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Adjusting samples for obtaining better l_2-norm minimization based sparse representation ☆

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ABSTRACT

l_2-norm sparse representation (l_2-SR) based face recognition method has attracted increasing attention due to its excellent performance, simple algorithm and high computational efficiency. However, one of the drawbacks of l_2-SR is that the test sample may be conspicuous difference from the training samples even from the same class and thus the method shows poor robustness. Another drawback is that l_2-SR does not perform well in identifying the training samples that are trivial in correctly classifying the test sample. In this paper, to avoid the above imperfection, we proposed a novel l_2-SR. We first identifies the training samples that are important in correctly classifying the test sample and then neglects components that cannot be represented by the training samples. The proposed method also involve in-depth analysis of l_2-SR and provide novel ideas to improve previous methods. Experimental results on face datasets show that the proposed method can greatly improve l_2-SR.

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1. Introduction

Sparse representation (SR) has a good reputation in the fields of pattern recognition, machine learning, and computer vision [1–6]. The SR based face recognition method has been viewed as a breakthrough in face recognition [7]. SR also has a close relationship with the well-known compressed sensing, which has made a remarkable contribution in the field of signal processing [8,9].

SR assumes that the test sample can be approximated by a certain linear combination of all training samples. After determining the linear combination, SR then exploits it to classify the test sample. Conventional SR is usually imposed with the constraint of the l_1-norm minimization. In other words, conventional SR is usually implemented with the assumption that the smaller the l_1-norm of the linear combination coefficients the better the solution. A small l_1-norm means that some of the linear combination coefficients are equal or close to zero. It can also be declared that SR with the constraint of the l_1-norm minimization has sparse coefficients.

Though conventional SR is usually based on l_1-norm minimization, recently l_2-norm minimization based SR was also proposed [10–14]. This kind of method also tries to obtain a certain linear combination of all training samples that can well approximate the test sample. Its main difference from l_1-norm minimization based SR is that in l_2-norm minimization based SR the constraint to minimize the l_2-norm of the linear combination coefficients is imposed. After determining the linear combination, SR then exploits it to classify the test sample, Huang et al. [15] utilized a multi-manifold metric learning based method to classify the test sample. Other classifying related method include feature extraction method, e.g., a kernel trick proposed by Han et al. [16], there are also methods considering the relationship between image resolution and face recognition [17]. The two-phase test sample SR previously proposed [10] is a typical example of l_2-norm minimization based SR. It uses a simple and mathematically tractable strategy to achieve sparse coefficients and obtains very promising performance. The extensions of l_2-norm minimization based SR also do well in face recognition [11,18,19]. It should also be noted that the l_{21}-norm minimization based SR became a new member of SR family in 2011 [20]. Besides SR being applied to face recognition, it is also applied to palmprint recognition [21], feature selection [22], image super-resolution [23,24] and image denoising [25]. Moreover, novel SR methods such as structured sparse representation [26,27], group sparse [28–30], kernel sparse representation [31,32], and sparse coding [33–35] have been proposed. For a survey of SR, please refer to the literature [36].

It should be pointed out that some SR methods such as linear regression classification (LRC) [37,38] can be viewed as a special

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SR method and do not belong to either of the l_1 or l_2-norm minimization based SR. This method respectively first constructs a linear combination of the training samples of each class to represent the test sample and then exploits the representation result to determine the class of the test sample. The distinct characteristic of LRC is that no constraint on the norm of the linear combination coefficients is imposed on it.

Among various SR methods, collaborative representation classification (CRC) [12] is notable due to its simplicity and promising accuracy. CRC is a l_2-norm minimization based SR method. CRC only needs to solve a linear equation to obtain its solution. As shown in the literature [12], the main merit of SR is to propose a way to produce the collaborative representation and to devise the corresponding classifier, which contributes the most to the good performance of SR. As CRC also has this merit, it performs very well in pattern recognition problems. According to Shi et al. [39] and Zhang et al. [12], the sparseness of the coefficients itself does not contribute as much as expected to the good performance of SR in comparison with the way to produce the collaborative representation and the corresponding classifier. This also means that though the l_2-norm minimization usually obtains less sparse coefficients than the l_1-norm minimization, the l_2-norm minimization based SR can still lead to high accuracy. The study showed that the l_2-norm minimization based SR is able to outperform the l_1-norm minimization based SR in some cases [12,39]. Moreover, if the l_1-norm minimization and l_2-norm minimization based SR obtain the same accuracy for a problem, the l_2-norm minimization based SR will be favored due to its high computational efficiency and simplicity.

In this study, we identify flaws that CRC still has. Thus, we propose a novel method, which inherits the advantages of CRC such as simplicity and high computational efficiency and has better properties. It has the following two important characteristics. The first is that it adjusts the test sample by neglecting components of the test sample that cannot be represented by the linear combination of the training samples. The second is that it adjusts the training samples by putting emphasis on some significant training samples. Extensive experiments showed that the proposed method not only greatly outperforms CRC but also obtains higher accuracy than other l_2-norm minimization based SR methods. This study also enables readers to clearly see the significant factors that influence the effect of l_2-norm minimization based SR methods and provides novel and feasible ways to improve them.

The remainder of the paper is organized as follows. Sections 2 and 3 describe the proposed method and its rationale. Section 4 shows the experimental results. Section 5 presents the conclusion.

2. The proposed method

In this section, we will explain the proposed work in detail.

Without loss of generality, we assume that there are C classes and each class has n training samples. Let $\boldsymbol{x}_1,\ldots,\boldsymbol{x}_N$, be all the N training samples ($N = Cn$). $\boldsymbol{x}_{(i-1)n+k}$ stands for the kth training sample of the ith class. Let $\boldsymbol{y}$ stands for the test sample. For the proposed work, SR including works only for column vectors, $\boldsymbol{x}_1,\ldots,\boldsymbol{x}_N$ and $\boldsymbol{y}$ are all column vectors. $\boldsymbol{X}_i$ is defined as $\boldsymbol{X}_i = [\boldsymbol{x}_{(i-1)n+1},\ldots,\boldsymbol{x}_{i^*n}]$. In other words, $\boldsymbol{X}_i$ is the matrix consisting of all training samples of the ith class.

We assume that the following equation is approximately satisfied

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{B} \tag{1}$$

where $\boldsymbol{B} = [b_1,\ldots,b_N]^T$ is the vector formed by coefficients, c is the matrix constructed by all the training samples aligned column by column.

CRC [12] proposed an objective function

$$\min_{\boldsymbol{B}} \|\boldsymbol{y} - \boldsymbol{X}\boldsymbol{B}\|_2^2 + \mu\|\boldsymbol{B}\|_2^2 \tag{2}$$

The corresponding solution of this objective function is usually obtained using

$$\hat{\boldsymbol{B}} = (\boldsymbol{X}^T\boldsymbol{X} + \mu\boldsymbol{I})^{-1}\boldsymbol{X}^T\boldsymbol{y}. \tag{3}$$

where μ is a small positive constant and $\boldsymbol{I}$ is the identity matrix.

If $\boldsymbol{X}^T\boldsymbol{X}$ is not singular, the solution of Eq. (1) can be also obtained using

$$\hat{\boldsymbol{B}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y}. \tag{4}$$

where $\hat{\boldsymbol{B}} = [\hat{b}_1,\ldots,\hat{b}_N]^T$.

In CRC, the residual of the test sample with respect to the ith class is calculated, using $r_i = \|y - X_i\hat{B}_i\|$, where $\hat{B}_i = [\hat{b}_{(i-1)^*n+1}\ldots\hat{b}_{i^*n}]^T$. If $k = \arg\min_i r_i$, then CRC assigns the test sample to the kth class.

While in the proposed method, the main idea is to adjust each training sample and the test sample to obtain better results.

2.1. The first step of the proposed method

The first phase of the proposed method uses all of the training samples to represent each test sample and exploits the representation result to adjust each training sample.

It first assumes that the following equation is approximately satisfied:

$$\boldsymbol{y} = b_1\boldsymbol{x}_1 + b_2\boldsymbol{x}_2 + \cdots + b_n\boldsymbol{x}_n \tag{5}$$

where $\boldsymbol{B} = [b_1,\ldots,b_N]^T$ and $\boldsymbol{X} = [\boldsymbol{x}_1,\ldots,\boldsymbol{x}_N]$ is defined the same as in Eq. (1).

Rewrite and reverse the above equation, we can solve $\boldsymbol{B}$ by using $\hat{\boldsymbol{B}} = \boldsymbol{X}^{-1}\boldsymbol{y}$, if and only if $\boldsymbol{X}$ is not a singular matrix, otherwise, we can solve it by using

$$\hat{\boldsymbol{B}} = (\boldsymbol{X}^T\boldsymbol{X} + \gamma\boldsymbol{I})^{-1}\boldsymbol{X}^T\boldsymbol{y}$$

Eq. (5) shows that every training sample makes its own contribution to representing the test sample. The ith training sample makes a contribution with proportion of $b_1\boldsymbol{x}_1$. This contribution, can be also evaluated by

$$d_i = \|\boldsymbol{y} - b_i\boldsymbol{x}_i\|^2 \tag{6}$$

where d_i can also be somewhat viewed as a measurement of the reference to adjust the training sample set. In other words, d_i is a measurement of the distance between the test sample and the ith training sample, the larger the d_i, the larger scale of adjusting for the ith training sample. We consider that a small d_i means that there is little need to adjust the ith training sample. This conclusion will be further verified in the second step of the proposed method.

2.2. The second step of the proposed method

The second phase of the proposed method using the adjusted training sample set as the new training samples and apply the first step again for the test samples.

$$\hat{\boldsymbol{y}} = \hat{\boldsymbol{X}}\hat{\boldsymbol{B}} \tag{7}$$

where $\hat{\boldsymbol{y}}$ is referred to as the reconstruction of test sample $\boldsymbol{y}$.

The adjusted training sample i is constructed as

$$z_i = \hat{b}_i x_i \tag{8}$$

where z_i is the adjusted ith training sample.

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