Automatic multi-organ labeling in thoracic low-dose CT images with the internal dosimetry prospective using the pix-to-pix GAN deep learning method (preliminary study)

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Abstract
The Monte Carlo method plays a significant role in internal dosimetry and has led to the development of accurate patient-specific approaches. Regarding the facts that voxelized patient phantom is a crucial part of the simulation, organ segmentation based on CT images must be performed accurately and automatically. This study aimed to survey an automatic multi-organs segmentation method using low-dose CT images based on the pix-to-pix GAN network. Evaluation metrics, such as DSC and MSD, were assessed to estimate the similarity of the output to ground truth images, and close matching was found between organ automatic delineation and manual contouring.
Keywords: GAN, segmentation, low-dose CT

Introduction
Internal dosimetry has emerged as the most crucial issue, and numerous studies have emphasized its significant role [1]. In recent researches has been a dramatic alter in different methods to compute the correct organ doses according to injected radioactivity distribution, admittedly Monte Carlo simulation has brought high accuracy results in voxel-based dosimetry techniques. Patient-specific dosimetry based on the Monte Carlo approach was performed using a voxelized phantom and voxelized source based on PET/CT patient images generated using organs labeled via low-dose CT images [2]. Therefore, accurate organ delineation is crucial for the outcome of patient-specific dosimetry. In this issue, organs labeling are normally delineated manually on patient CT images, which is time consuming and laborious. Substantial progress has been made in the development of automatic organ labelling methods to precisely and consistently delineate organs. The atlas-based method is an applicable approach for automatic segmentation, which is highly depended on accurate registration and resampling. Owing to the success of deep learning techniques in medical imaging and the potential to explore image features to facilitate different tasks, such as classification, detection, and segmentation, this study aims to survey a method in organ labeling from an internal dosimetry perspective [3]. In this paper, we investigated the conditional GAN pix-to-pix network to generate thorax organ labeling based on corresponding paired low dose-CT images in the preliminary state.

Experimental
Data sets
The 40 sets of whole-body low-dose CT images with approximately 1200 paired slices used in this study were obtained using a PHILIPS PET/CT scanner (series Ingenuity TF 64 slices) from Kosar Hospital. Image processing procedures such as denoising (median filter with neighbor size: 1,1,1 and smoothing with sigma 2), contrast enhancement techniques with histogram equalization, normalization across the image scale, resizing to 256×256 pixels, and cropping were performed to prepare the trained and test samples. According to the supervised GAN framework paired images were prepared, in which low-dose CT was collected as the source domain input and labeled images as the target domain. The organ ROIs with the goal of collecting target domain samples were manually segmented on transvers CT images by a nuclear medicine physicist for three thorax organs (right and left lung, heart).

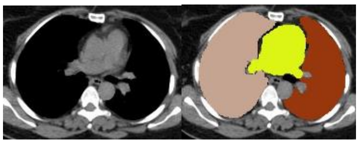

Figure1: the source and target image

Image-to-image translation
Based on the success of conditional GANs (cGANs), the generator network is replaced with a conditional variant to adapt adversarial networks from image generation to translational tasks. In this approach, the translation is mapped between two domains, a source domain image and a corresponding ground truth target image, via the mapping function [4]. The pix-to-pix model is the underlying principle of the cGAN, in which the generated output image is conditional on an input. In this case, the adversarial loss, and L1 loss play significant role in training and encouraging the generator to generate plausible images via the target

domain [5]. The final training objective is given by Equation 1: $min_G max_D LcGAN +_{\lambda} L_{l1}$
The various losses affect the model in the training procedure, resulting in tuning of dataset and hyperparameters to achieve optimized results. To evaluate and assess the performance of the trained model, evaluation metrics were calculated. In this study, the pix-to-pix GAN network was trained to generate labeled images related to low-dose CT images as the input samples that used in the internal dosimetry simulation with the MATLAB 2021 deep learning toolbox. The images were trained in 200 epochs, and the U-net GAN architecture was considered to translate paired datasets (Figure 3). We implemented the proposed method on 40 sets which 34set images for training and validation and the remaining set for testing. The binary cross entropy with loss weight 0.5, Adam optimizer with learning rate 0.0002 and beta 0.5, and batch sizes set to 1, were tuned as hyper parameters. The performance of the method was estimated using three metrics: the dice similarity coefficient (DSC) and mean surface distance (MSD) .

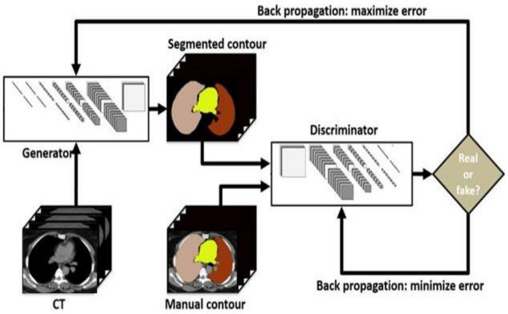

Figure2: the pix-to-pix framework

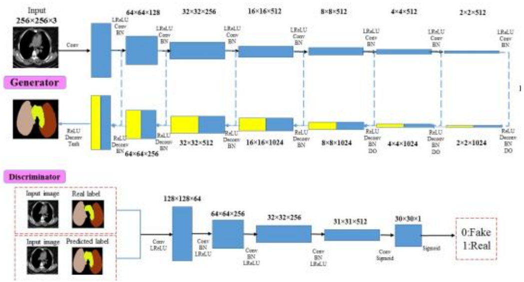

Figure3: the convolution architectur of GAN model

Results and discussion

Figure 3 shows the 2D segmentation results on one test patient sample using the pix-to-pix GAN method. This method successfully labeled and delineated the right and left lungs and the heart wall. To assess whether and to what extent the label output matched the input test images, the quantitative evaluation metrics were surveyed. The proposed method based on low-dose CT images achieved high segmentation accuracy in the left and right lungs and the heart wall, with a mean DSC of 0.95, 0.93, and 0.89, respectively. Table 1 summarize DSC, and MSD values for different labeled organs. The values show close matching of the GAN method and ground truth on the lung parts, but some deviations were estimated near the contour of the heart wall. It is important to bear in mind the possible bias due to the reduced image contrast, especially in the heart wall region. A possible explanation for the inconsistency in the part of the heart wall between the ground truth and the generated image might be the low quality of the images. The findings, while preliminary, suggest an automatic method to prepare low-dose patient CT images for dosimetry or deep learning approaches.

Figure4: a) manual contouring (ground truth) b) labeled GAN method

Table 1. results of evaluation metrics

	Heart	**Right lung**	**Left lung**
DSC	0.89 ± 0.05	0.95 ± 0.02	0.93 ± 0.02
MSD (mm)	1.50 ± 0.90	0.62± 0.63	0.65± 0.53

Conclusions

We have surveyed a deep-learning approach with GAN framework to label the thorax using low-dose CT images with the goal of preparing a patient-voxelized phantom in the internal dosimetry field. There is abundant room for further progress in labeling with high accuracy and whole-body CT images with ultralow dose quality.

References

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