only a small number of classes or a portion of training samples to produce an approximate representation of a test sample. The original sparse representation method and collaborative representation (CR) [17] are both typical examples of holistic representation methods. LRC can be viewed as a very easily understood local representation method. In LRC, only training samples of a class are exploited to obtain an approximate representation of the test sample. The two-phase test sample sparse representation (TPTSSR) method [18] and the coarse-to-fine sparse representation (CFSR) method proposed in [19] are also examples of local representation methods. From the viewpoint of the norm used, conventional sparse representation methods all belong to l_1 norm based sparse representation methods. On the other hand, l_2 norm based (sparse) representation methods such as collaborative representation and the methods presented in [20–22] are competent with high computational efficiency and accuracy. For more knowledge on sparse representation, please refer to corresponding literatures [23–25].

We see that most of previous sparse representation methods do not take into account relationship between representation coefficients of different classes. For example, though LRC respectively exploits training samples of each class to generate approximate representations of a test sample, it does not impose any constraint on representation coefficients of different classes. Most of other sparse representation methods also do so. It seems that some extensions of sparse representation methods use special constraint. For instance, the dictionary learning method proposed in [16] uses a discriminative constraint. The original sample based method proposed by Mi et al. [26] also designs a constraint condition for obtaining representation coefficients of different classes. However, because the method in [26] uses two separate procedures to obtain the solution, it appears that the designed constraint does not bring the desired performance. For better summarizing existing sparse representation methods, we give the following figure (Fig. 1).

In our opinion, designing a proper constraint for representation coefficients of different classes is beneficial to obtain better approximate representations of a test sample. In this paper, we propose a novel sparse representation method, differentiated collaborative representation (DCR). This method not only can obtain an approximate representation of a test sample via training samples but also makes representation coefficients on a test sample generated from a class improper for other classes. We propose a new classification procedure for the designed method, which is beneficial to correct classification of the test sample. Another merit of the paper is that a new classification procedure is proposed for the designed method. The classification procedure allows DCR to better exert its performance.

The other parts of the paper are organized below. Section 2 presents the proposed method including its objective function and procedure to obtain the solution. Section 3 interpret idea and rationale of the proposed method. Section 4 describes similarity and difference between our method and other methods. Section 5 shows experiments and results on face recognition and object classification. Section 6 provides conclusions of the paper.

2. The proposed method

Given N training samples $y_1, ...y_N$ from L classes. N is the number of all training samples. Suppose that each class has m training samples. Let $Y_i = [y_{(i-1)^*m+1}, ...y_{i^*m}]$ be training samples of the i-th class. Let x be a test sample. $y_1, ...y_N$ and x are all column vectors. For image data, they should be first converted into column vectors and be denoted by $y_1, ...y_N$ and x.

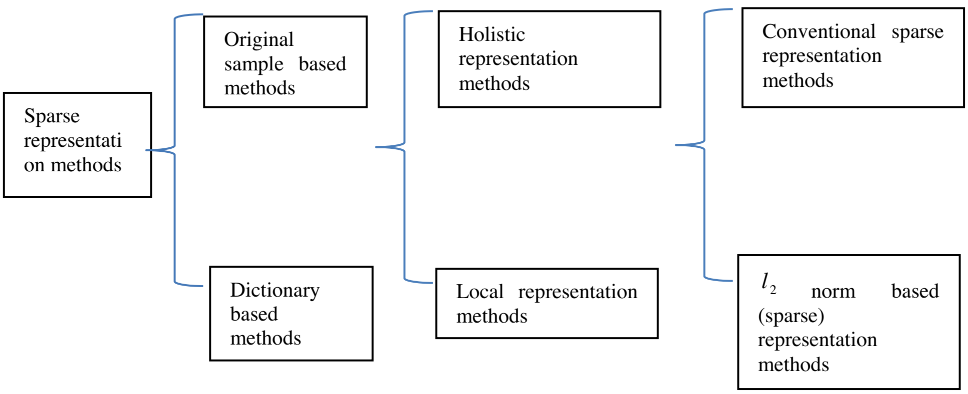

Fig. 1. Flowchart to summarize existing sparse representation methods.