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Study on compressed sensing reconstruction algorithm of medical image based on curvelet transform of image block

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ABSTRACT

Traditional MRI technology may easily generate artifact due to slow imaging speed, therefore, MRI has low imagining quality and over-long sampling duration. Since wavelet transform cannot achieve the best approximation, image block theory is introduced in compressed sensing image reconstruction. In combination of the advantage of curvelet transform – it is suitable for expressing edge detail information and curve information, curvelet transform is utilized to conduct sparse representation of MRI image and proposed compressed sensing reconstruction algorithm of MRI image based on curvelet transform of image block. Signal to Noise Ratio (SNR), Relative L2 norm error (RLNE) and matching degree served as the evaluation indexes, and 4 groups of experiments about the influence of noise-free image, noised image, different sampling frequencies and different regularization parameters on the quality of reconstructed image were done. The results show that during image reconstruction, the algorithm proposed in this paper is superior to SIDCT and PBDCT in terms of three evaluation indexes. Besides, the algorithm owns strong ability to resist noise and good effects on keeping image detail and edge.

1. Introduction

Magnetic resonance imaging (MRI) technology provides detail image of viable tissue and has no radioactive harm to human body, so it is widely used in imaging of human brain, chest, heart and other parts. But, slow imaging speed of MRI technology will cause heart imaging, abdomen imaging and functional imaging to generate artifact. In addition, overlong sampling duration will result in patients' psychological discomfort. To improve MRI data sampling speed and imagining speed, Crawley and Wajer et al. adopted partial Fourier transform and non-Cartesian sampling to achieve undersampling of k space data, but the artifact will be caused for some images. Compressed Sensing (CS) was proposed by Donoho [1] and Cande et al. [2] at the earliest time. It breaks the restriction of traditional sampling theory for sampling frequency and achieves sampled signal compression during acquiring data. It reduces data sampling quantity, and save computation time and data storage space. CS was first introduced in MRI image collection and reconstruction by Lustig [3]. Based on analyzing MRI image sparsity, the artifact resulting from random undersampling of k space is deemed as the noise, and the artifact in MRI image is eliminated through nonlinear reconstruction of minimized l_1 norm.

Finite difference method cannot sparsely represent smooth transition of images, which results in ladder-shaped artifact during undersampling of MRI image. To solve this problem, Knoll et al. [4] proposed a method based on high-order total variational method to eliminate image reconstruction artifact. The experiment result indicates that the method can effectively restrain ladder-shaped artifact. Conventional-transforms such as discrete cosine transform, wavelet transform and total variation have been used to sparsely represent MRI.

According to the perceived matrix structure, DeVore [5] used polynomial to construct consistent matrix to meet uncertain features, but for sparse degree K has larger limit. In view of MRI image sparse reconstruction aspect, optimization algorithm and OMP algorithm are mainly used to resolve this problem.

Qu et al. [6] put forward MRI image reconstruction algorithm based on joint sparse transform. The algorithm achieves inhibition of another sparse transform through artifact reconstruction with sparse transform, eliminating MRI image artifact and improving image reconstruction quality.

Islam et al. [7] combined wavelet domain and Gaussian Model to come up with MRI image undersampling reconstruction algorithm of Gaussian scale mixture model based on wavelet domain. The result showed that the algorithm improved 0.5 dB SNR and had good effects, comparing with traditional method.

Recently, block image methods [8] have attracted considerable interests in MRI based on compressing sensing because sparse

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representations can be processed with easy manipulations on block image.

At present, sparse transform and representation play an important role in MRI image reconstruction. Curvelet transform, as an important mode of image sparse transform, has been extensively applied in image processing. But, traditional curvelet transform can only extract limited directional information, and transform basis is preset. Thus, traditional curvelet transform cannot completely restrain image noise or keep image edge information. Aiming at the defects of traditional curvelet transform, image block theory is introduced in CS image reconstruction. By combining the advantage of curvelet transform – suitable for expressing edge detail information and curve information, curvelet transform is utilized to conduct sparse representation of MRI image and proposed compressed sensing reconstruction algorithm of MRI image based on curvelet transform of image block. In this way, MRI image noise is restrained and edge information is retained.

2. CS-MRI

2.1. CS

We assume that one-dimensional signal is $X \in R^{N\times 1}$. X can be expressed by a group of $N \times N$ orthogonal basis $\psi = \{\psi_1, \psi_2, \dots, \psi_N\}$, as shown in Formula (1) [9,10]:

$$X = \sum_{k=1}^{N} \psi_k \theta_k = \psi\theta \tag{1}$$

In Formula (1), $\theta_k = <X, \psi_k>$, where X, θ are $N \times 1$-dimensional vectors. When the signal X is on an orthogonal basis ψ, and there are $K << N$ non-0 coefficients θ_k, ψ is sparse basis of the signal X.

During sparse sampling, the signal X can be projected on measurement matrix ϕ, so sampling data Y can be expressed as:

$$Y = \phi X, Y \in R^M \tag{2}$$

Where, Y refers to measured matrix of $M \times 1$; ϕ refers to measurement matrix of $M \times N (M << N)$. Relational expression (3) between sample data and transformation matrix can be gained according to Formula (1) and Formula (2).

$$Y = \phi X = \phi\psi\theta \tag{3}$$

Sparse sampling can greatly reduce the quantity of collected data and boost data sampling efficiency. However, sparse sampling will also result in signal reconstruction and "pathosis" problem. CS theory holds that signal reconstruction problem will turn into the problem of solving l_0 norm minimization [11,12]:

$$\widehat{\theta} = \min_{\theta} \|\theta\|_{l_0} \quad s.\,t. \quad y = \phi\psi\theta \tag{4}$$

$\widehat{\theta}$ can be figured out according to the Formula (4) and signal restoration will be achieved. The restored signal is:

$$\widehat{X} = \psi\widehat{\theta} \tag{5}$$

2.2. CS-MRI

We assume that MRI image is sparse in a transform domain. CS-MRI can make MRI image sparse through random undersampled k space data and constrained reconstructed image so as to eliminate the artifact in MRI image [13,14]. In CS-MRI, measurement matrix ϕ is usually expressed with Fourier undersampling operator F_U, where U is undersampling matrix, with matrix size of $M \times N (M << N)$. $F \in C^{N\times N}$ refers to Fourier transform. It is known from Formula (5) that, if x can be sparsely represented in the transform domain, MRI image reconstruction can be achieved through solving constrained optimization problem [15,16]:

$$\widehat{\theta} = \min_{\theta} \|\theta\|_{l_0} \quad s.\,t. \quad y = F_U\psi\theta \tag{6}$$

Thus, undersampled K space data of MRI image can be expressed with Formula (7) [17]:

$$y = F_U x + \varepsilon \tag{7}$$

Where, $y \in C^M$ refers to K space data gained; x is reconstructed MRI image; ε refers to the noise.

2.3. Sparse transform of MRI image

Do et al. found that two-dimensional wavelet transform could not sparsely represent smooch edge and profile so that the artifact still exist in the reconstructed MRI image. Since wavelet transform cannot realize the best approximation, this paper combines the advantage of curvelet transform – suitable for expressing edge detail information and curve information, and adopts curvelet transform for sparse representation of MRI image.

Because l_0 norm in Formula (6) is non-convex, sparse reconstruction of MRI image is actually the problem of solving l_1 norm optimization [18,19]:

$$\min_{\alpha} \|\alpha\|_1 \quad s.\,t. \quad y = \phi F_U \alpha \tag{8}$$

In Formula (8), l_1 norm $\|\alpha\|_1$ is defined as the sum of absolute value of all elements in the vector α. Alternate direction optimization algorithm is widely applied in MRI image reconstruction. It can be used to transform optimization problem in Formula (8) to [20]:

$$\min_{x} \frac{1}{2}\|y - F_U x\|_2^2 + \lambda\|\psi^H x\|_1 \tag{9}$$

In Formula (9), ψ^H refers to sparse transform and mainly achieves sparsification of image x.

3. CS-MRI image reconstruction of patch-based directional curvelet transform (PBDCT)

3.1. Patch-based directional curvelet transform (PBDCT)

We make ϕ^T represent two-dimensional positive curvelet transform of image x and make R_j represent the operator $b_j = R_j\phi^T x (j = 1, 2, \dots, J)$ used to divide the coefficient $\phi^T x$ of image x into blocks to achieve image block divisions. The candidate direction set is $\theta = \{\theta_1, \theta_2, \dots, \theta_d, \dots, \theta_D\}$. For geometrical direction of the jth block, geometrical direction w_j of subband coefficient block within curvelet transform domain can achieve estimation through minimum approximate error of S curvelet coefficients [21,22]. MRI image block result is shown in Fig. 1.

$$w_{j,q} = \arg \min_{\theta_{j,d} \in \theta} \|\tilde{c}_{j,d}(\theta_{j,d}, S) - \psi^T P(\theta_{j,d}) R_j \phi^T x\|_2^2 \tag{10}$$

In Formula (10), ψ^T represents positive transform of one-dimensional orthogonal Radon curvelet transform; $\tilde{c}_{j,d}(\theta_{j,d}, S)$ refers to the largest S coefficients in curvelet coefficient $\psi^T P(\theta_{j,d}) R_j \phi^T x$; $\theta_{j,d}$ is the dth candidate direction of the jth block; $P(\theta_{j,d})$ is rearranged pixel parallel to the direction $\theta_{j,d}$. The coefficient of image x in PBDCT can expressed as follows:

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