How to overcome the data limited segmentation in abdominal CT: Multi-planar UNet coupled with augmented contrast-boosting

Sihwan Kim[a, b], Chulkyun Ahn[b, c], Jong Hyo Kim[a, b, d, e, f, *]

[a] Department of Applied Bioengineering, Graduate School of Convergence Science and Technology, Seoul National University, Seoul, Republic of Korea;
[b] ClariPi Research, Seoul, Republic of Korea;
[c] Department of Transdisciplinary Studies, Graduate School of Convergence Science and Technology, Seoul National University, Seoul, Republic of Korea;
[d] College of Medicine, Seoul National University, Seoul, Republic of Korea;
[e] Department of Radiology, Seoul National University Hospital, Seoul, Republic of Korea;
[f] Advanced Institutes of Convergence Technology, Seoul National University, Suwon, Republic of Korea.
*Corresponding Author: kimjhyo@snu.ac.kr

ABSTRACT

The quantity and variety of CT imaging data are essential components for effective AI-model training. However, the availability of high-quality CT images for organ segmentation is quite constrained, and the AI-based organ segmentation could be impacted by the varying intensity of contrast agents. Therefore, to improve the robustness of the segmentation both with and without a contrast agent, as well as to solve the data shortage issue, we proposed a multi-planar UNet with augmented contrast-boosting technique. A contrast-enhanced CT dataset was utilized to develop the AI-model, while a non-contrast CT dataset was used to assess the model's performance. The results of axial-plane UNet and multi-planar UNet were evaluated quantitatively using a dice-similarity coefficient. Furthermore, the effect of augmented contrast-boosting on the AI-model performance was analyzed. Throughout the contrast-boosting algorithm, even though only 30 patients' CT data were used, diversity and the amount of data were both increased, and it improved the mean dice-value of axial-plane UNet by 20% in non-contrast CT data. The mean dice-value was over 90% even in non-contrast CT data when multi-planar UNet was used, and it was 5% higher than when the augmented contrast-boosting wasn't applied. Our findings demonstrate that the spleen could be precisely segmented using multi-planar UNet coupled with augmented contrast-boosting, even with a small amount of CT dataset. The results would positively impact conventional AI-based segmentation strategy and its robustness. Any program employing the proposed method may see greater benefits from reducing the burden of large-scale dataset preparation, improving the AI-model training efficiency.

Keywords: CT, deep learning, segmentation, contrast enhancement, multi-planar reconstruction, augmentation, CNN

1. DESCRIPTION OF PURPOSE

In the quantitative analysis of CT images, a segmentation has been considered as one of the most fundamental procedures. In recent studies, to achieve a generalizable organ segmentation, most researchers use a deep learning-based model approach requiring a large amount of training data. In AI-based organ segmentation, as deep learning is a data-driven approach, the amount of CT image data and their diversity are key factors for successful AI model training. However, the availability of good quality CT image data for segmenting specific organs is quite limited even in a clinical environment, and the diverse intensity of contrast agents in the available CT data could affect the stability of AI-assisted organ segmentation. Therefore, we proposed a multi-planar UNet with augmented contrast-boosting algorithms, increasing the robustness of the AI-based segmentation, both with and without contrast agents, and solving the data shortage issue.

2. METHODS

2.1 Datasets

This study took part in two separate datasets. The first is the decathlon open challenge dataset for multi-organ segmentation, and it was used for the spleen segmentation model development. The open challenge dataset was composed of 3,650 contrast-enhanced abdominal CT images and corresponding organ contouring labels acquired from 41 patients [1]. For applying an AI-based multi-planar segmentation approach, the first dataset was additionally reconstructed to the coronal and sagittal planes, within the target organ's VOI. To overcome the limited number of training data and adapt the AI model to both contrast and non-contrast CT images, the first dataset was augmented with commercial contrast-boosting software (ClariACE, ClariPi, Republic of Korea) [2]. The contrast-boosting was conducted with five different boosting-factors of 0.25, 0.75, 1, 1.25, and 1.5. Training and tuning of the AI model used the augmented CT images of 30 patients and 11 patients, respectively, and the total amount of augmented data increased five-fold in each anatomical plane. The second dataset composed of 120 patients' non-contrast abdominal CT scans was retrospectively collected and anonymized. The non-contrast dataset was imaged by six multi-detector CT machines, and CT images of 20 patients per machine were collected. For the quantitative evaluation of spleen segmentation, a corresponding organ contouring label was created by a skilled technologist and double-checked by an experienced radiologist. Scan parameters for each dataset were summarized in Table 1.

Table 1. CT scan parameters of the data used for AI-assisted segmentation model development and its evaluation.

Scan parameters on training/tuning dataset						
# of patients	41 (training = 30, tuning = 11)					
Tube voltage (kVp)	120					
Tube current-time product (mAs)	range from 33 to 220					
Slice thickness (mm)	4.4 ± 1.5					
Scan parameters on testing dataset						
CT vendor	GE		Philips		Siemens	
CT machine	Discovery	Revolution	Ingenuity	IQon	Definition	Force
# of patients	20	20	20	20	20	20
Tube voltage (kVp)	100	100	100	100	105 ± 9	Sn100[a]
Tube current-time product (mAs)	163 ± 16	108 ± 22	68 ± 4	41 ± 16	101 ± 9	384 ± 13
Slice thickness (mm)	2.5	2.5	3	3	3	3
Reconstruction kernel	Standard	Standard	B	B	I40f	Br40

[a]Sn100 kV represents the tube voltage of 100 kV passing through the tin filter.

2.2 Contrast-boosting algorithm

The augmented contrast-boosting technique was conducted by an AI-powered augmented contrast enhancing solution (ClariACE, ClariPi) for contrast-enhanced CT images. The pre-trained deep learning model allows to selectively boost contrast agent components in CT images. The model used a U-net [3] as the base architecture, with an encoding and decoding path bridged by a concatenation (Figure 1). The encoding path was composed of a convolution layer with a 3x3 kernel followed by a rectified linear unit (ReLU), and a 2x2 max-pooling layer. The decoding path was similar to the encoder module except for the max-pooling layer replaced by a 2x2 up-sampling layer with nearest-neighbor interpolation. At the last layer, a 1x1 convolution layer was used for dimension reduction of extracted iodine features.

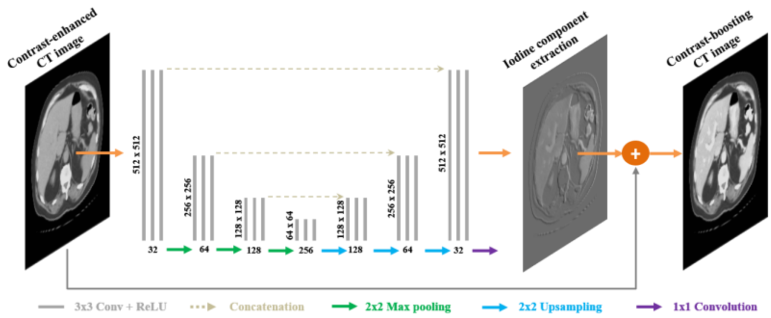

Figure 1. Schematic diagram of the augmented contrast-boosting algorithm (ClariACE).

2.3 AI Segmentation with multi-planar reconstruction

Our approach for multi-planar segmentation in non-contrast CT images composed of two phases as shown in figure 2. In the training phase, the contrast augmented CT images and corresponding organ contours in the axial plane were obtained, and additionally reconstructed to coronal and sagittal planes within the specific VOI. The VOI was defined as the three-dimensional range of axially stacked organ contours in the challenge dataset. Three independent segmentation models were trained separately using the data of axial, coronal, and sagittal planes. All trained models used the UNet as deep learning architecture with a depth of 5 and the Adam optimizer with a learning rate of 0.00005. Using the early-stopping method, an optimal training epoch was determined. In the evaluation phase, the 3D CT image was first segmented in the axial plane, and the VOI range was defined using the stacked volume of AI-predicted organ contours. Followed by the VOI range definition, the image data within it was extracted and reconstructed individually to coronal and sagittal planes. For each anatomical plane image, the two-dimensional segmentation was independently conducted, and their results were fused with the prediction result in the axial plane. All segmentation results by the AI prediction were filtered with a largest-connected-component algorithm.

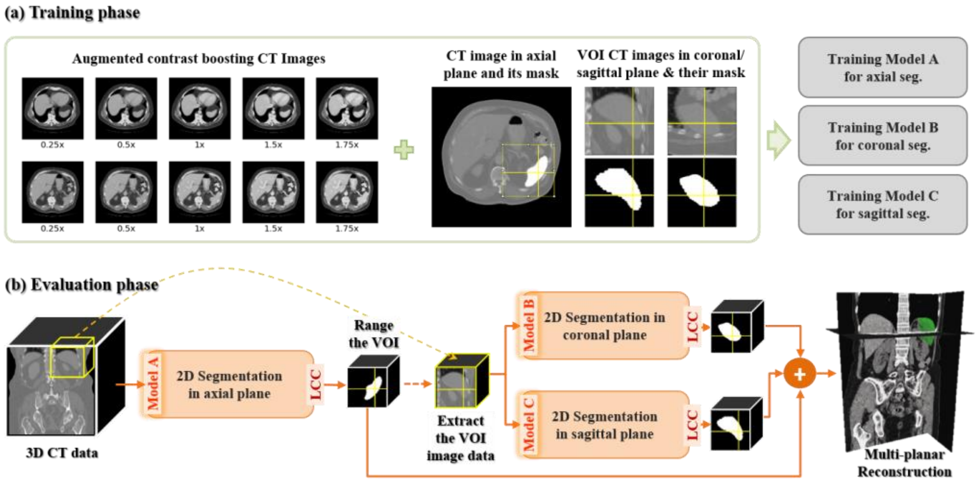

Figure 2. The schematic diagram for AI-assisted spleen segmentation trained with augmented contrast boosting CT images. (a) supervised learning using multi-planar augmented CT images with different boosting factors (0.25-1.75) and paired masks. (b) multi-planar reconstruction using deep learning-based segmentation for three representative anatomical planes.

2.4 Quantitative comparative analysis

To evaluate the model performance on non-contrast abdominal CT data, in quantitative comparative analysis, the segmentation performance from multi-planar UNet was compared to that of axial-plane UNet. Furthermore, the AI model's performance after the application of augmented contrast-boosting was analyzed. The evaluation metric for segmentation was the dice-similarity coefficient (scores 0 to 1), and its mean and standard deviation were calculated.

3. RESULTS & DISCUSSION

In this study, we presented a novel segmentation strategy for organ segmentation with a limited amount of contrast-enhanced CT data. Through the contrast-boosting algorithm, even though only 30 patients' contrast-enhanced CT data were used for segmentation training, diversity and the amount of data were simultaneously increased, and it improved the segmentation performance of axial-plane UNet by 20% in non-contrast CT data (Table 3). It had been found that the multi-planar UNet had a higher dice-similarity than the axial-plane UNet by supplementing locally failed segmentation results with the segmentation results from coronal and sagittal planes. When multi-planar UNet coupled with augmented contrast-boosting was used, the mean dice-value was over 90% even in non-contrast CT data, and it was 5% higher than without the augmented contrast-boosting. The limitations of the study were as followed. Firstly, the axial plane UNet trained only with contrast-enhanced CT data had a limitation of having a low dice-similarity in the segmentation of non-contrast CT data. However, it was confirmed that the AI model's generalizability could be further improved through the collaboration of augmented contrast-boosting and multi-planar UNet. Secondly, the organ segmentation target was limited to only the spleen. While the study only focused on spleen segmentation in non-contrast CT images, the proposed approach could be applied to the segmentation of any other organ in both contrast and non-contrast CT images. In addition, if the study used a large amount of data for comparative analysis of the results, a more convincing conclusion could be drawn regarding the trained model's segmentation performance. At last, further research was needed to evaluate the segmentation performance using 3D UNet. Nevertheless, the strategy of segmentation model training with limited CT data showed successful spleen segmentation results for the non-contrast CT data from multi-vendors and different CT machines. We hope the proposed methodology could contribute to AI-assisted medical imaging segmentation procedures and quality improvement of medical care.

Table 3. Comparison of segmentation results for evaluation data according to the types of augmentation and the AI-model architecture. All the calculated values in the table were dice-similarity coefficient, ranging from 0 to 1.

Augmentation	AI-model Architecture	GE		Philips		Siemens		Whole data
		CT Machine						
		Discovery	Revolution	Ingenuity	Iqon	Definition	Force	
without augmented contrast boosting	Axial-plane UNet	0.62 ± 0.28	0.71 ± 0.20	0.76 ± 0.12	0.58 ± 0.28	0.70 ± 0.21	0.69 ± 0.18	0.68 ± 0.22
	Multi-planar UNet	0.87 ± 0.14	0.91 ± 0.06	0.92 ± 0.04	0.81 ± 0.18	0.90 ± 0.07	0.88 ± 0.08	0.86 ± 0.16
with augmented contrast boosting	Axial-plane UNet	0.82 ± 0.19	0.87 ± 0.18	0.92 ± 0.08	0.81 ± 0.20	0.88 ± 0.13	0.88 ± 0.12	0.88 ± 0.11
	Multi-planar UNet	0.89 ± 0.12	0.92 ± 0.10	0.94 ± 0.04	0.89 ± 0.09	0.92 ± 0.09	0.93 ± 0.05	0.91 ± 0.09

4. CONCLUSIONS

Our results show that the spleen can be accurately segmented, even in a small amount of CT dataset, using Multi-planar UNet coupled with augmented contrast-boosting. The results would positively impact conventional AI-based segmentation strategy and its robustness. Any program employing the proposed method may see greater benefits from reducing the burden of large-scale dataset preparation, improving the AI model training efficiency.

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