Automatic Scar Segmentation from DE-MRI Using 2D Dilated UNet with Rotation-based Augmentation

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Abstract. Delayed enhancement (DE) MRI is an important sequence in diagnosis of cardiovascular disease as it can reveal different characteristics of the myocardium including scar and no-reflow. Automatic segmentation of different regions has the advantage of improved accuracy and reduced inter-observer variability in quantifying key imaging biomarkers such as percentage of scars. In recent years deep learning has led to drastic performance improvement in automatic segmentation tasks using the UNet architecture. Cardiac MRI segmentation is a challenging task due to the high variability in imaging contrast, orientation and signal-to-noise ratio; specifically, for short-axis views, as they are double-oblique slices, due to the different orientations of the heart and operator choice, the orientation can vary significantly, which poses a challenge to the neural networks as they cannot learn a consistent global anatomy. In this paper we developed a rotation-based augmentation to address this issue in both training and testing steps by eliminating the variance in orientations and demonstrated its effectiveness. 2D dilated UNet was used as the backbone network structure.

Keywords: Scar Segmentation, DE-MRI, LGE, Dilated UNet, Rotation-based Augmentation

1 Introduction

Delayed enhancement (DE) MRI, also called late gadolinium enhancement (LGE) MRI, is a key MRI technique in cardiac applications. By injecting contrast agent and performing T1-sensitive acquisitions, myocardium regions with different characteristics can be clearly revealed including scars and no-flow regions. Furthermore, by segmenting the whole myocardium, the percentage of scar can be calculated, which is a key imaging biomarker in many diseases for diagnosis and risk stratification [1]. In recent years the deep learning methods, represented by the UNet architecture [2], have led to drastic performance improvement in many medical image segmentation tasks. Cardiac MRI segmentation is a challenging task due to the high variability of imaging contrast, orientation and signal-to-noise ratio in the images. Specifically, as most sequences acquire the short-axis views of the heart and cover the heart with multiple slices, the orientations of the heart can vary significantly, leading to different in-plane anatomy. For example, some views will have the chest on the left while others will have it on the top. This poses a challenge for neural networks as they cannot learn the global anatomy as efficient as from images acquired on standard axial, coronal or sagittal views. In this study we proposed a rotation-based augmentation in both training and testing stages to address this challenge. The EMIDEC Segmentation Contest [2] provides an open platform with a large and diverse dataset to compare different algorithms. We used the dataset and validated our method in the scope of this contest.

2 Methods

For the DE-MRI segmentation task, the steps in our proposed method include pre-processing of the images, training and deployment of neural networks, and post-processing. The target regions-of-interest (ROIs) include left ventricle (LV) blood pool, normal myocardium, myocardial infarction area and no-reflow area. Note that not all regions exist in every case as myocardial infraction and no-reflow represent pathological regions. Details are described as follows.

2.1 Image Pre-processing

Substantial image preprocessing was performed by the challenge organizers. Specifically, to address the shifts among different short-axis slices due to different breath holds, all slices were realigned based on the gravity center defined by the epicardial contour. In our preprocessing workflow, we further normalized the pixel spacings to be 1.367 x 1.367 mm^2 and center-cropped or zero-padded the resulting images to have the same matrix size as 224 x 224. All labels were processed using the same workflow; to reduce the effect from resampling, each label was converted to binary maps and processed separately. Finally, each slice is normalized to have 0 mean and unit standard deviation to reduce variations in global intensity values.

2.2 Network Structure

Although the pre-processing to align different slices was performed, due to the very large slice thickness and the imperfect alignment, the spatial continuity along the slice direction is assumed to be small. Therefore, even if a 3D network can potentially take advantage of information from neighboring slices, it often leads to inferior performance compared with 2D counterparts. Compared with conventional convolutions, dilated convolutions can increase the receptive field without increasing the number of parameters and have shown advantages in many applications [3]. In cardiac MRI segmentation, we also observed that the dilated convolutions often outperform the conventional convolution when all other parameters are kept the same. Therefore, we decided to use 2D UNet with dilated convolutions as the backbone network structure so that it has an increased robustness against misalignment of different slices as it only takes one slice to make segmentation.

For the final dilated 2D UNet, the number of features at the first layer was set to 48 and was doubled for every encoding block comprising of 2 consecutive convolution layers, batch norm and rectified linear unit activation layers. The weighted cross entropy plus soft Dice loss was used as the loss function to address class imbalance.

2.3 Rotation-based Augmentation

Augmentation is a key step in training neural networks, especially in medical image applications as the dataset size is often small. As a main variability of the short-axis images is the orientation and in-plane rotation and the neural networks are not designed to be rotation-invariant but instead shift-invariant, we aimed to train a network that can ignore the differences in orientation by providing images that were randomly rotated within the full possible range (0 – 360). Therefore, during training, we forced the network to ignore the image orientation but instead learn the contrast and anatomical relationships. Furthermore, during testing, in addition to deploying the network to the original image, we also deployed it to images rotated at certain angles as a testing augmentation step. Practically, to balance the time it takes per image and the expected accuracy, we deployed to images rotated at 9 evenly distributed angles between 0 and 360 and averaged the resulting probabilities after rotating back to the original orientation. This was able to maximumly eliminate the impact from different short-axis orientations and reduce random errors with a single image. In addition to rotation-based augmentation, during training, random shift, scaling and shearing were also applied to emulate more images to further increase the generalizability of the network. In addition, as the myocardial infarction and no-reflow regions are much smaller than normal myocardium in the whole dataset, in each epoch, instead of looping over all images equally, we favored more slices that contain these two regions by looping over them 6 times per epoch.

2.4 Post-processing

As the network is trained end-to-end to directly generate all desired ROIs, no further post-processing was performed except for padding/cropping to the original field-of-view and resampling to the original pixel spacing. Similarly, the label for each ROI was performed separately to reduce any resampling errors.

2.5 Experiments

In model development, we randomly split the 100 training cases into 57 for training and the remaining 43 for internal validation. To evaluate the impact of the rotation-based augmentation, especially during testing, we compared the results with and without the proposed augmentation after the model was trained. Finally, we trained a model using all 100 cases and deployed it to the 50 testing cases with the rotation-based augmentations. All experiments were performed using a Nvidia Ttian Xp GPU with 12 Gb memory using the Tensorflow framework.

3 Results

3.1 Validation

Table 1 shows the calculated Dice scores with (second row) and without (first row) the rotation-based testing augmentation. The rotation-based testing augmentation significantly increased the performance, especially for the infarction and no re-flow regions.

Table 1. Dice scores with and without rotation-based testing augmentation

	LV blood pool	Myocardium	Infarction	No re-flow
No augmentation	0.929	0.813	0.477	0.624
With augmentation	0.933	0.824	0.578	0.697

3.2 Testing

The performance on the testing data after submitting to the challenge organizer was given in Table 2.

Table 2. Dice scores with and without rotation-based testing augmentation

	Myocardium	Infarction	No re-flow
Dice	0.833	0.547	0.722
Volume difference (mm^3)	15187.48	3970.73	883.42
Hausdorff Distance/Ratio difference	33.77 mm	2.89%	0.53%

4 Conclusion

In this paper we developed an automatic DE-MRI segmentation method using dilated 2D UNet with the rotation-based augmentation during training and testing. The effectiveness of rotation in overcoming the varied short-axis orientations was demonstrated in the experiments performed without and with the rotation.

One disadvantage of the rotation augmentation during testing is that it significantly prolongs the deployment time; however, as we adopted the 2D UNet with only 3 encoding blocks and run on a relatively fast GPU, the deployment time is not a major concern.

The final Dice scores for the myocardium, infraction and no-reflow regions were 0.833, 0.547 and 0.722. Although the Dice score for myocardium is high, the pathological regions may not be segmented accurately, especially for infarction region with a mean ratio difference of 2.89%, which may affect the risk stratification if directly using the automatic segmentation results. Therefore, future studies are needed to continue to improve the robustness and accuracy of the model.

References

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