MRI Image Reconstruction Based on Artificial Intelligence

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Abstract. Artificial intelligence is a new high and new technology, which has powerful functional advantages in processing big data, complex and non-deterministic data, and in-depth mining of hidden information behind the data. Magnetic resonance is a common diagnosis and treatment technology in medical clinics. The use of magnetic resonance imaging technology to construct medical images has a great auxiliary effect for doctors to make accurate medical diagnosis. This article proposes to combine artificial intelligence and magnetic resonance technology to construct magnetic resonance images based on artificial intelligence, in order to reconstruct high-quality magnetic resonance images, thereby improving the efficiency of doctors' diagnosis and treatment and reducing misdiagnosis. This paper uses the deep learning algorithm of artificial intelligence to compare the analytic dictionary method, the synthetic dictionary method and the deep dictionary method based on convolutional neural network, and obtain the peak-to-noise ratio of the image reconstructed by the three algorithms under the same sampling rate. They are 42.56, 44.17 and 45.55 respectively; the structural similarity is 0.9387, 0.9536 and 0.9867, respectively. The study concluded that the deep dictionary method based on convolutional neural network has more advantages in reconstructing MRI images, and the effect is more obvious.

Keywords: Artificial Intelligence, Magnetic Resonance, Image Reconstruction, Three-Dimensional Modeling

1. Introduction
At present, clinical medicine often borrows some auxiliary medical diagnosis images to diagnose and treat diseases, which to a large extent makes up for the influence of human subjective cognition on medical diagnosis, greatly improves the diagnosis rate, and also reduces the time spent in diagnosis and treatment, and improves the efficiency of diagnosis and treatment. In addition to X-ray and CT, there is another common medical imaging technology, namely MRI. Although MRI has more advantages than X-ray and CT technology, it has some performance characteristics that the former two do not have, but it also has some defects, such as the equipment scanning time is long, which makes patients often have to wait for a long time, which aggravates the pain and economic burden of patients.
Therefore, this paper proposes to apply artificial intelligence technology to the reconstruction of magnetic resonance image, which can improve the scanning speed and image quality of MRI equipment.

Due to the slow acquisition of MRI data, the speed of MRI in clinical diagnosis and treatment is also greatly reduced, so many experts have launched research to change this defect. Wen B, ravishankar s, and Pfister l indicate that although magnetic resonance imaging (MRI) is widely used in clinical practice, it has traditionally been limited by its slow data acquisition. Therefore, they proposed a MRI compression sensing (CS) technology to reduce the time of MRI data acquisition while maintaining high image quality. Liang D, Cheng J and Ke Z et al. Indicated that under sampled k-space data reconstruction image plays an important role in fast magnetic resonance imaging (MRI), so they proposed a deep learning based MRI image reconstruction method [1].In addition, Jia y, gholipour A and he Z pointed out that in magnetic resonance (MR), due to hardware constraints, scanning time constraints and patient motion, anisotropic 3-D is usually obtained in out of plane views with limited spatial resolution. Therefore, they constructed isotropic high-resolution (HR) 3-D MR images by up sampling and fusion of orthogonal anisotropic input scanning, and proposed a multi frame super-resolution (SR) reconstruction technology based on sparse representation of MR images [2].Chun I y, Noh s and love d j, et al. Believe that parallel coils on transmitters and receivers can be used to provide more control over MRI systems, which may improve the performance of high-field MRI. They propose a new MSE based excitation mode (MSE exp) design for image reconstruction in parallel transmit and receive sensitivity coding (pttxrx sense) MRI to maximize the performance of MRI by using the transmit and receive coil array [3].

From the above studies, although MRI plays an important role in medical clinical diagnosis and treatment, the slow data acquisition time is indeed a problem that can not be underestimated. In order to improve the quality of magnetic resonance image and maximize its effect in clinical diagnosis and treatment, it is necessary to study the image reconstruction. Based on this background, this paper discusses the application of artificial intelligence technology in MR image reconstruction. It is expected that the combination of MRI and artificial intelligence technology can reconstruct high-quality MRI images, thus providing help for improving the efficiency of clinical diagnosis and treatment.[4]

2. Artificial Intelligence and MRI

2.1. Artificial Intelligence

(1) Development and rise of artificial intelligence

Artificial intelligence, referred to as AI, is an interdisciplinary subject in the development of computer science. It has been greatly developed since its rise in the 1960s and 1970s. It is a high-tech means by giving computer system with consciousness thinking and learning ability similar to human beings, so that machines can think, deal with and solve problems like human beings. With the deepening of the research, people's research on artificial intelligence is no longer limited to a certain aspect or field, but from the pursuit of universal, universal general research to the specific field of research, expanding the research field and scope of artificial intelligence, making artificial intelligence really go to all fields of society, to the side of the public, so that people really feel the charm of artificial intelligence and its great changes to our lives [5].

(2) Deep learning of artificial intelligence

With the development of the times, people are more and more committed to looking for a kind of machine which can be competent for some complex work that usually needs human intelligence to complete, so that some dangerous work or the work that is not suitable for human to complete can be completed by machine, and artificial intelligence makes it possible. However, the complexity of different work content is not the same. In order to make the machine better and more perfect to complete the goal, it is necessary to carry out deep learning on the machine [6]. Deep learning can make the machine learn to think and make decisions, so that it has the same more flexible thinking
ability as people. It can not only acquire knowledge and information by self-learning, but also improve the ability to deal with and solve problems in learning.

(3) Application of artificial intelligence in medicine

Artificial intelligence has been widely used in many fields of society, and medicine is one of the most widely used fields of artificial intelligence. Artificial intelligence includes many aspects, such as artificial neural network, machine learning, deep learning, expert system and so on, and these technologies are related to medicine. For example, artificial neural network and machine learning can process complex medical diagnosis data, mine and analyze the disease regularity of some diseases, help doctors make auxiliary judgment in diagnosis and treatment, and at the same time, it can also help doctors carry out pre-operative simulation training and medical course education through modeling; deep learning and expert system can make use of the self-learning and adaptability of computer machines and the characteristics of self-solving problems to optimize some technical means in medicine, so that they can better serve the medicine [7-8].

2.2. Magnetic Resonance Imaging

(1) Magnetic resonance and magnetic resonance imaging

Magnetic resonance, referred to as MR, is a kind of physical phenomenon about the theory of magnetic field gravity. It is an imaging technology for the diagnosis and treatment of clinical diseases with the help of the principle of magnetic resonance imaging. The proton in the human body can be regarded as a spin nuclear system in the strong magnetic field environment. By applying external matching RF energy to it, it will continuously absorb the energy emitted, and gradually be magnetized. When the proton in the human body, that is, the spin nuclear system in a strong magnetic field, is magnetized to form a macroscopic magnetization vector, it will be driven by the RF field applied vertically to it. In the process of the magnetization vector from being driven to restoring the equilibrium position, it will continue to revolve around the spin nuclear system, and finally form a closed coil. The coil will produce a kind of magnetic resonance signal under the influence of the continuous rotation of the nuclear system. Because the magnetic resonance signal cannot distinguish the different positions of the spin nucleus, it is necessary to apply ladder in different directions of the spin nucleus. In this way, we can analyze the corresponding relationship between the spatial position of the magnetic resonance image and the pixels, thus forming a planar two-dimensional image [9]. With the continuous rotation of the nuclear system, the spatial position of MR image will continuously correspond to different pixel coordinates until a three-dimensional image is formed to locate the lesion position of the patient.

(2) K-space data of MRI

The k-space data is an array representing the spatial frequency in the magnetic resonance image. If the image in the k-space data is regarded as a galaxy, then every star in the galaxy comes from the magnetic resonance signal. The brightness of each star represents its contribution to the image. The brighter the image is, the greater its contribution to the image is, the clearer the image will be. Although the k-space data and the corresponding MR images are very different, they actually represent the information of the same scanning object. The k-space data represents the spatial frequency information of the scanned object, and the MR image represents the image information of the scanned object. These two kinds of information can be converted to each other. Through certain mathematical calculation, the k-space data can be converted into MR images, and the images can also be converted into k-space images [10].

(3) Magnetic resonance image processing

Generally, medical images can only be used after initial cleaning, denoising, enhancement and other operations. This is because in the process of image acquisition, there will be different degrees of external interference, resulting in unclear or noisy images. Magnetic resonance image is obtained by the interaction of human magnetic field and the radio wave of nuclear magnetic resonance scanner. When human proton interacts with radio wave energy, magnetic resonance signal will be generated. These signals will correspond to different position coordinates of human tissue to be examined, and
different points will be combined to form the tissue image of human body. For image processing, we often use image data processing technology, the method is as follows:

1) Image filtering and denoising. There are two commonly used algorithms: one is the dual tree complex wavelet transform method; the other is the top hat transform method.

First, the dual tree complex wavelet transform method. The dual tree complex wavelet is derived from the complex wavelet, and a filter is added on the basis of one filter, so that the complex wavelet transform can be carried out on two filters at the same time.

\[ \psi(t) = \psi_h(t) + i \psi_g(t) \]

When complex wavelet transforms into dual tree complex wavelet, its two-dimensional data transformation formula is as follows:

\[ \psi(x, y) = \psi(x) \psi(y) \]

Dual tree complex wavelet is better in decomposition and reconstruction, and is more conducive to the processing of image information details.

Second, top hat transform. Top hat transform belongs to morphological transformation, which is evolved from open close operation

\[ f \circ B = (f \Theta B) \oplus B \]
\[ f \bullet B = (f \oplus B) \Theta B \]

Then the top hat transform can be expressed as

\[ WTH(x, y) = f(x, y) - f \circ B(x, y) \]
\[ BTH(x, y) = f \bullet B(x, y) - f(x, y) \]

2) Image enhancement. There are mainly spatial method and frequency domain method.

Firstly, spatial method is to process image pixels in the space where the image is located, so as to achieve the purpose of enhancing contrast. It mainly selects the corresponding mapping space for gray level mapping transformation according to the characteristics of the original image and specific application. The expression of airspace method is as follows:

\[ g(x, y) = E[f(x, y)] \]

\((x, y)\) represents the pixel coordinates in the image, \(f(x, y)\) represents the image before enhancement, \(g(x, y)\) represents the image after enhancement, and \(E\) represents the process of mapping transformation.

Second, the frequency domain method is to enhance the image indirectly in the region of image transformation. It transforms the image first, then enhances the transformed parameters, and finally transforms the enhanced image into the initial region.

3. MRI Reconstruction Based on Artificial Intelligence

In order to improve the speed of scanning objects and the long time of collecting data, this paper proposes to use the deep learning algorithm of artificial intelligence technology to optimize and improve the magnetic resonance imaging technology. The dictionary learning method is adopted, and three different dictionary learning methods (namely fixed analytic dictionary, synthetic dictionary with adaptive ability and convolution neural network) are used respectively. The speed and quality of the three learning algorithms are compared to find the most effective acceleration imaging method.

3.1. MR Image Reconstruction Based on Analytic Dictionary
At present, there are many methods to parse the dictionary. Here, we use the total variation minimization method to perform sparse transformation on MRI images. The steps are as follows:

First, we find the norm of determining the total variation, which is defined as

$$TV(v) = \iint \nabla v(x, y) \, dx \, dy = \iint \left| \frac{\partial v}{\partial x} \right| + \left| \frac{\partial v}{\partial y} \right| \, dx \, dy$$

(6)

To minimize the total variation norm of MRI image is to minimize the gradient value of the image, which is a process of flattening the image. Since $$\|\nabla v(x, y)\|_2$$ is also a sparse transformation, a two gradient norm is used to approximate a gradient norm, and a small parameter $$\Phi$$ is introduced to prevent the infinity phenomenon after the partial derivative of total variation of image is obtained. In this case, the total variation norm can be defined as

$$TV(v) = \iint \|\nabla v(x, y)\|^2_2 + \Phi^2 \, dx \, dy = \iint \left( \frac{\partial v}{\partial x} \right)^2 + \left( \frac{\partial v}{\partial y} \right)^2 + \Phi^2 \, dx \, dy$$

(7)

According to the total variation norm, the magnetic resonance image model is optimized, as shown in equation (8)

$$\min_x \|F_i x - y\|_2^2 + \lambda TV(x)$$

(8)

3.2. MRI Reconstruction Based on Composite Dictionary

Different from the simple and fast calculation method of analytic dictionary, the composite dictionary can describe the features of more complex images, and has certain adaptability, which can reduce the noise and filtering problems caused by down sampling in the analytical dictionary. This paper mainly introduces the sparse representation, dictionary construction and reconstruction process of composite dictionary.

The so-called dictionary is a transformation matrix constructed according to the corresponding points of magnetic resonance signal. The sparse representation of magnetic resonance image is

$$y = D\alpha$$

(9)

Where $$D$$ represents the dictionary matrix and $$\alpha$$ represents the sparse coefficient. Use the matching algorithm to improve the synthetic dictionary. The calculation steps are: (1) Calculate the dot product of each column of the signal $$y$$ and the dictionary $$D$$, and select the most accurate atom with the most accurate value in this iteration. Divide the signal by the vertical projection element and the rest of the atoms that best match it; (2) Repeat step (1) to find the atom that matches the residual, until the residual is less than a certain range, the iteration can end, and the signal $$y$$ can be approximated. The ground is sparsely represented by linear combinations of these atoms.

Then construct a synthetic dictionary, the mathematical model is as formula (10)

$$\min_{D, x} \|y - DX\|_2^2, \ s.t. \ \forall i, \|x_i\|_0 \leq T$$

(10)

Finally, the constructed dictionary is used to reconstruct the image, and the MRI image reconstruction model based on the synthetic dictionary is shown in formula (11)

$$\min_{X, D, \alpha} \sum_{ij} \|R_{ij} x - D\alpha_{ij}\|_2^2 + \nu \|F_w x - y\|_2^2$$

$$s.t. \ \|\alpha_{ij}\|_0 < T \forall i, j, t$$

(11)
3.3. Magnetic Resonance Image Reconstruction Based on Deep Dictionary

The deep dictionary here is a combination of the convolutional neural network algorithm, and uses the strong adaptability and self-learning of the artificial neural network to reconstruct the magnetic resonance image. Previously we introduced two dictionary learning methods. Among them, the analytical dictionary is a fixed transformation, which can only handle some simple image transformations, and the sparse expressiveness is poor; although the synthetic dictionary has a certain degree of adaptability, the ability to denoise and filter the image is better. Strong, but in the case of less image data, the reconstructed image effect is not satisfactory. Therefore, we once again propose a deep dictionary method based on convolutional neural networks. The model is defined as follows:

$$ R(x) = \sum_{k=1}^{k} \phi_k(U_k x) $$  \hspace{1cm} (12)

Among them, $x$ represents the image to be reconstructed, $k$ represents the number, $U_k$ represents the transformed matrix, and $\phi_k$ represents a function. Use dimensionality reduction to optimize the model and get

$$ x(x') = \lambda \lambda^T (Ax' - y) + \sum_{k=1}^{k} (U_k') \gamma_k (U_k x') $$  \hspace{1cm} (13)

Finally, convolve the model to get the iterative reconstruction image

$$ x^{t+1} = x' - \left( \lambda \lambda^T (Ax' - y) + \sum_{k=1}^{k} (U_k') \gamma_k (U_k x') \right) $$  \hspace{1cm} (14)

4. Comparative Analysis of the Effect of MRI Reconstruction Based on Different Deep Learning Algorithms

According to the MRI images reconstructed by the three different dictionary learning algorithms used in the third part, in this chapter, we will compare the three kinds of reconstructed MRI images and compare the three different dictionary learning algorithms used. Find the best learning algorithm with the best MRI image reconstruction quality and speed based on their respective performance effects. Before reconstruction, we first collected the original magnetic resonance image data. Taking the clinical magnetic resonance image data of the People’s Hospital of our city as an example, we collected 500 magnetic resonance images with a size of 200×250 pixels. Dictionary learning algorithm to reconstruct the image. The analytical dictionary, synthetic dictionary and deep dictionary are divided into three learning algorithm groups. The first two groups each take 100 magnetic resonance images as original image data for reconstruction, and the third group takes 300 for image reconstruction.

4.1. Quantitative Evaluation of Analytic Dictionary and Synthetic Dictionary Reconstruction Results

Use the analytical dictionary and synthetic dictionary methods to sample the original MRI images. According to different sampling rates, set 30% sampling rate, 40% sampling rate, 50% sampling rate and 60% sampling rate. Compare the two under the same sampling rate. Different kinds of learning calculate the peak signal-to-noise ratio and structural similarity of the reconstructed image. The statistical results are shown in Table 1 and Table 2.

| Table 1. Quantitative evaluation of the reconstruction results of analytic dictionary |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
| Peak signal to noise ratio     | 30% sampling    | 40% sampling    | 50% sampling    | 60% sampling    |
|                                 | 31.25           | 35.29           | 38.47           | 42.56           |
| Structural similarity          | 0.7521          | 0.8735          | 0.9174          | 0.9387          |
Table 2. Quantitative evaluation of the reconstruction results of synthetic dictionary

|                        | 30% sampling | 40% sampling | 50% sampling | 60% sampling |
|------------------------|--------------|--------------|--------------|--------------|
| Peak signal to noise ratio | 33.24        | 38.55        | 40.45        | 44.17        |
| Structural similarity  | 0.8741       | 0.9045       | 0.9279       | 0.9536       |

It can be seen from Table 1 and Table 2 that under the background of the same sampling rate, the peak signal-to-noise ratio and structure similarity of the synthetic dictionary are larger than the value of the analytical dictionary, indicating that the synthetic dictionary has a better image reconstruction effect. In order to show and compare the differences more clearly, we summarized them on the bar graphs shown in Figure 1 and Figure 2.

Figure 1. Peak signal-to-noise ratio after reconstruction of analytic dictionary and synthetic dictionary

Figure 2. The structural similarity between the analytic dictionary and the synthetic dictionary after reconstruction

Figure 1 shows the difference in image peak signal-to-noise ratio between the two algorithms at the same sampling rate; Figure 2 shows the difference in image structure similarity between the two algorithms at the same sampling rate. Combining Figure 1 and Figure 2, it can be seen that as the sampling rate increases, the peak signal-to-noise ratio and structural similarity of the image are also increasing. When the sampling rate is 60%, the structural similarity of the synthetic dictionary reaches
0.9936, which is higher than the analytical dictionary, 0.9787, indicating that the synthetic dictionary is better than the analytical dictionary for the reconstruction of magnetic resonance images.

4.2. Quantitative Evaluation of Deep Dictionary Reconstruction Results

The deep dictionary algorithm proposed in this paper is based on a convolutional neural network. According to the characteristics of the neural network, sample training and testing are required. Divide the selected 300 original magnetic resonance images into two groups, namely the training group and the test group, randomly select 250 images into the training group, and put the remaining 50 images into the test group, with 50, 100, 150, 200, 250, 300 perform iterative training and testing, and record the peak-to-noise ratio and structural similarity of each image in different sample intervals. The results are shown in Table 3 and Figure 3.

Table 3. Quantitative evaluation of deep dictionary reconstruction results

| Sample Size | Peak Signal to Noise Ratio | Structural Similarity |
|-------------|---------------------------|-----------------------|
| 50          | 34.25                     | 0.9318                |
| 100         | 36.15                     | 0.9457                |
| 150         | 40.47                     | 0.9479                |
| 200         | 41.26                     | 0.9531                |
| 250         | 42.28                     | 0.9658                |
| 300         | 45.55                     | 0.9867                |

Figure 3. Quantitative evaluation of deep dictionary reconstruction results

It can be seen from Table 3 and Figure 3 that as the number of samples increases, the larger the quantified evaluation value of the image reconstructed by the deep dictionary method, the better the effect, and it can be seen from the structural similarity that the image reconstructed by the deep dictionary is better than the previous image. The images reconstructed by the two algorithms are more restored to real MRI images. When the sample size is 300, the structural similarity value reaches 0.9867, which is much higher than the previous two algorithms. It can be seen that among the three dictionary learning methods, the MRI image reconstructed by the deep dictionary method based on the convolutional neural network is the best, the quality is the best, and the imaging speed is also the fastest.

5. Conclusions

Magnetic resonance imaging is an advanced auxiliary diagnosis and treatment imaging technology in medical clinics. It is an important help for assisting doctors to judge and diagnose and treat various intractable clinical diseases. Although magnetic resonance has more advantages than CT and X-ray technology, there is also the obvious defect of slow acquisition of image data. In order to improve this problem, this paper proposes a deep learning algorithm using artificial intelligence to reconstruct the
magnetic resonance image to speed up the imaging speed of magnetic resonance and obtain higher quality medical images. Through the comparison of three dictionary learning algorithms, it is concluded that the deep dictionary method based on convolutional neural network has more advantages and better results in reconstructing MRI images.

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