

MTGAN: Mask and Texture-driven Generative Adversarial Network for Lung Nodule Segmentation

Abstract: Accurate segmentation for lung nodules in lung computed tomography (CT) scans plays a key role in the early diagnosis of lung cancer. Many existing methods, especially U-Net, have made significant progress in lung nodule segmentation. However, due to the complex shapes of lung nodules and the similarity of visual characteristics between nodules and lung tissues, an accurate segmentation with low false positives of lung nodules is still a challenging problem. Considering the fact that both boundary and texture information of lung nodules are important for obtaining an accurate segmentation result, we propose a novel Mask and Texture-driven Generative Adversarial Network (MTGAN) with a joint multi-scale L1 loss for lung nodule segmentation, which takes full advantages of U-Net and adversarial training. The proposed MTGAN leverages adversarial learning strategy guided by the boundary and texture information of lung nodules to generate more accurate segmentation results with lesser false positives. We validate our model with the LIDC-IDRI dataset, and experimental results show that our method achieves excellent segmentation results for a variety of lung nodules, especially for juxtapleural nodules and low-dense nodules. Without any bells and whistles, the proposed MTGAN achieves significant segmentation performance with the Dice similarity coefficient (DSC) of 85.24% on the LIDC-IDRI dataset.

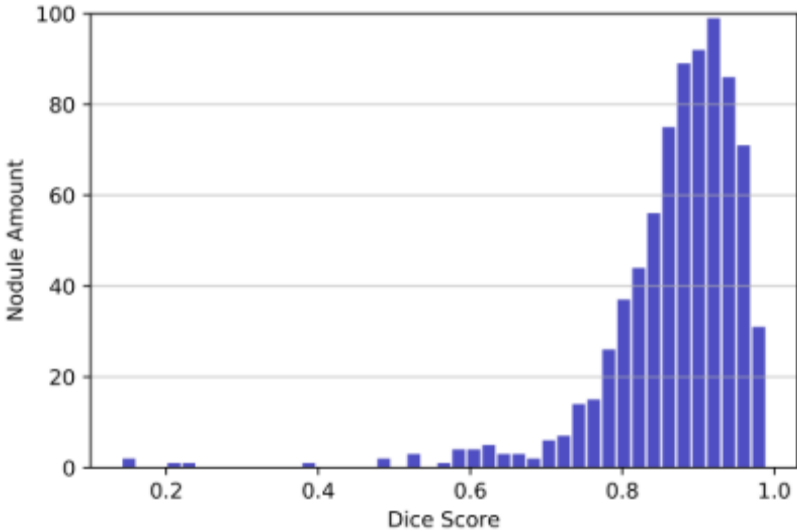
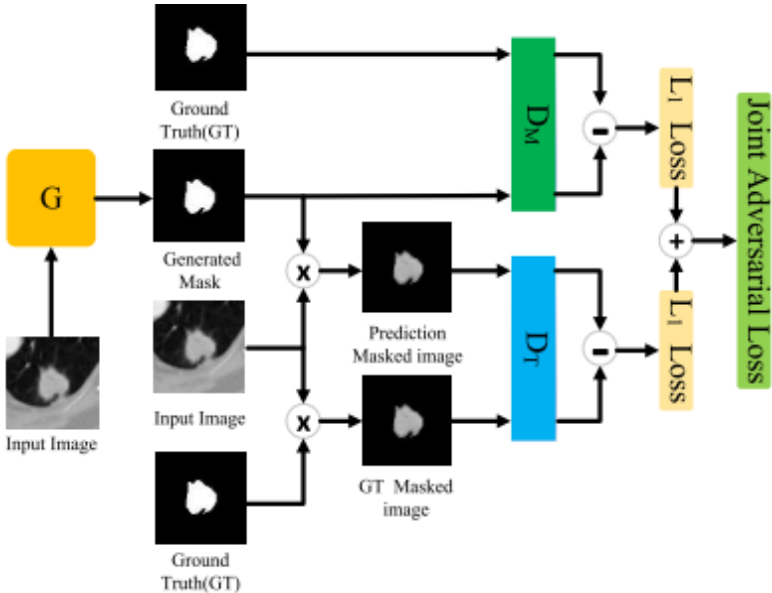
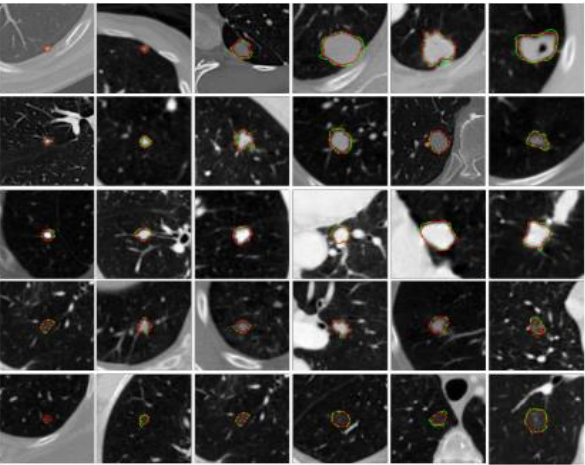
Method

The proposed MTGAN is built upon the adversarial network, and its overview is illustrated in Fig.2. As shown in this figure, our MTGAN mainly consists of three networks: a generator (G), a mask discriminator (D_M) and a texture discriminator (D_T). The generator is trained to generate segmentation masks of lung nodules from CT images. D_M aims to learn the boundary information of lung nodules by measuring the difference between generated masks and ground truth. D_T takes the masked regions as inputs to focus more on the texture information of lung nodules. The training process for our MTGAN is similar to a min-max game in which the generator is trained to minimize the objective function, D_M and D_T do the opposite. Both D_M and D_T are only used during the training process to enhance the performance of the generator without increasing any parameters and computation during model testing.

Result

1. Visualized segmentation results

Visualized segmentation results of the proposed MTGAN are shown in this figure. The segmentation results generated by the proposed MTGAN are highly coincident with the ground truth. This comparison indicates that our MTGAN can effectively segment various types of nodules with precise segmentation boundaries. This verifies that our D_M can effectively capture the boundary information of lung nodules.



DSC distributions of the testing set. The Dice values of most nodules are higher than 0.8. Eventually, our MTGAN achieves an average Dice value of 85.24% on the testing set.

2. Experimental results

Method	DSC%	IoU%
Level Set [37]	60.63 ± 17.39	-
Graph Cut [37]	68.90 ± 16.03	-
CF-CNN [37]	82.15 ± 10.76	-
Dual-branch Resnet [38]	82.74	-
U-Net (Multi-orientation) [16]	83.00	76.00
NoduleNet [39]	83.10 ± 8.85	71.85 ± 10.48
Priori-based U-Net [36]	85.86 ± 1.24	-
MTGAN	85.24 ± 9.01	75.22 ± 12.26

Model	DSC%	IoU%
G (Modified U-Net)	84.93 ± 9.05	74.74 ± 12.13
$G + D_M$	84.96 ± 9.50	74.85 ± 12.86
$G + D_T$	85.12 ± 9.12	75.07 ± 12.37
$G + D_M + D_T$	85.24 ± 9.01	75.22 ± 12.26

(a)Ablation study.

(b) Comparison with other methods.