다시 그리기를 이용한 준지도 복부 다중 장기 분할

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Semi-Supervised Abdominal Multi-organ segmentation by Redrawing

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Abstract

Semi-supervised learning algorithms based on consistency regularization have been proposed by leveraging unlabeled data. However, it is very challenging to apply this to multi-organ segmentation because this method neglected that the segmentation of abdominal organs is more difficult than other organs such as brain and heart due to morphological and structural complexity and low contrast of soft tissue. In this paper, we proposed to use redrawing. We improved the performance of segmentation by redrawing the image from the segmented result and comparing it to the original image. Furthermore, rather than employing only a few labels as ground truth, we facilitate a large number of unlabeled images as ground truth. In the experiment, DSC increased by 2.9 % in the proposed model rather than mean-teacher which is a representative technique of consistency normalization.

1. Background

Medical image segmentation is an essential prerequisite for diagnosis, decision making, and clinical applications such as radiotherapy. Recently, many methods for medical image segmentation have been proposed with deep learning, most of which are supervised learning that requires a lot of annotated data. However, it is difficult and time-consuming to obtain labeled data. On the contrary, the unlabeled data is easy to obtain and very abundant. For this reason, semi-supervised learning has been proposed to increase the performance of deep learning networks by utilizing a large amount of unlabeled data together with a small amount of labeled data.

In this study, we proposed to use redrawing, a new method of semi-supervised, and Multi-label mean-teacher mechanism which is based on consistency regularization, one of the semi-supervised learning methods. Abdominal organs are more difficult to segment than organs in other locations such as the brain and heart, because of low contrast of soft tissues and morphological and structural complexity [1]. Myriad of the existing semi-supervised using consistency regularization neglected the characteristic, which caused degradation of abdominal multi-organ segmentation. To improve this, we design a redrawing network based on the assumption that different areas for each object are defined first (segmentation), and a complete image is generated based on it [2]. If this network does not make a proper image, segmentation is not adequately defined. By comparing the original image with the generated image, the redrawing network renders the definition of segmentation modified again to generate a correct image through the redrawing network. Consequentially, the segmentation of our network relies on not only labels as ground truth but also input images.

2. Methods

The BTCV [3] dataset was used in the experiments and it consisted of 30 patients who had abdominal CT scans with 13 organs labeled (spleen, right kidney, left kidney, gallbladder, esophagus, liver, stomach, aorta, inferior vena cava, portal vein and splenic vein, pancreas, right adrenal gland, left adrenal gland). Dividing this data by 4 to 1, 24 were used for training and 6 were used for validation. For the convenience of the experiment, the origin 3D CT and PET images were resampled with 144 mm × 144 mm × 144 mm pixel spacing by 3rd-order interpolation due to different voxel sizes for each patient image. The intensity of the CT image was truncated in the range of [-1024,1024] Hounsfield units. It was then mapped to a range of [-1,1]. As a data augmentation method, random flip and random rotation were applied randomly with a probability of 0.5

Our proposed consists of three networks as shown in Figure 1. First, the segmentation network ($\boldsymbol{S}$) deduces segmented results with 14 channels (13 organs and background) from 1 channel input CT image about labeled and unlabeled input, respectively. Dice loss is calculated only for labeled data ($\boldsymbol{L_{dsc}}$). 3D U-Net was used in the experiment. Secondly, we employed the teacher network ($\boldsymbol{T}$) in the multi-label mean teacher [4] mechanism. To regularize consistency between the individual outputs of the segmentation network and teacher network, we used cosine similarity loss ($\boldsymbol{L_{cons}}$), which applied only to unlabeled data. So far, the segmentation model is trained through loss ($L_{cons} + L_{dsc}$) once. Finally, the inferred segmentation result is concatenated with the original image and fed as input to the redrawing network ($\boldsymbol{R}$). Then, the reconstructed loss is computed between the original and generated images from redrawing network and we proceed with the second training of the segmentation model using the loss (L_{recon}).

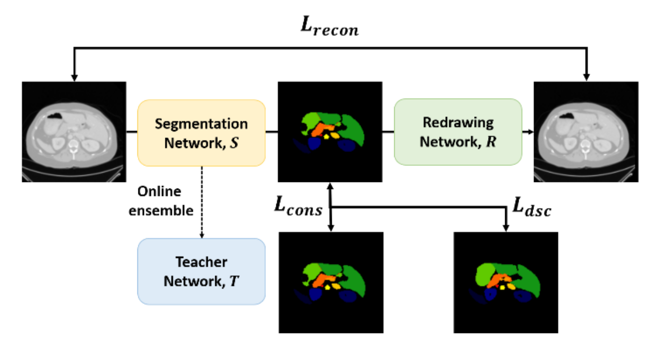

Figure 1. Architecture of our proposed network.

3. Results

To estimate the performance of our proposed, we applied four methods for training: supervised with only 12 labeled data (Sup_12), supervised with only full labeled data (Sup_24), the mean teacher with 12 unlabeled and 12 labeled data (MT), and the proposed model with 12 unlabeled and 12 labeled data. For supervised learning, U-Net was used.

Table 1. segmentation results on BTCV

	Supervised		Semi-Supervised	
	Sup_12	**Sup_24**	**MT**	**Proposed**
DSC(%)	71.81	77.11	71.92	74.82

As can be seen from Table 1, when supervised learning is done with a large amount of data, the results are satisfactory. Also, since semi-supervised learning has higher performance than supervised learning, it can be seen that the performance improves when using unlabeled data and the DSC value of our proposed model increased by 2.9% compared to the existing mean teacher (MT).

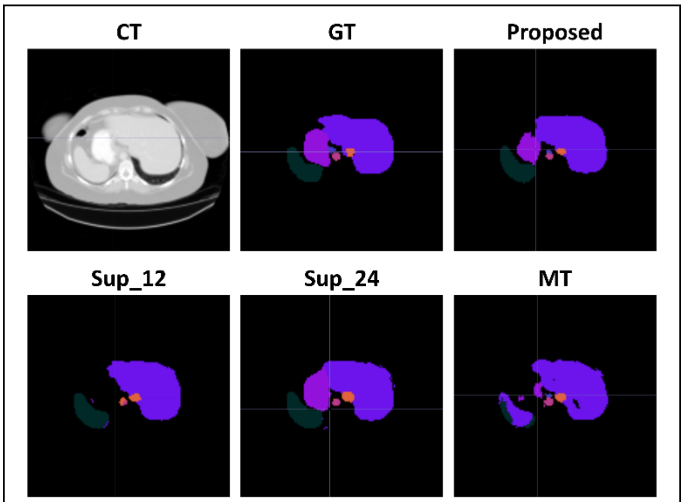

Figure 2. Exemplary outputs of supervised and semi-supervised methods

Figure 2 shows that the proposed model compensates for the disadvantages of multi-organ segmentation using the existing mean-teacher. The spleen is classified as the liver by mean-teacher, while the stomach is not fragmented. Our proposed model, on the other hand, segments the spleen and stomach appropriately.

4. References

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