A Joint Multi-scale Convolutional Network for Fully Automatic Segmentation of the Left Ventricle

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Abstract

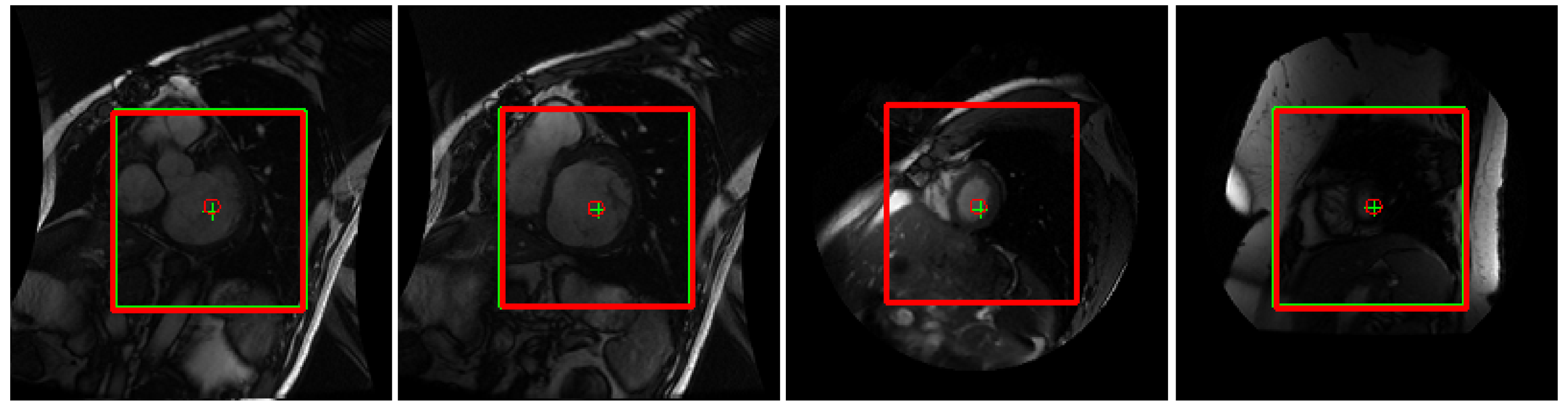
Left ventricle (LV) segmentation is crucial for quantitative analysis of the cardiac contractile function. In this paper, we propose a joint multi-scale convolutional neural network to fully automatically segment the LV. Our method adopts two kinds of multi-scale features of cardiac magnetic resonance (CMR) images, including multi-scale features directly extracted from CMR images with different scales and multi-scale features constructed by intermediate layers of standard CNN architecture. We take advan-tage of these two strategies and fuse their prediction results to produce more accurate segmentation results. Qualitative results demonstrate the effectiveness and robustness of our method, and quantitative evaluation indicates our method achieves LV segmen-tation with higher accuracy.

Our Method

We firstly employ ConvNets to coarsely detect the region of interest (ROI) of the LV. Then, we train a joint multi-scale convolutional neural network (JMS_CNN) to accurately segment the LV. JMS_CNN utilizes two kinds of multi-scale features, which are from CMR images of different scales and from different layers of a standard CNN trunk, respectively.

1. ROI Detection

The raw CMR imaging datasets usually include the heart and surrounding organs. we firstly detect ROI containing the LV from raw input images using CNN, which has 7 layers with weights: three convolutional layers, three pooling layers and a fully connected (FC).



2. P_CNN

We utilize different scales of the input image to train S networks in parallel. S is the scale number in total. We refer to the S CNNs as P_CNN_1, P_CNN_2,…, P_CNN_S. To improve the robustness of the entire network, we do not train the CNNs separately, but train them assembly and simultaneously. In the stage of back propagation, we update weights of each P_CNN separately.

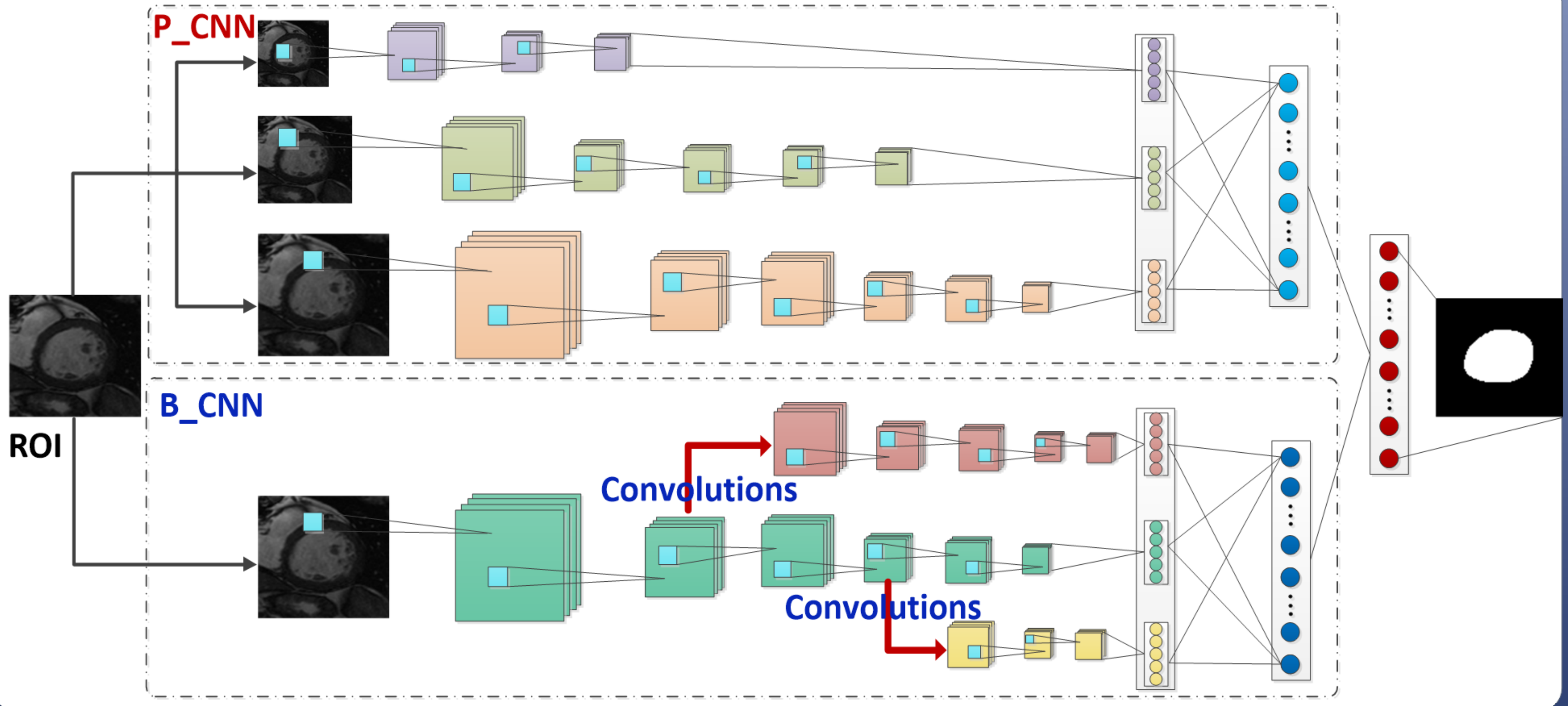
3. B_CNN

To obtain variable receptive field sizes and improve the ability to tackle the segmentation task of different sizes, we utilize the feature maps emanating from intermediate layers of the trunk network to accomplish multi-scale representation. Different branches are referred to as B_CNN_1, B_CNN_2, …… , B_CNN_D. B_CNN_1 denotes the trunk network and D is the numbers of branches.

4. JMS_CNN Architecture

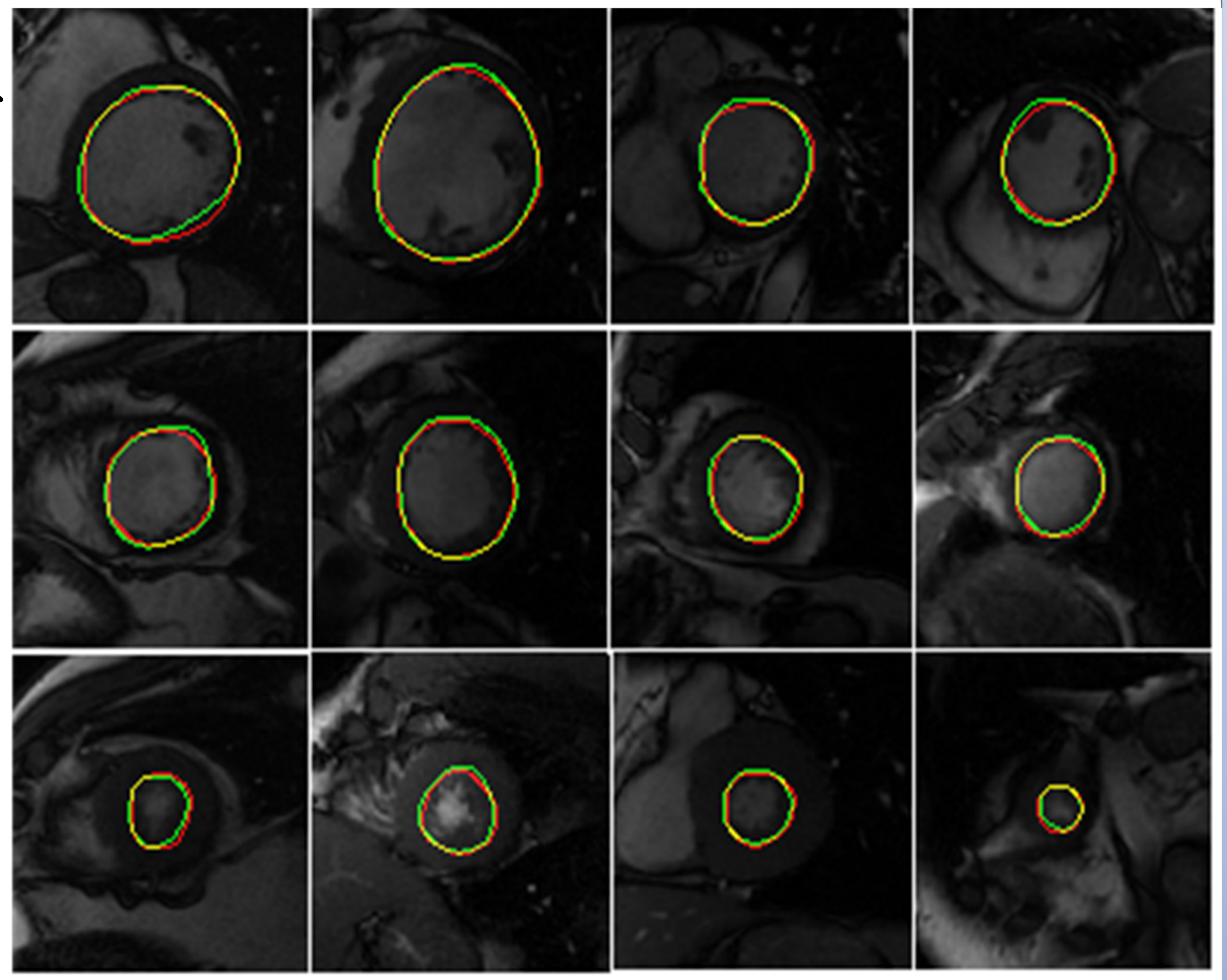
P_CNN and B_CNN both accomplish multi-scale representation of input image $\boldsymbol{I}$. We fuse the predicted results of P_CNN and B_CNN for each pixel. The predicted mask B_{mask} of the input ROI image is calculated as follows. $\boldsymbol{I}_P(i,j)$ and $\boldsymbol{I}_B(i,j)$ are the predicted results of P_CNN and B_CNN. $[m_1, n_1]$ is the size of B_{mask}. $\Gamma(\cdot)$ denotes to match the binary results to the input ROI image to obtain the contour of the LV.

$$B_{mask} = \mathop{\Gamma}\limits_{i=1,j=1}^{i=m_1,j=n_1} (average(\boldsymbol{I}_P(i,j), \boldsymbol{I}_B(i,j)))$$



Segmentation results

We assess the performance of our method by comparing its segmentation contours (red line) with that of manual anno-tation by experts (green line), and yellow indicates better matching. JMS_CNN can over-come the difficulties of gray level inhomogeneity, presence of papillary muscles and influ-ence of surrounding areas. The LV can be accurately segmen-ted even its size is very small.



We compare the segmentation performance between our JMS_CNN and other machine learning methods. Our percentage of good contours (GC) is 96.80, which is much higher than Avendi et al. [3].

Method	GC(%)	APD	DM	CC
[3]	88.46	2.90	0.89	0.77
S_CNN	94.92	2.16	0.91	0.80
P_CNN	94.98	2.15	0.91	0.80
B_CNN	95.53	2.13	0.91	0.81
Proposed	**96.80**	**2.08**	**0.91**	**0.81**

([3] MR Avendi et al, "A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac mri," Medical image analysis, vol. 30, pp. 108–119, 2016.)

Conclusion

This paper proposes a joint multi-scale convolutional neural network for accurate segmentation of the LV. The method can cover different LV sizes by utilizing multi-scale representation not only from images of different scales but also that from multiple intermediate layers of a standard CNN architecture. We will try to accomplish multi-scale representation on other networks such as fully convolu-tional networks and evaluate our method on larger data sets.