Generate CT from CBCT using DDIM

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Abstract. Cone-Beam Computed Tomography (CBCT) scans are commonly used now. But the image quality is not very good because of severe artifacts and inaccurate Hounsfield unit (HU) values. It is crucial to obtain CBCT scans with a quality comparable to that of a CT scan. This work aims to develop a conditional diffusion model to perform image translation from the CBCT to the CT domain for the image quality improvement of CBCT. The proposed method is a denoising diffusion probabilistic model (DDPM) with the condition CBCT.

Keywords: DDPM, CBCT

1 Introduction

1.1 SynthRAD2023

This task is for SynthRAD2023 task2: generation CT from CBCT.

Compared to traditional diagnostic CT images, CBCT images often suffer from considerable artifacts such as streaking, shading, cupping, and scatter contamination, resulting in severe inaccuracies of the Hounsfield unit (HU) values [1]. In this work, we proposed a conditional DDPM [2] framework for CT generation from CBCT images.

1.2 Conditional DDPM

The conditional DDPM method is similar as [3], and the condition is CBCT image. To speed up, because of time constraints within 15 mins per image, the SSIM [4] was used to reduce the number of iterations from 500 to 15.

2 Methods

2.1 Image Preprocessing

All images were Interpolate into 256 × 256 and the HU values were cut between -1024~2000, and normalized to [-1, 1] before being fed into the network. The HU values of several pixels are 3000 in some images, which are normalized to 2000.

2.2 Train parameter

The denoising diffusion model is a common Unet with four times down sampling and attention modules in the third down sampling. The first channel is 128. With each down sampling, the number of channels is doubled. The iteration times in DDPM is 500. But when in inference, the iteration is reduced into 15 using DDIM to be able to run within the specified time. The model is 2D, and each slice of an image runs separately.

3 Result

3.1 Result samples

The following (see **Fig.1.** and **Fig.2.**) is a presentation of some generated results, the first row is the original CT image, the second row is the generated CT image, and the third row is the original CBCT image.

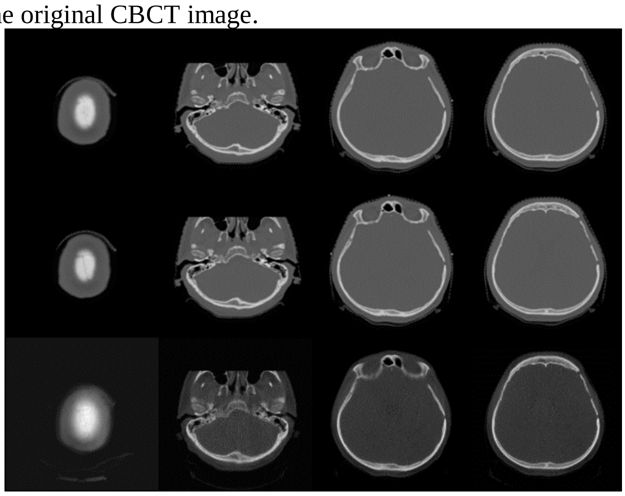

Fig.2. Generation result in brain image.

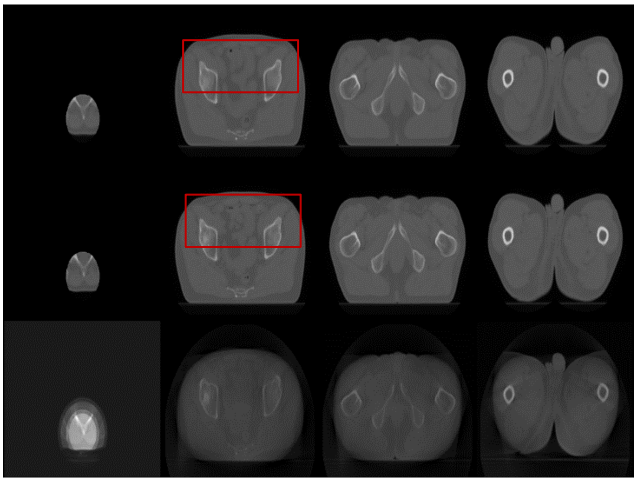

Fig.2. Generation result in pelvis image.

We believe that this method produces clear results at relatively distinct boundaries, such as bone and muscle boundaries. However, the generated results within the organization could be wrong, as shown in the red box in the figure.

References

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