A Hybrid Network for Automatic Myocardial Infarction Segmentation in Delayed Enhancement-MRI

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Abstract. Delayed enhancement DE-MRI plays an important role in the diagnosis of various myocardial damages (such as myocardial infarct and no-reflow phenomenon). This paper proposes a hybrid U-net network to achieve the simultaneous segmentation of the background, left ventricle, left myocardium, myocardial infarction, and no-reflow regions in DE-MRI. The hybrid U-net architecture introduces the squeeze-and-excitation residual (SE-Res) module and selective kernel (SK) block in the encoder and decoder parts, respectively. The SE-Res module can address the dependencies of all feature channels, and increase the weight value on the more informative channel. The SK block can adaptively adjust the receptive field size to obtain the multi-scale feature information. Two types of labels (category label and segmentation label) and hybrid branches are used to control the whole segmentation process, which produces robust segmentation performance. The experimental result shows that the proposed model achieves high segmentation performance with the Dice score of 0.8455 for myocardium, 0.6455 for infarction, and 0.6698 for no-reflow on the validation set.

Keywords: Myocardial Infarction · Segmentation · Delayed myocardial enhancement MRI · Convolution neural network.

1 Introduction

In 2015, according to statistical analysis, there were about 15.9 million people suffering from myocardial infarction in the world [12]. The No-reflow zone is characterized by persistent hypoperfusion caused by reduced blood flow [9]. Delayed enhancement magnetic resonance imaging (DE-MRI) is currently used for the diagnosis of myocardial involvement (myocardial infarction and no-reflow) in the current clinical environment. The myocardial infarction and no-reflow regions occupy only a fraction of the left myocardium and less area of the entire heart image. Thus, accurate delineation of the endocardial and epicardial borders of the left myocardium is a prerequisite. The manual segmentation for the left ventricle, myocardium, and myocardial damage is a time-consuming (around

30 minutes per case), tedious, and experienced-dependent task. Computer-aided technology is urgently required to assist radiologists in workflow optimization.

In current years, a majority of studies have focused on the left myocardium segmentation on the late gadolinium enhancement MRI. It is known that the delayed enhancement MRI targets to highlight the myocardial damage region (myocardial infarction or no-reflow). The boundaries of ventricles are more unclear in the delayed enhancement MRI than that in the balanced-steady state free precession (BSSFP) MRI (As shown in Fig. 1). To overcome these challenges, several methods segment the myocardium region by combining the prior information from the corresponding BSSFP MRI [2–4, 13, 16]. These multi-modality based segmentation methods require paired MRI sequences and complex image registration operations. In addition to the segmentation of the left myocardium, 2019 MICCAI MS-CMRSeg challenge aims to simultaneously segment left ventricle, right ventricle, and left myocardium from LGE MRI with the complementary information from other MRI modalities [17]. For the small lesion myocardial infarction region, very few studies have designed automatic segmentation algorithms based on cine cardiac MRI [15] and enhancement MRI [14, 11].

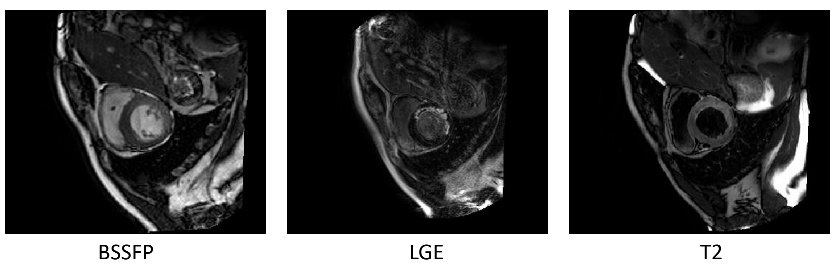

Fig. 1. Visualization for the representation of cardiac structure in balanced-steady state free precession (BSSFP), late gadolinium enhancement (LGE), and T2-weighted cardiac MRI modalities. The variations of image intensity and contrast result in different ventricles and myocardium boundary discrimination.

However, in the current literature, the left ventricle, left myocardium, myocardial infarction, and no-reflow have not been considered together. The extent of these regions is all important in the evaluation of cardiac diseases and the guide for the following treatment. This paper proposes a hybrid U-net architecture with multi-task learning to automatically segment these four regions (if have) in the DE-MRI. The encoder part in the U-net is substituted by the SE-Resnext50 [5], and the hybrid decoder part with the embedding of SK (selective kernel) block has two task branches (MI (myocardial infarction) segmentation and full segmentation) [8]. The MI segmentation branch helps target small lesion region, which is used only in the training process. The full segmentation means the simultaneous segmentation for the left ventricle, left myocardium, myocardial infarction, and no-reflow (As shown in Fig. 2). Inspired by the idea of deep supervision, a classification branch is introduced to consider both the category of each image and the pixel-level classification in each image.

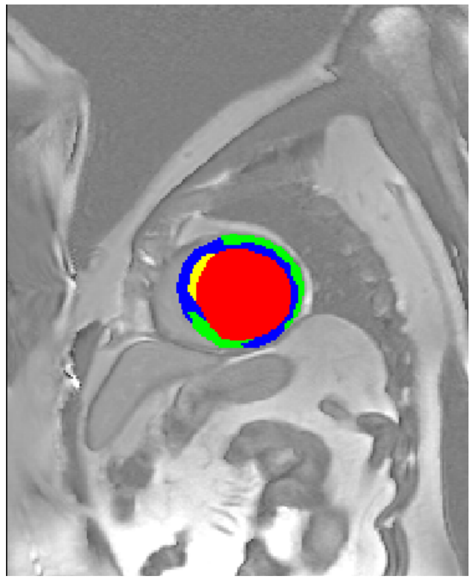

Fig. 2. An example for the left ventricle, left myocardium, myocardial infarction and no-reflow region in one DE-MRI slice. The read denotes left ventricle; green represents left myocardium; blue is the myocardial infarction region; and the yellow corresponds to the no-reflow region.

2 Method

In this section, the proposed cardiac structure segmentation algorithm is introduced from three parts: image preprocessing, hybrid network architecture, and image postprocessing.

2.1 Image Preprocessing

In order to remove the influence of the surrounding organ of heart in the DE-MRIs, region of interest (ROI) extraction is a crucial step in the prepossessing stage. Thus, this paper performs a statistical work to roughly locate the position of the heart. The second step in the preprocessing process is to normalize the input images as the distribution of zero mean and variance of 1. Finally, to fully utilize the dependences between slices, the neighbored three slices are stacked as the new three-channel image that has the same mechanism as the RGB channel in the color image.

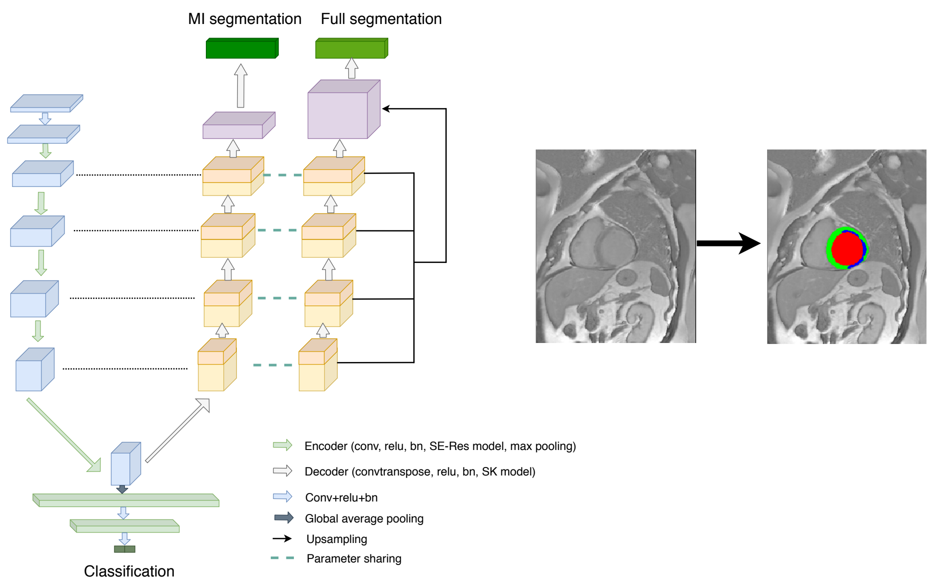

Fig. 3. The overall structure of our proposed segmentation network. The myocardial infarction (MI) segmentation branch only targets to segment the MI region in the training procedure. The full segmentation means the simultaneous segmentation of the background, left ventricle, left myocardium, myocardial infarction, and no-reflow regions, which is adopted as the final segmentation. The classification is also used only in the training phase to deeply supervise the segmentation network.

2.2 Network Architecture

The modified U-net architecture adopts the SE-Resnext50 module as the encoder part, and the SK block is embodied in the decoder part. The SE-Resnext50 model helps capture the channel correlations, and the SK block with multiple kernels and different kernel sizes can adaptively adjust the respective field size. Fig. 1 illustrates the overall structure of the proposed MI detection model.

As shown in Fig. 3, the encoder part reduces the spatial resolution and extracts high-level features to obtain more precise classification results. In this architecture, the encoder sequentially includes the convolution, pooling, rectified linear unit, batch normalization, SE-Res module, and max pooling. The decoder part recovers the missing spatial information by adding the deconvolution operation. The decoder part includes the deconvolution, rectified linear unit, batch normalization, and the SK block.

Two types of labels are adopted to supervise the training procedure of the network. One label is the categorized label of each patch, which interprets whether the image is a normal or pathological slice. Another label is the segmentation mask, which includes the pixel location of the myocardial region. The two types of labels can achieve better segmentation results.

Two segmentation branches exist in this architecture. The myocardial infarction (MI) segmentation only performs the myocardial infarction region segmentation in the network training procedure, which is controlled by the category annotation provided by the readers. It is worth noting that the MI segmentation branch is used to assist the final lesion detection, which will no longer work during the test phase. The full segmentation branch actually segments five regions (the background, left ventricle, left myocardium, myocardial infarction, and no-reflow), which is adopted as the final output in our segmentation network.

2.3 Image Postprocessing

The image postprocessing process aims to refine the result of the cardiac segmentation. First, the hole filling technique is applied to attain more complete segmentation. Then, a connected component analysis for all the obtained segmentation is performed. Segmentations that exceed the largest connected range will be removed.

2.4 Loss Function

In the classification branch, the binary cross-entropy (BCE) loss is used as the loss function to optimize the network performance. In the two segmentation branches, Dice loss and BCE loss are combined to complete the segmentation task. These loss functions are listed as follows.

$$L_{Cls} = L_{BCE} = -\sum_{l} \left[(y_l \log \hat{y}_l) + (1 - y_l) \log (1 - \hat{y}_l) \right] \tag{1}$$

where y_l and $\hat{y}_l$ denote the ground truth label and predicted output for the l^{th} samples, respectively.

$$L_{DICE} = -\frac{2}{|C|}\sum_{k\in C}\frac{\sum_i y_{i,k}\hat{y}_{i,k}+\varepsilon}{\sum_i y_{i,k}+\sum_i \hat{y}_{i,k}+\varepsilon} \tag{2}$$

where C and N represent the number of classes and the number of training images, respectively. y and $\hat{y}$ denote the ground truth label and predicted output, respectively. ε is a small positive number used to ensure numerical stability.

$$L_{Seg} = L_{BCE} + L_{DICE} \tag{3}$$

3 Experimental Results and Discussions

3.1 Dataset and Experimental Setup

Our algorithm is evaluated on the Automatic Evaluation of Myocardial Infarction from Delayed-Enhancement Cardiac MRI (MICCAI 2020 EMIDEC challenge). The dataset consists of 150 DE-MRI cases (50 cases with normal MRI after the injection of a contrast agent and 100 cases with myocardial infarction (and then with a hyperenhanced area on DE-MRI)) [7]. The training set comprises 100 cases (67 cases with myocardial damage, 33 normal cases) and the testing set is composed of 50 cased (33 cases myocardial damage, 17 normal cases). There are no overlapped cases in the training and testing sets.

Due to the very limited number of training images, real-time data augmentation is applied to simulate an enlarged dataset to further improve the model generalization capability. The adopted data augmentation operations include randomized image transpose, flipping, cropping, gamma noise, and rotation. Adam optimizer is used as the optimization method for model training [6]. The initial learning rate is set to 0.0003, and reduced by a factor of 10 at the 40th and the 60th epoch, with a total of 90 training epochs. The min-batch size is set as 16.

3.2 Results

Since the labels of the test data are not opened, these experimental results are tested on the training data using the 5-fold cross-validation. Our network has three outputs, and the loss functions assigned on these outputs are cross-entropy, weight cross-entropy + dice, and weight cross-entropy + dice, respectively. The dice score is adopt-ed as an indicator to evaluate the performance of the proposed model. The proposed U-net model is compared with the Linknet [1] and several U-net based models [10], which are listed in Table 1.

4 Conclusion

This paper proposes an improved U-net architecture for the simultaneous segmentation of the background, left ventricle, left myocardium, myocardial infarction, and no-reflow regions in the DE-MRI. Our segmentation algorithm adopts

Table 1. The dice score of the myocardium, infraction, and no-reflow regions segmentation using various network architectures.

Network architectures	**Dice score**		
	Myocardium	Infarction	No-reflow
Linknet	0.8023	0.5823	0.5963
U-net1(SE-Resnext50)	0.8069	0.5946	0.6038
U-net2(SE-Resnext50 + SK block)	0.8135	0.6046	0.6287
U-net3 (SE-Resnext50 + SK block) + cls branch	0.8135	0.6222	0.6464
U-net4 (SE-Resnext50 + SK block) + cls branch +hybrid branches	0.8455	0.6455	0.6698

multi-task learning to deeply supervise the final segmentation. The ablation study results have demonstrated the algorithm validity. It has the promise for clinical application in assisting radiologists for the diagnosis of cardiac diseases.

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