Summary of our reconstruction method

Ours contestants

December 14, 2023

1 Introduction

We noticed that in low-dose CT, the image quality is degraded due to quantum noise and other factors. Machine learning based denoising methods can be used to recover high-quality images that facilitate diagnosis. However, for a specific degradation model, we can train an end-to-end, supervised neural network model to solve the image restoration problem. But for real-world medical image processing applications, more flexible approaches are often needed to deal with potential multiple degradation models. Therefore, unsupervised methods based on learning priors can adapt more effectively to different problems in real-world applications. Meanwhile, unsupervised methods are not task-specific and usually rely on inefficient iterative algorithms. Introducing Denoising Diffusion Restoration Models proposed by Bahjat Kawar et al. can alleviate this problem to some extent. DDRM is a denoising diffusion generative model that gradually and stochastically denoises a sample to the desired output, conditioned on the measurements and the inverse problem.

Our code implemented CT image reconstruction based on ths SVR(Slice-to-Volume) methods and the DDRM , achieving good performance on the competition dataset. By adopting the generative diffusion model, the quality of images is improved.

2 Model architectures

Our model consists of three parts: 1. Train a diffusion model based on the competition training dataset and OpenAI guided-diffusion model. 2. Use DDRM to recover the reconstructed image from the pretrained model based on the prior distribution of the image to be recovered. 3. The SVR method converts data between the three-dimensional volume and the slices.

When the 3D numpy array is transformed into 2D slices, we denoise the images based on these slices. We referred to the parameters of the pre-trained model of guided-diffusion released by OpenAI and trained on the slices to obtain a diffusion model effective for medical images. In the image reconstruction process, an iterative procedure is adopted to recover the result image step-by-step from a random initial value through the prior distribution, pre-trained model, and well-designed variational objective function. Moreover, in the process, some image enhancement and other data processing methods were used to improve the quality of the images. Finally, the processed slices were converted into volumes as the output of the model.

3 Traing details

Our program requires training mainly a DDPM model that provides good approximations to the optimal solution. During training, in order to enhance the generalization ability of model, some data augmentation techniques were adopted to improve diversity of the training data. In addition, considering the reconstruction results of the dataset are 256*256*256 three-dimensional matrices, we chose parameters close to the officially released 256x256_diffusion.pt checkpoint by OpenAI to train our model.

Our reconstruction is mainly an iterative process of recovering reconstructed images from random initial values through a certain number of iteration steps. In this process, some relevant work on diffusion models can reduce the number of iterations and lower the spatial complexity. Although the original number of diffusion steps was 1,000, the jump approximation update rule allows high-quality images to be recovered in just 20 steps. Performing singular value decomposition of the degradation operator can reduce the space requirements during the calculation process. Moreover, Testing the noise levels of CT images with different doses is necessary to help us determine the degree of image restoration.