

Cine-MR Image Segmentation for Assessment of Small Bowel Motility Function Using 3D U-Net

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Abstract In this study, we propose an automated method for assessing small bowel motility function with cine MRI using 3D U-Net which is a kind of deep fully convolutional neural networks for 3D semantic segmentation. In the proposed method, the cine MR images (temporal MR image sequence) is treated as a 3D image. We applied 3D U-Net, which employs 3D convolution, to automatically segment the temporal small bowel image sequence. Compared with the conventional 2D U-Net, in which the small bowel was segmented without temporal information and just segmented frame by frame, the proposed 3D U-Net can accurately and simultaneously segment all frames using temporal information. This is the first 3D fully convolutional network for small bowel segmentation in cine MR images (temporal sequence images) to the best of our knowledge. The small bowel motility function is assessed by the use of the segmented temporal MR image sequence. Experimental results demonstrate the effectiveness of the proposed method.

Index Terms cine-MR image, fully convolutional neural network, U-Net, 3D, small bowel, motility

I. INTRODUCTION

The small bowel is responsible for digestion and absorption activities that are essential to human life activity. Therefore, the measurement of this contraction movement is important for the treatment or inspection of the small intestine [1]. Recently, invasive testing methods using some endoscopes is a common method [2]. However, in this measurement method, the mental and physical burdens of patients are large. The workload of doctor is also very large. For this reason, it was needed to develop an assessment method of the small bowel contraction movement, which has the smallest burdens. In our previous study, we proposed an MR image-based assessment method based on MR imaging techniques [3], [4]. Cine MR images [5]-[7] are temporal sequence

images that can show small bowel contraction movement. Fig. 1 shows an example of cine-MR images (four frames) where white squares show the targeted small bowel. We measured temporal changes of the small bowel radius, which show the movement of the small bowel. Then we assessed the small bowel contraction movement based on frequency analysis. The limitation of our previous study is that the measurement and analysis were done manually and takes an enormous amount of time and efforts. We also proposed several automatic assessment methods based on image processing techniques [8]-[13]. They can be divided into three groups (1) segmentation methods [9]; (2) tracking methods [10], [11]; (3) temporal correlation or temporal difference methods [12], [13]. Since the segmentation based method is more intuitive and contains more information about the small bowel, we focus our research on the segmentation-based method in this paper.

In recent years, deep convolutional neural networks have outperformed state-of-the-art methods in many computer vision tasks, including image classification, image segmentation, and image detection. Particularly fully convolutional networks (FCNs) [14], [15] have been proposed for semantic segmentation and have achieved impressive performance. U-Net [15] is another deep learning-based semantic segmentation method, which is based on an encoder-decoder architecture. U-Net has been applied in many research fields including medical image segmentation [16]. Since the medical images (such as the CT image) are volume images, 3D U-Net [17] was introduced for medical volume image segmentation, in which 3D convolution as well as 3D pooling operations are employed. Cine MR images are 2D images in spatial space, but they are temporal sequence images (temporal 2D images). Though we can use conventional 2D U-Net to segment the small bowel frame-by-frame, it is time-consuming and lacks temporal smoothness among frames.

In this paper, we treat the cine-MR image as a 3D image and use a 3D U-Net to segment the small bowel

Manuscript received July 2019; revised November 7, 2019.

from the cine-MR images. Compared with the 3D fully convolutional network for small bowel conventional 2D U-Net, in which the small bowel was segmented in cine-MR images (temporal sequence segmented frame by frame and no temporal information). The small bowel motility function is assessed by used, the proposed 3D U-Net can segment all frames by the use of the segmented temporal MR image sequence simultaneously and accurately by using temporal information. Experimental results demonstrated the effectiveness of information. To the best of our knowledge, this is the first proposed method.

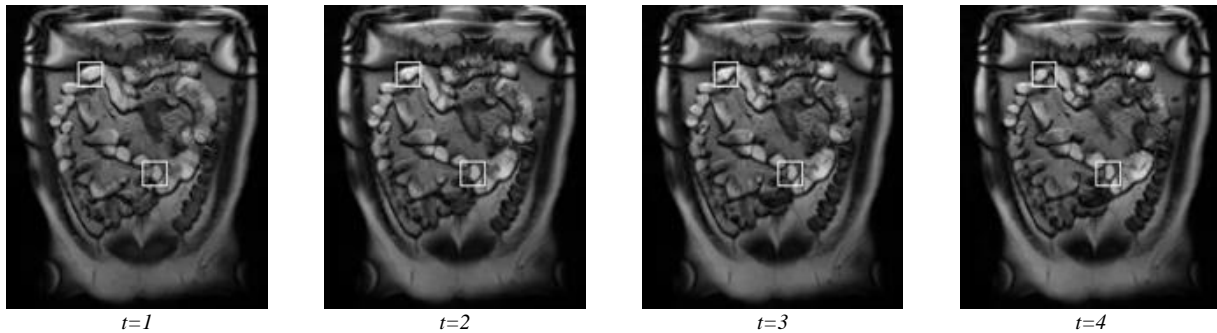


Figure 1. An example of cine MRI time sequence images. Two small bowels in the left-up and right-down areas are selected manually as the region of interest (ROI) for the analysis, which are indicated using white squares. It is evident that the shape of small bowel changes in time series. Temporal ordering is from left to right.

The remainder of this paper is organized as follows: related works have been summarized in Section II, Section III gives a detailed description of the proposed method, experimental results have been presented and discussed in Section IV, and Section V presents the conclusion.

II. RELATED WORKS

In our previous study, we proposed an optical flow method based on the automatic feature points tracking method [10]. This method comprises of two steps. In the first step, users select two arbitrary points on the boundary of the small bowel in the initial frame. The distance between the two points represents the size of small bowel. In the second step, each of the two points are automatically tracked by the use of Kanade-Lucas-Tomasi (KLT) feature points tracking method [18], [19] in the temporal sequence images. The KLT feature tracker is commonly used for feature point tracking in dynamic images (temporal sequence images). The KLT uses spatial information to search the most appropriate position of the tracking point in the next frame. Examples of automatic feature point tracking results are shown in Fig. 2.

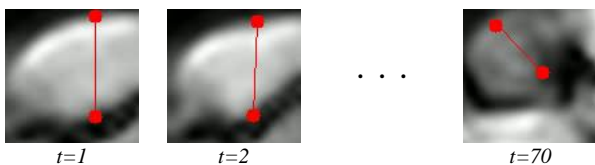


Figure 2. Automatic feature point tracking results. Users arbitrarily specify the red dots in the initial frame. Temporal ordering is from left to right (t=1 to t=70).

Though the tracking method is faster than conventional techniques, there is a problem that the tracking results depend on the initial points setting and it is a semi-automatic method

III. MATERIALS AND METHOD

A. Dataset

The data used in this research are cine MRI DICOM images (256 pixel × 256 pixel × 70 frames) of four healthy male participants, as shown in Table I. Cine-MR DICOM image is a medical image obtained by consecutively imaging an arbitrary cross-sectional area over a period of time to capture the continuous display of the organ contraction motion in time-sequence (similar to a video image). First, the participant is first in a prone state, and an MR image of the entire abdomen with respect to the coronal plane is captured. Next, concerning the obtained abdomen MR image of the coronal surface, the plane in which the entire area of the small intestine best appears is regarded as the noted section. Finally, by sequentially imaging the section of interest within an arbitrary time, the cine MR temporal sequence images showing the entire small intestine are captured. We performed the cine MRI 10, 15, 30, 45 and 60 min after oral administration of 1500 ml of non-absorbable fluid. When performing the MRI, we obtained 70 frames of cine MRI 30 s with suspended breathing. Fig. 1 shows a typical cine MR image. In this research, we only focused on a small bowel, which is called the Region of Interest (ROI). An expert manually labels the ROIs. For each cine MR image, we labeled two ROIs in the left-up and right-down areas (which are indicated by white squares in Fig. 1), respectively, for analysis. Each temporal sequence contains 70 frames. The ROI size in each frame is 16 × 16 pixels. As shown in Table I, we have 32 ROI temporal sequence images in all.

TABLE I. DATA USED IN THIS RESEARCH

Patient No.	Sex	Area	Elapsed time [min]
103	Male	LU, RD	10,15,30,45,60
104	Male	LU, RD	10,15,30,45,60
105	Male	LU, RD	15,30,45
106	Male	LU, RD	15,30,45

B. Network Architecture

In this paper, we proposed an analysis method based on a 3D U-Net [17]. The 3D U-Net usually propagate three-dimensional images as inputs and outputs. Also, we leveraged an image sequence (2D image + time sequence) as inputs and outputs. This modification enables 3D U-Net to maintain and propagate time sequence information along the 3D structure. Fig. 3 illustrates the 3D U-Net network architecture. Like conventional 2D U-Net, the 3D U-Net has contracting and expanding path. In the contracting path, each layer contains two 3x3x3 convolutions each followed by a leaky rectified linear unit (Leaky ReLU), and then a 2x2x2 max pooling with two strides in each dimension. In the expanding path, each layer has an up convolution of 2x2x2 by strides of two in each dimension, then two 3x3x3 convolutions each followed by a ReLU. Shortcut connections from layers of same tensor shape in the contracting path provide the essential high-resolution features to the expanding path. In the last layer, a 1x1x1 convolution reduces the number of output channels to the number of labels; we set output channels as 1. The input to the network is a 3D data which consists of 16x16x8 in x, y, and t directions, respectively. The output in the last layer is also 3D data of 16x16x8. We also introduce a batch normalization (BN) before each ReLU, and dropout to avoid overfitting.

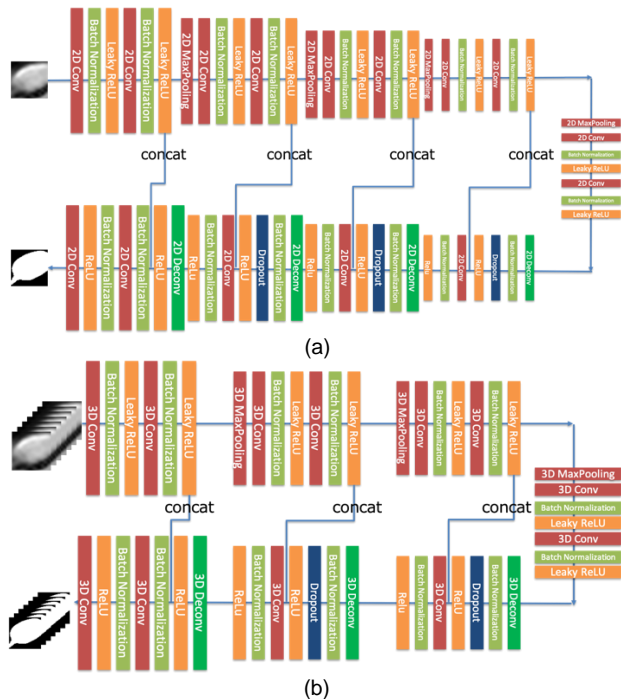


Figure 3. (a) is the architecture of U-Net and (b) is the architecture of 3D U-Net. Red boxes represent the convolutional and max pooling operations, respectively. Light Green boxes represent batch normalization. Blue boxes represent dropout Layer.

IV. EXPERIMENTAL RESULTS

A. Training and Testing

Training 3D U-Net from scratch requires a large amount of labeled training data. In order to increase the number of training data, each ROI temporal sequence

image is divided into 63 sub-temporal sequence images as 3D input images. Each sub-temporal sequence contains eight frames. The frame numbers for each sub-sequence are 1-8, 2-9, 3-10, ..., 63-70. As we described in Sec.3, there are 32 ROI temporal sequences; hence, we have 2016 3D data for training and testing of the proposed 3D U-Net. The size of the 3D data is 16x16x8. (63 3D ROI images).

We divided our data into four groups with each containing a patient. Table II shows the data distribution. We carried out experiments with 4-fold cross-validation. Three groups were used as training, and one group was used for testing.

The whole network (3D U-Net) is trained end-to-end. Moreover, we ran 300 training epochs on an Nvidia Titan X GPU, which took approximately a day for each phase. We set the learning rate as 1e-4 for ADAM optimizer and the batch size to 32. The network output and ground truth labels are compared using a sigmoid function with weighted cross entropy loss. Furthermore, the outputs of overlapping areas were combined using majority voting.

TABLE II. DATA DISTRIBUTION

Group No.	Patient No.	Number of 3D data
1	103	630
2	104	630
3	105	378
4	106	378

B. Evaluation Metrics

We used two evaluation metrics, normalized correlation and the Dice coefficient for quantitative evaluations. We used the normalized correlation value of the time-series waveform of the small intestinal contraction movement (temporal areas of the small bowel) between the ground truth (manually segmented results) and the automatically segmented result. Equation (1) expresses the normalized correlation, where x_i and y_i are manually and automatically segmented results (areas of segmented small bowel) of i th frame, respectively. Moreover, \bar{x} and \bar{y} are means of x and y , respectively. The normalized correlation value is close to 1.0, indicating that the segmentation result is similar to the ground truth.

$$Correl(\mathbf{x}, \mathbf{y}) = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(\sum(x_i - \bar{x})^2)(\sum(y_i - \bar{y})^2)}} \quad (1)$$

The Dice coefficient is used as a measure of segmentation accuracy for each frame, which is defined by Eq. (2), where x and y are manually and automatically segmentation results (binary masks) for each frame,

$$DSC(x, y) = \frac{2|x \cap y|}{|x| + |y|} \quad (2)$$

Also, using Fourier transform analysis we examined the frequency of small bowel contraction movement. Eq. (3) represents the Fourier transform, where f is the frequency, and N is the number of temporal frames.

$$F(u) = \sum_{x=0}^{N-1} f(t) e^{-i \frac{2\pi t u}{N}} \quad (3)$$

C. Results

Fig. 4 shows typical segmentation results using the proposed 3D U-Net. For comparing the method proposed in this paper and the conventional 2D U-Net, we have presented the segmentation results obtained using conventional 2D U-Net in Fig. 4. Also, Fig. 4 shows

results of the manual segmentation by experts, while their waveforms are shown in Fig. 5. Their Fourier transform results are shown in Fig. 6. As shown in Fig. 4-Fig. 6, it is evident that the 3D U-Net achieved more accurate segmentation than the other method. Table 4 summarizes the results. For all cine MR images, the proposed 3D U-Net achieved better results as compared to the conventional U-Net. The effectiveness of proposed method has been confirmed experimentally.

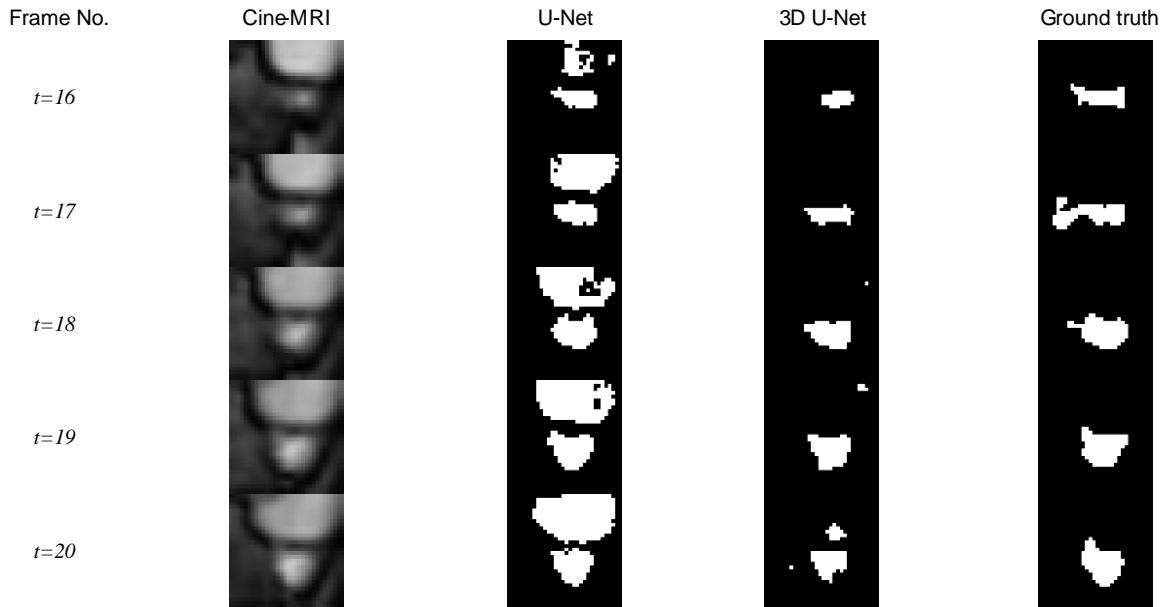


Figure 4. Visualization results of our test set.

TABLE III. COMPARISON OF THE 3D U-NET WITH U-NET ON SMALL BOWEL MOTILITY FUNCTION CINE-MRI SEGMENTATION

		Normalized correlation		Frequency error		Dice coefficient	
No.	Time	U-Net	3D U-Net	U-Net	3D U-Net	U-Net	3D U-Net
103	10	0.79	<u>0.81</u>	0	0	0.82	<u>0.87</u>
	15	0.75	<u>0.81</u>	0	0	0.80	<u>0.82</u>
	30	0.72	0.72	0	0.033	0.87	<u>0.88</u>
	45	0.62	<u>0.67</u>	0	0	0.81	<u>0.82</u>
	60	0.63	<u>0.70</u>	0.067	0.033	0.79	<u>0.80</u>
104	10	0.46	<u>0.62</u>	0.067	0	0.64	<u>0.74</u>
	15	0.60	<u>0.64</u>	0	0	0.72	<u>0.79</u>
	30	0.82	<u>0.87</u>	0	0	0.75	<u>0.79</u>
	45	0.66	<u>0.76</u>	0.033	0.033	0.81	<u>0.82</u>
	60	0.78	<u>0.84</u>	0	0	0.83	<u>0.85</u>
105	15	<u>0.76</u>	0.73	0	0.033	0.81	<u>0.82</u>
	30	0.65	<u>0.98</u>	0.067	0	0.81	<u>0.82</u>
	45	0.87	<u>0.91</u>	0	0	0.86	<u>0.87</u>
	60	0.54	<u>0.67</u>	0.1	0	0.90	<u>0.93</u>
106	15	0.66	<u>0.67</u>	0	0	0.54	<u>0.59</u>
	30	0.48	<u>0.50</u>	0.067	0	0.62	0.58
	45	0.43	<u>0.48</u>	0.067	0	0.70	<u>0.71</u>
	60	<u>0.36</u>	0.31	0	0.1	0.58	<u>0.61</u>
Mean±std.		0.64±0.14	<u>0.70±0.15</u>	0.022±0.033	<u>0.012±0.025</u>	0.76±0.10	<u>0.78±0.10</u>

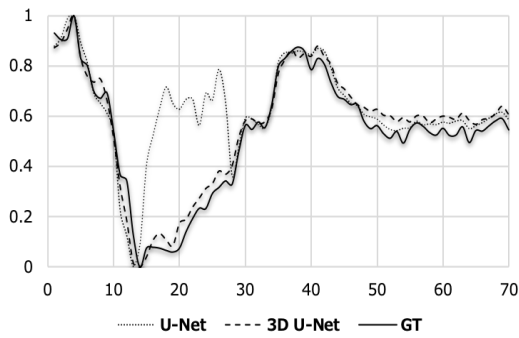


Figure 5. Time-series waveforms.

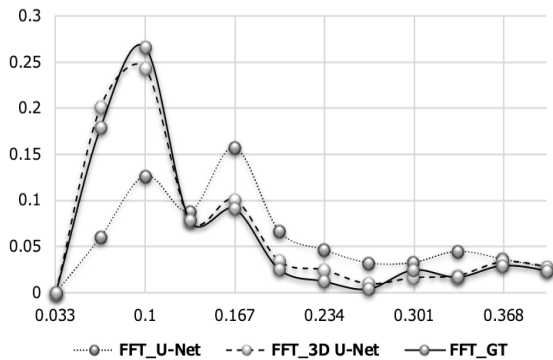


Figure 6. Comparison results of frequency analysis results.

V. CONCLUSION

In this paper, we proposed an automatic analysis method of small bowel motility function using 3D U-Net. For all cine-MR images used in our experiments, the proposed 3D U-Net achieved better results than conventional 2D U-Net. In the future, we are going to assess disease cases and compare them with the healthy cases.

ACKNOWLEDGMENT

This work was supported in part by the Grant-in Aid for Scientific Research from the Japanese Ministry for Education, Science, Culture and Sports (MEXT) under the Grant No. 2546183, and No. 18H03267.

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