Progressive Generative Adversarial Networks: Deep Learning in Head and Neck Cancer CT Images to Synthesized PET Images Generation for Hybrid PET/CT Application

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Abstract. We proposed a progressive Generative Adversarial Networks (GAN) to generate synthesized positron emission tomography (PET) images from computed tomography (CT) images for hybrid PET/CT application. It is observed the PET images, generated by using the progressive training strategy, are better in image quality than the PET images generated by using GAN both in mean absolute error (MAE) and peak signal to noise ratio (PNSR) evaluation indicators, indicating that the proposed method is suitable for generating medical images to use in hybrid systems.

Introduction

It has been a recent research interest to generate synthesized computed tomography (CT) images from conventional magnetic resonance imaging (MRI) sequence images in hybrid positron emission tomography (PET)-MRI system [1]. We proposed a nonlinear mapping method from structural CT image to generate synthesized PET functional images with the use of generative adversarial networks (GAN). In order to generate high-quality PET images, a segmented and progressive training strategy was adopted, in that low-resolution PET images generated in the previous stage were used as the condition of the following stage. This training strategy enabled the whole progressive GAN training process faster and more stable. Moreover, the final PET image quality would also be better than that of direct end-to-end training. We validated the proposed method in 16 head and neck cancer patients and found that high-quality PET images with functional information could be successfully generated even with complex tumor containing CT images.

Method

Inspired by GAN [2], Conditional GAN [3] and progressive GAN [4], we designed Figure 1 shows the schematic for the progressive training method for GAN. We begin the entire generation process by generating a low-resolution 32×32 PET image. After the 32×32 PET image has been successfully generated, the generated 32×32 PET image was input as the condition of the next generation network with a resolution of 64×64. The entire training process produced the required 256×256 size PET image from 32×32 to 64×64 to 128×128 in this order.
Experiment

The PET-CT images of newly diagnosed head and neck cancer patients were recruited: 16 subjects (12 males, 4 females; 31~68 years old) with the use of Discovery STE PET/CT (GE Healthcare, Milwaukee, USA) from the first affiliated hospital, Sun Yat-sen university; and the spatial resolution and image matrix of most CT images was $0.49 \times 0.49 \times 2.5 \text{mm}^3$ and $512 \times 512 \times 63$ respectively, while the spatial resolution and image matrix of the PET images was $1.56 \times 1.56 \times 3.27 \text{mm}^3$ and $256 \times 256 \times 48$ respectively. To make use of the information of both the PET image and the CT image, we performed co-registration of PET to CT images by sampling the PET images on z axis using linear interpolation in SPM8 (Wellcome Department of Imaging Neuroscience, London, United Kingdom).

In this study, patients were divided into training set and test sets by 80% and 20% respectively.

Training Detail

During the experiment, we trained each $256 \times 256$ scan layer individually to generate its corresponding PET image. The generator of the entire network was trained with the SGD optimizer at a learning rate of $1 \times 10^{-6}$, and the discriminator was trained with the SGD optimizer at a learning rate of $1 \times 10^{-5}$.

The entire code implementation was based on the Keras [5] deep learning framework. In order to verify that the progressive generation method proposed in this paper are better than the direct generation methods in image prediction, we also designed a GAN [2] to directly generate PET image of $256 \times 256$. In both experiments, the training set and testing set were the same.

Results

Similar to previous study [6,7], we evaluate the performance of proposed method by calculating mean absolute error (MAE) and peak signal to noise ratio (PSNR). Table 1 tabulates the results of progressive GAN and GAN. The PET image quality generated by the progressive GAN presented in this paper is better than the pet image quality generated by direct GAN, in which both of the MAE and PSNR obtained by the progressive GAN is better than those of direct GAN.
Table 1. Average of mean absolute error and peak signal to noise ratio on 16 subjects by the progressive GAN and GAN methods.

| Methodology  | MAE\( ^a \) (mean±std) | PSNR\( ^b \) (mean±std) |
|--------------|--------------------------|---------------------------|
| Progressive GAN\(^c\) | 9.530±1.768              | 21.153±2.228              |
| GAN\(^c\)    | 12.135±0.147             | 17.828±0.023              |

\(^a\)Mean Absolute Error; \(^b\)Peak signal to noise ratio; \(^c\)Generative Adversarial Networks.

Figure 2 shows progressively generated PET images without and with tumor, respectively. In the images with tumor, we found that the PET image with best results can correctly locate the tumor area, and the worst result cannot locate the position correctly. In the without tumor image, the shape and position of the brain area were relatively accurate in the image with best results and in the image with worst results, the area of the brain was not completely and clearly outlined.

Figure 2. The generated result of our method. The number 1, 2, 3 is the CT, PET and generated PET respectively of the same slice in a subject. The first row shows that the best generated result without tumor and with tumor. The second row shows that the worst generated result without tumor and with tumor.

**Conclusion**

We design a progressive training strategy for CT image to generate corresponding PET image for hybrid PET/CT application. This method employed a 256×256 CT image to progressively generate a corresponding PET image from a less resolution to a more resolution. It has been observed that PET images generated by using the progressive training strategy proposed in this paper are better than PET images generated by using direct GAN both in MAE and PNSR evaluation indicators, resulting that the proposed method is suitable for generating a larger resolution image. Although the method proposed in this paper only considers the case that CT generates PET images, the proposed model can also be applied to other related hybrid systems involved in the generation process in medical image analysis, such as super-resolution image generation.

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