Specification

GENERALIZED TREE SPARSE-BASED WEIGHTED NUCLEAR NORM MAGNETIC RESONANCE IMAGING RECONSTRUCTION METHOD

Technical Field

The present invention relates to the field of medical image processing technologies, in particular, to a generalized tree sparse-based weighted nuclear norm magnetic resonance imaging (MRI) reconstruction method, which is mainly used for the clear and rapid recovery of medical images, reducing the artifacts of reconstructed images and recovering more image details.

Background Art

Magnetic resonance imaging (MRI) has been widely used in the medical field because of its low damage and high diagnostic significance, which is built based on the principle of magnetic resonance. The basic physical concepts involved in magnetic resonance mainly include the atomic spin and magnetic moment, the energy state of the spin magnetic moment in the external magnetic field, the conditions for producing magnetic resonance, Larmor precession, magnetic intensity vector, and the magnetic intensity vector and relaxation process of the radio frequency field.

Traditional MRI technologies need to perform intensive sampling on the original data according to the Nyquist sampling theorem, and then reconstruct MRI images with the collected intensive data through an inverse Fourier transform, which will lead to the problem of huge sampling quantity required for reconstruction of an MRI image. The proposal of the compressive sensing (CS) theory allows undersampling of the original data space, so that the collected samples of the original data space can be much smaller than the number of the collected samples for the original data space in the traditional MRI imaging technologies, thus greatly reducing the data required for sampling and saving the sampling time. How to reconstruct a high-resolution magnetic resonance imaging (MRI) image from the under-sampled data samples is a

key factor for the success of the compressive sensing magnetic resonance imaging (MRI) imaging method, and also a research hotspot in recent years.

An existing image reconstruction method for compressive sensing of magnetic resonance imaging (CS-MRI) is to reconstruct an MRI image by utilizing the sparsity of the MRI image. At the present stage, many scholars make sparse representations of MRI images by choosing to use total variation, wavelet basis and adaptive dictionary learning and the like. Compared with total variation and wavelet basis, adaptive dictionary learning-based sparse representation has a remarkable advantage that can better describe the edge structures in an MRI image, but there are some problems in applying such adaptive sparse dictionary representation method for the practical process of MRI image reconstruction, for example, the internal structures of signals are not taken into consideration, and the structural relationships of the signals themselves are ignored.

In addition, the sparse representation coefficient of K-sparse recovery of an MRI image from under-sampled original data is an ill-posed inverse problem. The precision of image sparse decomposition can be effectively improved by fully exploiting the structure inside the signal. It has been proved that the structural sparse model is a more robust and accurate sparse model. However, the existing CS-MRI image reconstruction methods mainly are to use the sparsity of an MRI image to implement image reconstruction, without taking into account the inherent structural sparsity of the signals, so it is difficult to accurately reconstruct the original real MRI images, leading to difficulties in medical diagnosis.

Summary of the Present Invention

It is an objective of the present invention to overcome the disadvantages and shortcomings of the prior art by providing a generalized tree sparse-based weighted nuclear norm magnetic resonance imaging (MRI) reconstruction method, in which data of a low sampling rate of a sparse tree structure is used, an MRI reconstruction mathematical model is built based on weighted nuclear norm approximation, and the model is solved by iteration through an alternating direction iteration method, thus simplifying the calculation process and reducing the complexity of the algorithm. By

performing tree sparse structure transformation on under-sampled data, the present invention can reconstruct the image with fewer sparse coefficients and less computation. Therefore, the image may be further sparsely represented and the local information and non-local similarity of the image can be better utilized to obtain a better image reconstruction effect. A more accurate reconstructed image can be obtained with less measurement data, and the artifacts of reconstructed image can be reduced, which is more suitable for the actual scenarios.

In order to achieve the above objectives, the technical solution provided in the present invention is as follows: a generalized tree sparse-based weighted nuclear norm magnetic resonance imaging reconstruction method, comprising: firstly acquiring a test magnetic resonance imaging sampling data sample to perform Fourier transform; then constructing a tree-structured sparse signal according to a signal of the sample, and approximating a sparse expression of a constrained target function by using a weighted nuclear norm; next, optimizing the constrained target function by means of an Augmented Lagrangian method and performing an iterative update on the test data by means of an alternating direction search method, until estimated restoration data is obtained; and lastly, acquiring a final restoration image by means of constructing a tree sparse inverse transform, wherein the method comprises the following steps:

1) Providing sampling data by a clinical volunteer, and inputting Cartesian under-sampling data or non-Cartesian under-sampling data of magnetic resonance imaging (MRI), which depends on parameters of a device of a specific model and an object to be collected;

2) Performing corresponding Fourier transform on the under-sampled data, and constructing a corresponding tree sparse structure model by using the transformed data;

3) Solving a weighted nuclear norm approximation corresponding to each classification by means of adaptive singular value decomposition;

4) performing the iterative update by means of an alternating direction search method (ADMM) until the number of iterations reaches a preset threshold, so as to finally obtain a sparse vector corresponding to each classification; and

5) Finally solving a corresponding sparse vector reconstructed MRI image by performing inverse transform on the tree sparse vector.

Step 2) comprises the following sub-steps:

2.1) acquiring MR under-sampled data y by an MRI device;

2.2) performing the corresponding Fourier transform, namely: $\theta = Fy$; and

2.3) constructing a tree sparse structure model G, namely: $G\theta$.

In step 3), the weighted nuclear norm approximation is a new norm model having both the globality of a norm l_0 and the accuracy of the norm l_0, of which the goal is to find an optimal solution of a mixed norm and also satisfy a sampling constraint condition, and the corresponding model is:

$$\|x\|_{w,*} = \sum_i w_i \sigma_i(\mathrm{x})$$

where $\sigma_i(\mathrm{x})$ represents an i-th singular value of x, and w_i is a corresponding weight;

Weighted nuclear norm optimization problem:

$$\hat{\mathrm{x}} = \arg\min_{x \in R^N} \frac{1}{2}\|y - Ax\|_2^2 + \lambda \|x\|_{w,*}$$

Here, $\|x\|_{w,*} = \sum_i w_i \sigma_i(\mathrm{x})$, where $\sigma_i(\mathrm{x})$ is a corresponding singular value, and λ is an auxiliary parameter;

The solving of tree structure-based weighted nuclear norm minimization can be converted into an unconstrained minimization problem:

$$\min_{x \in R^N} \frac{1}{2}\|y - Ax\|_2^2 + \|G\theta\|_{w,*}$$

where y is under-sampled data, w represents a weight, $\| \|_*$ represents an nuclear norm, and A is an under-determined observation matrix;

And this optimization problem is equivalent to an unconstrained problem by the Augmented Lagrangian method:

$$L(\mathrm{x}, \mathrm{z}, \mathrm{d}) = \frac{1}{2}\|y - Ax\|_2^2 + \|G\theta\|_{w,*} + d(G\theta - z) + \frac{\rho}{2}\|G\theta - z\|_2^2$$

where z and ρ are auxiliary parameters, and d is a Lagrangian multiplier.

In step 4), in combination with the alternating direction search method, the optimization is decomposed into:

$$x^{k+1} = \arg\min_{x \in R^N} \frac{\rho}{2} \left\| G\theta - z^k + d^k \right\|_2^2 + \frac{1}{2} \left\| Ax^k - y \right\|_{w,*}^2$$

$$z^{k+1} = \arg\min_{z \in R^N} \frac{\rho}{2} \left\| G\theta - z + d^k \right\|_2^2 + \lambda \left\| G\theta \right\|_{w,*}$$

$$d^{k+1} = d^k - (G\theta - z + d^k)$$

Updating a variable in turn while keeping the other variables unchanged: keeping an auxiliary variable z^k unchanged, and solving x^{k+1}; keeping an image x^k unchanged, and updating z^{k+1} by using an iterative soft threshold method;

For the z sub-problem, the estimated data z can be solved by using the iterative soft threshold method, which is as follows:

$$S_W(z^{k+1}) = \max(\sigma_i(\mathrm{x}_i) - \mathrm{w}_i, 0)$$

where $S_W(z^{k+1})$ represents a soft threshold, $\sigma_i(\mathrm{x})$ represents an i-th singular value of x, and w_i is a corresponding weight;

And in step 5), the reconstructed image is solved by performing inverse transformation of the sparse signal tree structure by means of the data obtained through iterative optimization.

Compared with the prior art, the present invention has the following advantages and beneficial effects:

1. By means of constructing the generalized tree sparse signal structure in the image reconstruction, the present invention can more accurately restore the MRI image.

2. Because the present invention is combined with the ADMM algorithm, adaptive selection of this algorithm for the regular parameters makes the reconstruction method more robust and faster in recovery speed.

3. The present invention proposes that the method of weighted nuclear norm approximation is applied to make solution, with advantages over 1-norm problem, which makes the reconstructed image more accurate, presents fewer aliasing artifacts

and restores the image with better fidelity.

Description of Drawings

FIG. 1 is a flow diagram of a method of the present invention;

FIG. 2 is an illustration of comparison results of the recovery accuracies of the method according to the present invention and other five methods; and

FIG. 3 is a schematic diagram of a signal to noise ratio restored by the method under conditions of different iteration times.

Detailed Description of Embodiments

The present invention is further illustrated below in conjunction with specific embodiments.

As shown in FIG. 1, the generalized tree sparse-based weighted nuclear norm magnetic resonance imaging (MRI) reconstruction method described in this embodiment specifically comprises as follows: firstly, acquiring a test magnetic resonance imaging (MRI) sampling data sample to perform Fourier transform; then constructing a tree-structured sparse signal according to a signal of the sample, and approximating a sparse expression of a constrained target function by using a weighted nuclear norm; optimizing the constrained target function by means of an Augmented Lagrangian method and performing an iterative update on the test data by means of an alternating direction method of multipliers (ADMM), until estimated restoration data is obtained; and lastly, acquiring a final reconstructed image by means of constructing a tree sparse inverse transform. The method comprises the following steps:

1) providing sampling data by a clinical volunteer, and inputting Cartesian under-sampling data or non-Cartesian under-sampling data of magnetic resonance imaging (MRI), which depends on parameters of a device of a specific model and an object to be collected;

2) performing corresponding Fourier transform on the under-sampled data, and constructing a corresponding tree sparse structure model by using the transformed data (since the operation is performed on the under-sampled data, the scale thereof is

much smaller than that of the fully sampled data, and the data amount thereof depends on the sampling rate and sampling mode), which are specifically as follows:

2.1) acquiring MR under-sampled data y by an MRI device;

2.2) performing the corresponding undersampled Fourier transform, namely: $\theta = Fy$; and

2.3) constructing a tree sparse structure model G, namely: $G\theta$.

3) Solving a weighted nuclear norm approximation corresponding to each classification by means of adaptive singular value decomposition, which is as follows:

During CS-MRI reconstruction, l_1 norm minimization is to solve a linear convex optimization problem, which can ensure the stability of a reconstructed solution, but the obtained solution is not the best optimal solution. l_0 norm solution is the ideal optimal solution we desire, but l_0 norm problem is an NP-hard Problem and it is difficult to solve it directly. Therefore, how to ensure the accuracy and convergence of the solution is an important issue for reconstruction. Accordingly, the weighted nuclear norm approximation provided in the present invention is a new norm mode having both the globality of norm l_0 and the accuracy of norm l_0, of which the goal is to find the optimal solution of a mixed norm and also satisfy a sampling constraint condition and the corresponding model is:

$$\|x\|_{w,*} = \sum_i w_i \sigma_i(\mathrm{x})$$

where $\sigma_i(\mathrm{x})$ represents an i-th singular value of x, and w_i is a corresponding weight;

Weighted nuclear norm optimization problem:

$$\hat{\mathrm{x}} = \arg\min_{x \in R^N} \frac{1}{2}\|y - Ax\|_2^2 + \lambda \|x\|_{w,*}$$

Here, $\|x\|_{w,*} = \sum_i w_i \sigma_i(\mathrm{x})$, where $\sigma_i(\mathrm{x})$ is a corresponding singular value;

The solving of tree structure-based weighted nuclear norm minimization can be converted into an unconstrained minimization problem:

$$\min_{x \in R^N} \frac{1}{2}\|y - Ax\|_2^2 + \|G\theta\|_{w,*}$$

where y is under-sampled data, w represents a weight, $\| \|_*$ represents an nuclear norm, and A is an under-determined observation matrix;

This optimization problem is equivalent to an unconstrained problem by the Augmented Lagrangian method:

$$L(\mathrm{x},\mathrm{z},\mathrm{d}) = \frac{1}{2}\|y - Ax\|_2^2 + \|G\theta\|_{w,*} + d(G\theta - \mathrm{z}) + \frac{\rho}{2}\|G\theta - \mathrm{z}\|_2^2$$

where z and ρ are auxiliary parameters, and d is a Lagrangian multiplier.

4) Performing the iterative update by means of an alternating direction search method until the number of iterations reaches a preset threshold, so as to finally obtain a sparse vector corresponding to each classification, which is as follows:

By the ADMM algorithm, the optimization is decomposed into:

$$x^{k+1} = \arg\min_{x \in R^N} \frac{\rho}{2}\|G\theta - z^k + d^k\|_2^2 + \frac{1}{2}\|Ax^k - y\|_{w,*}^2$$

$$z^{k+1} = \arg\min_{z \in R^N} \frac{\rho}{2}\|G\theta - \mathrm{z} + d^k\|_2^2 + \lambda\|G\theta\|_{w,*}$$

$$d^{k+1} = d^k - (G\theta - \mathrm{z} + d^k)$$

Updating a variable in turn while keeping the other variables unchanged: keeping an auxiliary variable z^k unchanged, and solving x^{k+1}; keeping an image x^k unchanged, and updating z^{k+1} by using an iterative soft threshold method.

For the sub-problem of the estimated data z, it can be solved by using the iterative soft threshold method, which is as follows:

$$S_W(z^{k+1}) = \max(\sigma_i(\mathrm{x}_i) - \mathrm{w}_i, 0)$$

where $S_W(z^{k+1})$ represents a soft threshold, $\sigma_i(\mathrm{x})$ represents an i-th singular value of x, and w_i is a corresponding weight; and

5) Finally solving a corresponding sparse vector reconstructed MRI image by performing inverse transform on the tree sparse vector. In this case, through iterative optimization and inverse transformation of the obtained sparse signal tree structure, the reconstructed image is solved.

The effect of the present invention is further illustrated by the following experiments.

Experimental conditions: The present invention uses the standard nuclear resonance (MRI) up-sampling data for algorithm comparison. A programming platform used is MatlabR2010b, with an undersampling rate of 30%, and the quality of the restored nuclear resonance imaging is evaluated by using the following formula:

$$SNR = 10\log_{10}\left(\frac{\|x\|_2^2}{\|x-\hat{x}\|_2^2}\right)$$

where is x an original image and $\hat{x}$ is a restored image.

In FIG. 2, (a)-(e) indicate the reconstruction and simulation on a human brain image by using an RecPF method, an FCSA method, a WaTMRI method, an NESTA Tree method and the present invention, respectively; (f)-(i) indicate pixels which are lost after the human brain image is reconstructed corresponding to the RecPF method, the FCSA method, the WaTMRI method,the NESTA Tree method and the present invention, respectively.

As can be seen from the restored results of the human brain image shown in FIG. 2, the images restored by the generalized tree sparse-based weighted nuclear norm magnetic resonance imaging (MRI) reconstruction method according to the present invention is cleaner and clearer than those restored by other methods, have sharper image edges and more restored image details.

As shown in FIG. 3, it can be seen that the signal to noise ratios restored by several different methods vary with the change of iteration times under conditions of different iteration times. In particular, with the increase of iteration times, the method adopted by the present invention has a good recovery stability. It is further proven that the reconstruction result of the method according to the present invention can obtain clearer image contrast and more accurate anatomical structure description, and the restored image has better fidelity.

The foregoing embodiments are only preferred embodiments of the present invention and are not intended to limit the implementation scope of the present invention. Therefore, any change made in accordance with the shape and principle of

the present invention shall be covered by the protection scope of the present invention.

Claims

1. A generalized tree sparse-based weighted nuclear norm magnetic resonance imaging reconstruction method, comprising: firstly, acquiring a test magnetic resonance imaging sampled data sample to carry out Fourier transform; constructing a tree-structured sparse signal according to the sampled data, and approximating a sparse expression of a constrained target function using a weighted nuclear norm; next, optimizing the constrained target function by means of an Augmented Lagrangian method and performing an iterative update on said test data by means of an alternating direction search method until estimated restoration data is obtained; and lastly, acquiring a final restoration image by means of constructing a tree sparse inverse transform, wherein the method comprises the following steps:

1) providing sampling data by a clinical volunteer, and inputting Cartesian under-sampling data or non-Cartesian under-sampling data of magnetic resonance imaging (MRI), which depends on parameters of a device of a specific model and an object to be collected;

2) Performing corresponding Fourier transform on the under-sampled data, and constructing a tree-structured sparse signal by using the sparse tree transform;

3) Solving a weighted nuclear norm approximation model corresponding to each classification by means of adaptive singular value decomposition;

4) Performing the iterative update by means of an alternating direction optimization method until the number of iterations reaches a preset threshold, so as to finally obtain a sparse vector corresponding to each classification; and

5) Finally solving a corresponding sparse vector reconstructed MRI image by performing inverse transform on the tree sparse vector.

2. The generalized tree sparse-based weighted nuclear norm magnetic resonance imaging reconstruction method according to claim 1, wherein step 2) comprises the following steps:

2.1) acquiring MR under-sampled data y by an MRI device;

2.2) performing the corresponding undersampled Fourier transform, namely: $\theta = Fy$; and

2.3) constructing a tree sparse structure model G, namely: $G\theta$.

3. The generalized tree sparse-based weighted nuclear norm magnetic resonance imaging reconstruction method according to claim 1, wherein in step 3), the weighted nuclear norm approximation is a new norm pattern having both the globality of a norm and the accuracy of the norm, of which the goal is to find an optimal solution of a mixed norm and also satisfy a sampling constraint condition, and the corresponding model is:

$$\|x\|_{w,*} = \sum_i w_i \sigma_i(\mathrm{x})$$

where $\sigma_i(\mathrm{x})$ represents an i-th singular value of x, and w_i represents a corresponding weight;

Weighted nuclear norm optimization problem:

$$\hat{\mathrm{x}} = \arg\min_{x \in R^N} \frac{1}{2}\|y - Ax\|_2^2 + \lambda \|x\|_{w,*}$$

Here, $\|x\|_{w,*} = \sum_i w_i \sigma_i(\mathrm{x})$, where $\sigma_i(\mathrm{x})$ is a corresponding singular value;

The solving of tree structure-based weighted nuclear norm minimization can be converted into an unconstrained minimization problem:

$$\min_{x \in R^N} \frac{1}{2}\|y - Ax\|_2^2 + \|G\theta\|_{w,*}$$

where y is under-sampled data, w represents a weight, $\| \|_*$ represents an nuclear norm, and A is an under-determined observation matrix;

This optimization problem is equivalent to an unconstrained problem of the Augmented Lagrangian method:

$$L(\mathrm{x}, \mathrm{z}, \mathrm{d}) = \frac{1}{2}\|y - Ax\|_2^2 + \|G\theta\|_{w,*} + d(G\theta - z) + \frac{\rho}{2}\|G\theta - z\|_2^2$$

where z and ρ are the one auxiliary parameter, and d is a Lagrangian multiplier;

in step 4), in combination with the alternating direction search method, the optimization is decomposed into:

$$x^{k+1} = \underset{x \in R^N}{\arg\min} \frac{\rho}{2} \left\| G\theta - z^k + d^k \right\|_2^2 + \frac{1}{2} \left\| Ax^k - y \right\|_{w,*}^2$$

$$z^{k+1} = \underset{z \in R^N}{\arg\min} \frac{\rho}{2} \left\| G\theta - z + d^k \right\|_2^2 + \lambda \left\| G\theta \right\|_{w,*}$$

$$d^{k+1} = d^k - (G\theta - z + d^k)$$

updating a variable in turn while keeping the other variables unchanged: keeping an auxiliary variable z^k unchanged, and solving x^{k+1}; keeping an image x^k unchanged, and updating z^{k+1} by using an iterative soft threshold method;

for the sub-problem of the estimated data z, it can be solved by using the iterative soft threshold method, which is as follows:

$$S_W(z^{k+1}) = \max(\sigma_i(\mathrm{x}_i) - \mathrm{w}_i, 0)$$

where $S_W(z^{k+1})$ represents a soft threshold, $\sigma_i(\mathrm{x})$ represents an i-th singular value of x, and w_i is a corresponding weight;

And in step 5), the reconstructed image is solved by performing inverse transformation of the sparse signal tree structure by means of the data obtained through iterative optimization.