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Research Paper

Training samples-optimizing based dictionary learning algorithm for MR sparse superresolution reconstruction

Jun-Bao Li [a], Huanyu Liu [a], Jeng-Shyang Pan [b,c,*], Hongxun Yao [d]

[a] Department of Automatic Test and Control, Harbin Institute of Technology, Harbin 150001, China
[b] Fujian Provincial Key Lab of Big Data Mining and Applications, Fujian University of Technology, Fuzhou 350108, China
[c] Innovative Information Industry Research Center, Shenzhen Graduate School, Harbin Institute of Technology, Harbin 150080, China
[d] School of Computer Science and Technology, Harbin Institute of Technology, Harbin 150001, China

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ABSTRACT

Magnetic Resonance (MR) imaging is widely used in diseases diagnosis. The hardware imaging arrives the limitation of resolution, and the high radiation intensity and time of magnetic hurts the human body. The software-based image super-resolution technology is prospective to solve the problem, especially with good excellent performance by sparse reconstruction-based image super-resolution. Dictionary generating is crucial issue of effecting the performance of the super-resolution algorithm, because of without considering the potential discriminative information during dictionary generating. For this problem, we propose the training samples-optimized dictionary learning algorithm for MR sparse super-resolution reconstruction. The gray-consistency & gradient joined diversity-based dictionary representation method is proposed to select the optimal images for the dictionary training. The dictionary training method is evaluated with the framework of sparse reconstruction-based MR imaging. Results show that the proposed dictionary selection framework is feasible and effective to improve the quality of sparse reconstruction-based MR super-resolution.

1. Introduction

Dictionary learning methods are used in many areas, including medical image classification [1], data classification [2], face recognition [3], face identification [4], diagnostic magnetic resonance image super-resolution [5], image representation [6], joint sparse principal component analysis [7], patch alignment [8], object tracking [9], MR spectroscopy quantification [10], medical image superresolution [11]. Dictionary learning is the crucial issue of constructing sparse representation model. On dictionary learning-based image reconstruction, the sparse coefficients and dictionary are important issues for the performances of reconstruction.

Sparse representation-based signal representation is to approximate a signal with the linear combination of the different other signals, where these signal are called atoms and the signal sets are called dictionaries. So, the signal sparse coding is affected by the signals dictionary. Optimizing the dictionary learning is feasible and attracting the attentions in signal processing areas, for example, images [12] and audio [13]. The popular method of learning the dictionary is iteration-based minimization problem solution. In the sparse coding stage, the dictionary is fixed in advanced during solving sparse coefficients, and in the dictionary update stage, the dictionary is generated based on the obtained coefficients. In the sparse coding stage, many dictionary learning methods were proposed in the previous works. For example, Orthogonal Matching pursuit (OMP) [14] method is applied to Method of Optimal Directions (MOD) [15] based dictionary learning, and Iterative Shrinkage Thresholding (IST) algorithm is applied Majorization Method (MM) [17] based dictionary learning. MOD is to generate the observation matrix with pseudo inverse of representation matrix. Maximum A Posteriori (MAP)-based dictionary learning [16] method applied the gradient descent method and the normalization of dictionary columns. However, all methods did not consider the uncertain parameters of the cost function, i.e., the regularization parameter. As the other class of dictionary learning, machine learning-based dictionary learning method are used, for example, K-Singular Value Decomposition (K-SVD) [17]. A frame design technique for use with vector selection algorithms in previous work [18]. The features of the edges, textures, and the structures are extracted to generate the dictionary [19]. The constrain-based dictionary training method is

* Corresponding author at: Fujian Provincial Key Lab of Big Data Mining and Applications, Fujian University of Technology, Fuzhou 350108, China.
E-mail addresses: junbaolihit@126.com (J.-B. Li), jspan@cc.kuas.edu.tw (J.-S. Pan).

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Table 1
Gray-consistency & gradient jointed diversity-based dictionary representation.

Complex-gradient Algorithm:
Step 1. Compute the largest gradient and complexity of the training sample. *For the input image I_i, compute the first order and second order $f(I_i)$:* $\begin{cases} f_1 = [-1, 0, 1], & f_2 = {f_1}^T \\ f_3 = [1, 0, -2, 0, 1], & f_4 = {f_3}^T \end{cases}$ where $i = 1, 2, \ldots, p$, and p is number of images, where $x_i = \max(\lvert f(I_i)\rvert)$; Compute the complexity of all images I_i: $y_i = \sum_{a=2}^{m-1}\sum_{b=2}^{n-1}(I_i(a,b) - \bar{I}_i)^2, \bar{I}_i = \frac{1}{8}\left(\sum_{i=-1}^{1}\sum_{j=-1}^{1} I_i(a+i, b+j) - I_i(a,b)\right)$ where m and n are the number of row and column, and $I_i(a, b)$ is the pixel gray value of the point (a, b). *Step 2. Select the center line of two coordinates as the baseline.* *Step 3. Project the center of each class to the baseline, and cluster the image data to the center of each class.* *Step 4. Select the sample of the farthest distance from the center as the training sample.*

proposed to SR-based image super resolution [20]. The iteration computing method is applied to the sparse domain based image debluring with only training single high resolution dictionary [21]. In the previous work, the precise dictionary representation for sparse representation method [22] and dictionary selection [23] were proposed in dictionary-based sparse representation. These dictionary learning method directly sparse code directly from the dictionary updating, so these methods did not extract the potential expression information of dictionary quickly and sufficiently.

In this paper, we apply the training selection to improve the performance of dictionary learning. We use the limited MR training samples to generate dictionary through training sample selection. The excellent performance of image reconstruction is achieved with dictionary training through optimizing MR image with high dictionary diversity. We propose the training sample selection based gray-consistency & gradient jointed method. The method performs well on image superresolution from the two facts, that one is to judge the quality of training samples through the gray consistency method, and second is to effectively distinguish the global diversity through calculating the maximum two first and second order gradient. Some experiments are to evaluate the performance of super-resolution MR Imaging based sparse reconstruction.

2. Proposed algorithm

2.1. Problem

On the dictionary-learning based sparse representation image reconstruction, the dual high-resolution and low-resolution of images are trained to the sparse representation. The detail information of algorithm procedure is provided in Ref. [20]. In this procedure, the high-resolution image block dictionary D_h is trained with the high-resolution of MR images, and the low-resolution image block dictionary D_l is trained with low-resolution of MR images. The high-resolution I_{high} contains many image blocks B_{high}. The image is represented as a sparse linear combination of the D_h and the sparse representation parameter vector α. The SR coefficients are solved with sparse representation constrained optimization equation. The MR image is represented with dictionary and the SR parameters. So, the crucial problem is to choose the optimized training samples to train dictionary for image superresolution. Dictionary training depends on a large number of training samples, but it is hard to achieve the enough number of training sample.

The general framework of the dictionary learning problem is described in detail as follows. Given a $d \times n$ matrix X of n training samples $\{X_i\}_{i=1}^{n}$, $X_i \in \mathbb{R}^D$, then dictionary learning is to train the dictionary D of size $d \times m$ $(m \geq d)$, the sparse coefficients α, and the input image $X = D\alpha$. Then the problem is formalized as the minimizing the error cost function:

$$f(X, D) = \|X - D\alpha\|^2 \tag{1}$$

Given a training data matrix X, and the representation matrix by$\alpha = [\propto_1, \propto_2, \ldots, \propto_m]$, then the dictionary learning problem for sparse representations is described as the joint optimization problem as follows.

$$argmin\left\{\|X - D\alpha\|_F{}^2\right\} + \lambda\|\alpha\|_{1,1} \tag{2}$$

where $\|X - D\alpha\|_F$ is the Frobenius norm, $\|\alpha\|_{1,1} = \sum_i\sum_j |\propto_{i,j}|$ denotes the absolute sum of the individual entries of the matrix. λ is the regularization parameter. The regularization parameter is to balance the SR performance and the sparse level. The method of choosing the regularization parameter is different in the different practical applications. The crucial step is to choose the training samples for dictionary learning. The image quality is evaluated with the complex-gradient jointed method. The optimal MR image samples are selected to train the high-low MR image blocks. The dictionary diversity of MR training samples is higher, and then the quality of MR super-resolution is better. Not all MR images are used to train the dictionary, so we propose the complex-gradient jointed method to evaluate the quality of training image samples. The gray consistent and gray consistency method is to classify the MR image sample, and the first and second orders of MR image is to represent the discriminant local diversity. On the basis of discriminant MR training sample, the optimal training images with the high dictionary diversity are selected for the training dictionary.

2.2. Algorithm

We present the uniform framework of sample selecting via the gray-consistency & gradient jointed diversity-based dictionary representation. The framework applies the machine learning-based dictionary block learning for super-resolution construction. The optimized high resolution images are spliced into multiple image blocks to train the high resolution of dictionary. Accordingly, the low-resolution dictionary is trained by the low resolution images, and the low-resolution of images are achieved through downsampling high resolution images. The multiple image blocks are achieved through splicing the low resolution training images. The diversity of dictionaries depends on the types of object and representation method. The diversity is represented with the angle of the wholes, the angle of the regions, and the angle of the targets. The gray distributions reflect the spatial distribution and describe the size and the spatial distribution of the gray patches. The distributions reflect the correlation and symmetry of the image. The gray distribution includes concentrated/dispersed, gray consistency, the existence of repetition, symmetry. The detail information is described as follows.

$$U = \sum_{a=2}^{m-1}\sum_{b=2}^{n-1}\left(f(a,b) - \bar{f}\right)^2 \tag{3}$$

$$\bar{f} = \frac{1}{8}\left(\sum_{i=-1}^{1}\sum_{j=-1}^{1} f(a+i, b+j) - f(a,b)\right) \tag{4}$$

where $f(a, b)$ is the pixel value in the position (a, b), $\bar{f}$ is the mean value of 8 pixels round the center. Gray consistency shows the difference of each pixel and the pixel gray value accumulation.