Research on High Sparse Sampling CT Image Reconstruction Algorithm Based on Convolutional Neural Networks

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Abstract. CT plays an important role in medical diagnosis and industrial nondestructive testing. How to reduce the radiation to patients in the process of CT scanning has become a hot spot. An effective way is to use sparse sampling projection data to reconstruct the CT image. However, the image obtained by using the traditional CT reconstruction algorithm to deal with the sparse projection data has serious image distortion and artifact. This paper presents a CT reconstruction method based on CNN. This method learns the mapping relationship between the sparse projection data and the complete projection data in the training database, and uses the learned result to process the sparse sampling projection data. FBP algorithm is used to get the high resolution CT image. This paper uses CNN to carry out an end-to-end learning to repair the projection sinusoidal image with missing angle and improve the quality of CT image reconstruction.

Keywords: Sparse sampling, CNN, CT reconstruction.

1. Introduction

Computed tomography technology [1] obtains the internal information of the detected object or human body through ray projection measurement of the detected object or human body from different angles. In the field of medical diagnosis, CT technology provides a non-invasive detection method for the clinical diagnosis of difficult diseases. It has become a significant technical mean to obtain the information of the internal organs of the human body, and effectively enhances the ability to observe small lesions in any part of the body. However, patients are inevitably harmed by ray radiation in the process of CT scanning, so low-dose ray and sparse sampling can be adopted to reduce CT radiation. This paper studied the reconstruction of sparse projection data to obtain the high-resolution CT image under the condition of sparse sampling (i.e., to obtain the projection data of limited angle) in order to reduce radiation.

The CT image directly reconstructed from sparse sampling projection data has some problems such as image distortion and artifact. The most widely used method to solve these problems is the reconstruction of sparse sampling projection data based on dictionary learning algorithm [2-3], which has more advantages than the sparse coding of the fixed dictionary. Under the adaptive double dictionary [4], signal can be expressed more sparsely and the high-definition sinusoidal projection data...
can also be obtained for reconstruction. However, the reconstructed image obtained by the dictionary learning algorithm still has the problem of artifact, and the computation of iteration is large.

In recent years, the deep learning algorithm based on convolutional neural networks (CNN) [5-6] has been widely applied in many fields. There are several popular directions, such as image denoising [7], image super-resolution reconstruction [8], and image deconvolution [9], but only a few research directions are applied to image restoration. Therefore, this paper proposes to use the convolutional neural networks algorithm to repair the projection data of missing angles, use the three-layer CNN to learn the end-to-end CT images from the database, and combine with the FBP reconstruction algorithm to obtain the high-resolution CT images for medical diagnosis. In order to compare with the results of CT images reconstruction by using CNN, this paper also adopts the dictionary learning algorithm which is widely used at present to process CT images.

2. CT Reconstruction Process

2.1. Training of CNN

The basic structure of CNN is composed of two layers: one layer is used for feature extraction, and the input end of each neuron is connected to the output feature map of the upper layer, and local features are extracted. The second layer is the feature mapping layer, which is the pooling layer. In order to improve the training speed and obtain further abstract feature images in image recognition, the pooling layer generally reduces the number of features and parameters to a certain extent. Therefore, this paper does not use the feature mapping layer, but only uses the feature extraction layer to extract the training image. In this paper, the convolutional network is mainly used to process images, and each pixel is given a weight, which is obviously linear. However, for image samples, they are not always linearly separable, so the expression of linear function is not enough, and it is necessary to introduce nonlinear activation function. The purpose of using CNN is to reconstruct high-resolution CT images. For a CT projection image with missing angles, we firstly use bicubic interpolation to repair the data missing angles and obtain a low-resolution projection sinusoidal image, which is the only pre-processing in the process of using CNN. The process of processing low-resolution projected sinusogram using CNN consists of the following three steps: extraction and representation of image blocks, nonlinear mapping, and reconstruction. The CNN used in this paper is inspired by the structure of super-resolution reconstruction [10].

2.2. Parameter Analysis of CNN

Since the first layer is the extraction and representation of image blocks, the size of the convolutional kernel and the number of filters can be set larger to facilitate the extraction of features. From the first layer, it can be seen that CNN is mostly an operation between multi-channel feature map and multi-channel convolution kernel. In order to realize cross-channel information integration, a 1×1 convolution kernel is added to the upper convolution layer to realize the NIN structure [11]. In order to extract only the center pixel of the image block, the convolution kernel is set to be small.

![Figure 1. The process of reconstructing CT image by CNN.](image-url)
Finally, the FBP algorithm was combined to get the final CT image. In this paper, we discuss the reconstruction effect in the case of missing 145 angles (the channel number is 180). Figure 2 shows the projection sinusogram missing 145 angles and the original projection sinusogram respectively. We implemented our model using the Caffe framework [12] on Ubuntu14.04.

The projection sinusogram missing 145 angles were interpolated to get the low-resolution projection sinusogram. The dictionary learning algorithm and three CNN structures were used to reconstruct the low-resolution projection sinusogram to get the high-resolution projection sinusogram. Finally, the FBP algorithm was combined to get the final CT images.

3. Experiment and results
In this paper, a simulation image (180 projection angles of the sinusoidal image of the Shepp-Logan head) was used for reconstruction. In addition, in order to compare with the deep learning algorithm, the dictionary learning algorithm is used to process the projection sinusogram with missing angles. Finally, the FBP algorithm is combined to reconstruct the final CT image. In this paper, we discuss the reconstruction effect in the case of missing 145 angles (the channel number is 180). Figure 2 shows the projection sinusogram missing 145 angles and the original projection sinusogram respectively. We implemented our model using the Caffe framework [12] on Ubuntu14.04.

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![Figure 2. Full projection sinogram (Left) and projection sinogram missing 145 angle (right).](image)

![Figure 3. Comparison of CT reconstruction of different methods (a. The projection sinusogram missing 145 angles +FBP, b. Dictionary learning algorithm + FBP, c. 11-1-7 CNN+FBP, d. 9-1-5 CNN+FBP, e. 7-1-3 CNN+FBP).](image)
Figure 3(a) refers to the CT image reconstructed directly by FBP algorithm without any processing. If no repaired, there will be a large number of artifacts, blurred and unclear details of internal structure. Figure 3(b) is the CT image processed by the dictionary learning algorithm. Compared with Figure 3(a), the artifacts have been significantly improved, but there are still slight artifacts inside. Figures 3(c), (d) and (e) are the final results obtained by using the three structures of the CNN respectively. It can be seen that the visual difference between the three results is small, but the result is better than that of the dictionary learning algorithm, especially the edge structure of the middle part is obviously clearer than that of the dictionary learning algorithm. Next, we also calculated the PSNR value and SSIM value of the final CT image. The PSNR value is the most commonly used quality assessment standard [13], and its range is generally between 20 and 40, the larger the value, the better the image quality. PSNR cannot well reflect the subjective feelings of human beings. The SSIM value can better reflect the subjective feelings of human eyes, with a range of 0-1.

|               | Dictionary learning +FBP | CNN+F BP (7-1-3) | CNN+ F BP (9-1-5) | CNN+ F BP (11-1-7) |
|---------------|--------------------------|-----------------|------------------|--------------------|
| PSNR          | 30.7348                  | 33.9421         | 35.2165          | 35.9807            |
| SSIM          | 0.8500                   | 0.9600          | 0.9595           | 0.9635             |

It can be concluded from Table 1 that the CT image obtained by the CNN algorithm has the highest resolution, that is, the edge details are clearer. The above three structures all have good processing effect, and the reconstruction image obtained by the 11-1-7 structure is the best. Therefore, the larger the convolution kernel is, the more complete the feature extraction and detail retention of the image are, and the result obtained by the reconstruction is also better. The difference between PSNR value and SSIM value in these three cases is small, indicating that although the size of the convolution kernel can have an impact on the reconstruction effect, there is not much difference. In the three cases of using CNN algorithm, the worst result is obviously better than the dictionary learning algorithm, and there is a big difference in evaluation values, which shows the advantages of CNN algorithm.

4. Conclusions
We proposed a CNN method for CT image reconstruction with highly sparse sampling. This approach has little pre/post processing other than related optimization and FBP reconstruction. It can be seen from the research results that, compared with the dictionary learning algorithm, the CNN algorithm (the convolutional kernel size is 11-1-7) has better reconstruction image, clearer edge and more advantageous CT image when dealing with the sparse CT reconstruction problems.

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