A Fully Automated Two-Stage Segmentation Approach for Late Gadolinium-Enhanced Cardiac Magnetic Resonance Images in Personalized Cardiac Modeling

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Abstract

Accurate automatic segmentation of LGE-CMR images is vital for personalized cardiac modeling. We developed a two-stage method: a DL-based solution for left ventricular (LV) segmentation and an MGMM solution for infarct tissue (IT) in LV, enabling fully automated cardiac segmentation. Ventricular models were constructed for three patients using segmented LGE-CMR images, and programmed electrical stimulation induced VT. Our method achieved an 81.21 DS for LV and an 82.9 DS for IT. Simulation results for these patients matched manual methods, indicating the efficiency and reliability of our two-stage approach for personalized cardiac modeling.

1. Introduction

Sudden cardiac death (SCD) remains a global health concern [1], primarily attributed to ventricular tachyarrhythmia (VT) in individuals with myocardial infarction (MI) [2,3]. Personalized computational modeling offers a non-invasive approach to predict arrhythmia risk and reentry circuit locations, guiding VT ablation in clinical practice [4]. This patient-specific method relies on magnetic resonance imaging (MRI) for accurate heart model reconstruction. However, the LGE CMR modality, often characterized by poor image quality and fibrotic regions, presents challenges for LGE-CMR segmentation.

Traditional methods have been developed in recent years, but many still require manual or preparatory work, limiting efficiency, especially in clinical settings. With the advancements in artificial intelligence, automated segmentation methods have gained attention, with Convolutional Neural Networks (CNNs) and Transformers being noteworthy examples.

We developed a two-stage approach employing a deep learning (DL) solution using TransUNet [5], a hybrid of CNN and Transformer, for LV segmentation, and a modified Gaussian mixture model (MGMM) for infarct tissue (IT) segmentation within the LV, enabling fully automated cardiac segmentation. This architecture was evaluated on the 2020 MICCAI EMIDEC challenge dataset [6] and a private dataset. Subsequently, personalized cardiac modeling [4] was performed based on the segmentation results. The results demonstrate that this two-stage method is efficient and meets clinical requirements [1].

2. Method

2.1. Data Description

The study utilized CMR-LGE data from 168 hearts, with 100 patients sourced from the 2020 MICCAI EMIDEC challenge dataset, and 68 patients from Beijing Anzhen Hospital. Manual annotations included labels for background, normal myocardium, and myocardial infarction.

2.2. TransUNet

The TransUNet architecture, introduced by Chen et al. [5], combines ConvNets and Transformers to enhance medical image segmentation. Similar to U-Net[7], it employs ConvNets in the encoder for global context extraction and utilizes Transformers for capturing long-term dependencies. The decoder features a cascaded upsampler (CUP) with multiple upsampling steps, each comprising a 2× upsampling operator, 3×3 convolution layer, and ReLU activation. For more details, please refer to the published paper [5].

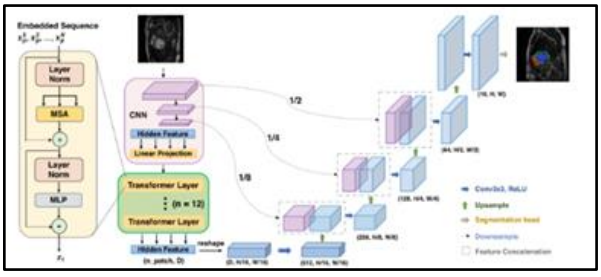

Figure 1. Overview of the framework.

2.3. Modified Gaussian Mixture Model Method

The GMM method uses Gaussian distribution for tissue intensity modeling in medical images, enabling classification into non-infarct and infarct regions via histogram fitting. Key details are available in our prior publication [8]. Subsequently, significant components are preserved while small clusters (fewer than 15 pixels) are eliminated. To further segment infarct tissue into the gray zone (GZ) and core scar, pixel intensity statistics are employed, designating pixels > 50% of the intensity range as core scar and the rest within the infarct area as GZ.

2.4. Model Construction And Simulation Protocol

Following image segmentation with CardioViz3D [9], low-resolution images were interpolated to approximately 0.4 mm resolution. 3D geometry of infarct tissue (core scar and GZ) was reconstructed using the log odds method [10] and merged with corresponding high-resolution ventricular images. The finite-element mesh for patient-specific bi-ventricular geometry was generated using Mimics Innovation Suite [9]. Fiber orientations were assigned using a rule-based method [11].

Electrophysiological properties were assigned as described previously [12,13], and electrical activity propagation was simulated with a finite-element method [14]. Simulations were executed with Neumann boundary conditions using the openCARP simulation environment [15] on high-performance computers at Dalian University of Technology, China. VTs were induced in the models of five patients using programmed electrical stimulation as in prior articles [12,13].

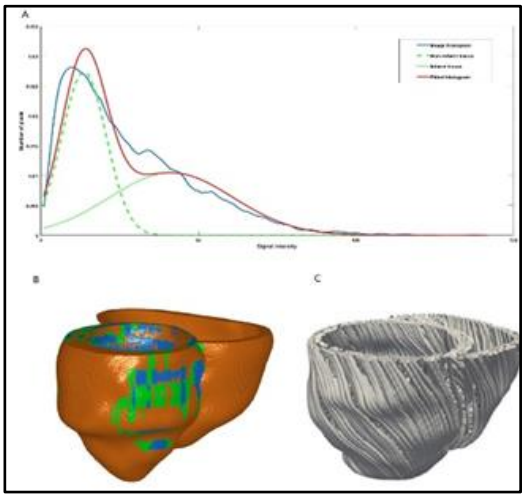

Figure 2. Overview of the MGMM and Virtual-heart modeling.

3. Result

We conduct experiments on EMIDEC Challenge dataset [6] and Anzhen private dataset. We divide the labeled EMIDEC public dataset which contains 100 cases into 85 patients training dataset and 15 test dataset randomly, Similarly, the Anzhen private dataset was divided into 58 training dataset and 10 test dataset.Table 1 shows the quantitative calculations and comparisons of MYO and infarct tissue on EMIDEC dataset with some state-of-the-art methods using the dice coefficients. Due to the random nature of data partitioning, the results of the other methods in Table 1 are taken from the results in the corresponding papers.As shown in Table 1, the best model achieves 87.8 dice score of myocardium, +7.2 better than TransUnet with 80.6, while the median accuracy of all the other methods -1.0 lower than TransUnet.

Table 1. Comparison on EMIDEC dataset

Methods	DSC (avg)	MYO	IT
Cascaded CNN	79.5	87.8	71.2
Deep convolutional network	62.0	84.0	40.0
Uncertainty-based U-net	45.3	68.9	21.6
TranUNet	51.1	80.6	41.2

Figure 3 shows the result of myocardial tissue on Anzhen dataset. By comparing layer by layer, the performance of myocardium segmentaion obtained by TransUnet is satisfactory, especially at the middle regions, which are very close to the true value.

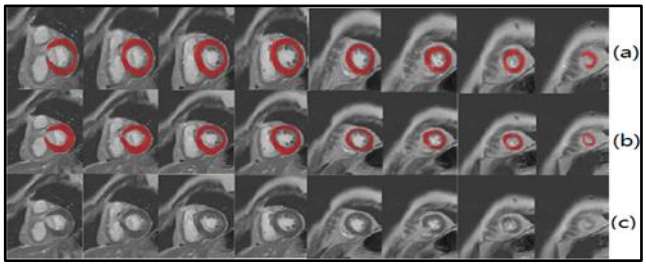

Figure 4. The result of infarct tissue with one and two classes of PAT01 based on MGMM method, (a) is original image, (b) is classification result with two categories and (c) is classification result with three categories.

For IT, in contrary to myocardium segmentation, TransUnet and almost all of the models in Table 1 achieve poor accuracy, considering the LGE CMR modality suffers from terrible image quality. In contrast, as shown in the Table 2, the IT segmentation accuracy of Anzhen private dataset using MGMM is 82.9, the good performance also can be seen by predicted result in Figure 4.

Table 2. Dice score of 3 patients on myocardium and IT respectively based on two-stage automatic segmentation method

PAT	Dice of Myocardium using DL-based method	Dice of Infarct tissue using MGMM method
PAT01	79．8	90．5
PAT02	82．2	78．4
PAT03	74．2	76．1
PAT04	81．7	82．1
PAT04	81．9	70．8

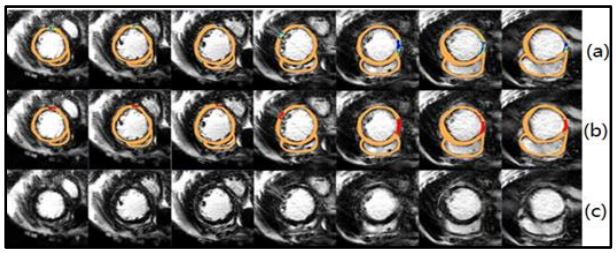

Figure 4. The result of infarct tissue with one and two classes of PAT01 based on MGMM method, (a) is original image, (b) is classification result with two categories and (c) is classification result with three categories.

Table 3 presents VTs induced in 5 patients, comparing the accuracy of our automatic segmentation with manual reentry. Patient 3, with the lowest Dice score for myocardium segmentation (Tables 3 and 4), also exhibited unsatisfactory IT segmentation and reentry accuracy, likely due to initial incorrect tissue segmentation. However, the remaining 4 patients demonstrated consistent reentry locations and morphologies using our method compared to manual. Figure 5 is simulation reentry based on our method on PAT04. The clinical diagnosis showed that there was no infarct related VT event when the patient was in hospital, in the same, there was no stable reentry induced in the model.

Table 3. Ventricular tachycardias induced in 5 patients based on automatic segmentation method

PAT	Induction ratio	Location	Morphology	%Accuracy
PAT01	1/5	Posterior Endocardium	Stable	100
PAT02	1/5	Apical Endocardium	Stable	100
PAT03	1/5	Inferior Epicardium	Stable	0
PAT04	0	Right Lateral Epicardium	Unstable reentry	100
PAT05	4/5	Apical Endocardium	Unstable reentry	100

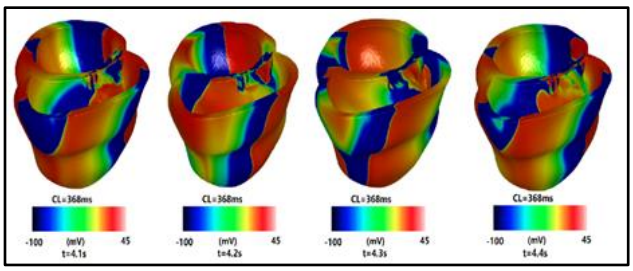

Figure 5 PAT04 simulation reentry based on two different segmentation methods.

4. Conclusion

This paper presents a two-stage approach, combining a CNN-Transformer hybrid for LV segmentation and MGMM for IT segmentation within the LV. The study demonstrates the method's feasibility in personalized cardiac modeling, indicating clinical potential. Efficient and satisfactory outcomes were obtained. The paper encourages further exploration of deep learning in cardiac modeling for improved clinical efficiency.

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