Fully automated segmentation of left ventricular scar from 3D late gadolinium enhancement magnetic resonance imaging using a cascaded multi-planar U-Net (CMPU-Net)

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Purpose: Three-dimensional (3D) late gadolinium enhancement magnetic resonance (LGE-MR) imaging enables the quantification of myocardial scar at high resolution with unprecedented volumetric visualization. Automated segmentation of myocardial scar is critical for the potential clinical translation of this technique given the number of tomographic images acquired.

Methods: In this paper, we describe the development of cascaded multi-planar U-Net (CMPU-Net) to efficiently segment the boundary of the left ventricle (LV) myocardium and scar from 3D LGE-MR images. In this approach, two subnets, each containing three U-Nets, were cascaded to first segment the LV myocardium and then segment the scar within the presegmented LV myocardium. The U-Nets were trained separately using two-dimensional (2D) slices extracted from axial, sagittal, and coronal slices of 3D LGE-MR images. We used 3D LGE-MR images from 34 subjects with chronic ischemic cardiomyopathy. The U-Nets were trained using 8430 slices, extracted in three orthogonal directions from 18 images. In the testing phase, the outputs of U-Nets of each subnet were combined using the majority voting system for final label prediction of each voxel in the image. The developed method was tested for accuracy by comparing its results to manual segmentations of LV myocardium and LV scar from 7250 slices extracted from 16 3D LGE-MR images. Our method was also compared to numerous alternative methods based on machine learning, energy minimization, and intensity-thresholds.

Results: Our algorithm reported a mean dice similarity coefficient (DSC), absolute volume difference (AVD), and Hausdorff distance (HD) of 85.14% ± 3.36%, 43.72 ± 27.18 cm³, and 19.21 ± 4.74 mm for determining the boundaries of LV myocardium from LGE-MR images. Our method also yielded a mean DSC, AVD, and HD of 88.61% ± 2.54%, 9.33 ± 7.24 cm³, and 17.04 ± 9.93 mm for LV scar segmentation on the unobserved test dataset. Our method significantly outperformed the alternative techniques in segmentation accuracy (P < 0.05).

Conclusions: The CMPU-Net method provided fully automated segmentation of LV scar from 3D LGE-MR images and outperformed the alternative techniques. © 2020 American Association of Physicists in Medicine [https://doi.org/10.1002/mp.14022]

Key words: convolutional neural network, late gadolinium enhancement magnetic resonance imaging, left ventricle myocardium, left ventricular scar, U-Net

1. INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death worldwide, ischemic heart disease being a dominant contributor. These patients suffer irreversible myocardial necrosis from ischemia leading to the replacement of contractile muscle with akinetic scar, inherently reducing cardiac function and leading to heart failure. Approximately one-third of these patients will also die suddenly from malignant ventricular arrhythmias (VA), most commonly provoked by electrical reentry circuits surrounding regions of myocardial scar. Recognition of these relationships has expanded the emphasis on myocardial scar imaging to guide the management of patients with chronic ischemic cardiomyopathy. In particular, characterizing myocardial scar volume, as well as its heterogeneity and geographic distribution, may aid clinicians in determining the appropriateness and procedural approach to percutaneous ablation (aimed at eliminating electrical channels) and cardiac resynchronization therapy.
Two-dimensional (2D) late gadolinium-enhanced (LGE) magnetic resonance (MR) imaging is the established reference standard for myocardial scar imaging, identifying the latter through enhancement from the retention of gadolinium-based contrast agents. However, the use of three-dimensional (3D) acquisition techniques is rapidly growing due to advancement in both hardware technology and experience, as well as strong interest from the electrophysiology community to use such images to guide interventions. This has been catalyzed by the capacity of 3D LGE-MR images to provide improved spatial resolution, while enabling volumetric reconstruction of scar geometry. Compared to 2D techniques, 3D LGE-MR images have been shown to provide higher signal intensity and contrast for myocardial scar with reduced overall acquisition times. However, the segmentation of scar from 3D LGE-MR images is highly tedious, time-consuming (≈54 min), and subject to high observer variability. Therefore, a fully automated method is quite desirable for this task. However, this is particularly challenging due to complex cardiac structure that is variable across basal, mid and apical regions of the LV, poor image contrast at the myocardial-blood boundary, as well as a higher prevalence of image artifacts.

Previous studies evaluating LV scar segmentation from 3D LGE-MR images can be divided into three main categories: (a) intensity thresholding-based [i.e., full width at half maximum (FWHM) or signal threshold to reference mean (STRM)], (b) energy minimization-based [i.e., hierarchical maximum flow (HMF) and convex max flow (CMF)], and (c) deep learning-based [i.e., convolutional neural network (CNN)] methods. Except for the HMF, all the other methods require manual segmentation of the myocardial borders to constrain a region of interest (ROI) for scar segmentation. Once myocardial boundaries are defined, the FWHM approach identifies the maximum intensity value of LV scar tissue (Iₚ) and considers this as a reference with scar classified as all myocardial tissue with signal intensity greater than Iₚ/2. In the STRM-based approach, the scar is considered as any regional signal above a mean intensity value of remote myocardium plus two (STRM2), three (STRM3), four (STRM4), five (STRM5), or six (STRM6) standard deviations. Although the intensity thresholding-based methods are very simple to implement, they maintain reliance on pre-segmentation of the myocardial borders. In contrast, the HMF technique, a multi-label convex optimization technique introduced by Rajchl et al., identifies scar without such requirements by an intensity log-likelihood criterion as a data term. This said it does still require the manual application of reference ROIs to inform what the expected signal histogram is of normal myocardium and all visible scarred regions, taking on average 7 min of expert time and being subject to high-operator variability.

In this paper, we describe a cascaded multi-planar U-Net-based method (CMPU-Net) for rapid, fully automated segmentation of LV myocardium and LV scar from 3D LGE-MR images with no user interaction. U-Net was introduced by Ronneberger et al. in which global and local features of an image are learned concurrently to retain high spatial consistency. This model is built using FCNNs and has been shown to be more accurate for numerous organ segmentation tasks across different modalities. Moreover, cascaded 2D and 3D FCNNs have been used for the regional segmentation of several anatomical structures (e.g., prostate, artery, portal vein, lungs, liver, spleen, stomach, gallbladder, and pancreas).

Our main contribution is the development of a new decision fusion strategy to comprehensively learn and integrate inter- and intra-slice features from 3D LGE-MR images, allowing for efficient context-based segmentation of myocardial tissue and scar. Inspired by human behavior, we tried to emulate human perception for 3D object recognition by integrating information from three orthogonal views. Our presented methodology is similar to the multi-view network used for brain MRI segmentation in M³Net with the difference that instead of merging features learned from different U-Nets, a decision fusion algorithm was applied to aggregate the predictions made by individual networks for final prediction.

2. MATERIALS AND METHODS

Figure 1 shows the workflow of CMPU-Net, which consists of two cascaded subnets (Myo-Net and Scar-Net) as the scar is enclosed within the LV myocardium. By segmenting the LV myocardium first, we may potentially be able to exclude other hyper-enhanced regions of the image, such as pericardial fat and blood pool.

A schematic diagram of the CMPU-Net framework is shown in Fig. 2. In the training phase, three U-Nets were trained using 2D slices extracted from 18 LGE-MR images in three orthogonal views. In the testing phase, 2D slices extracted from test images were fed to the trained network separately to generate the corresponding segmentation maps, which were then combined through a majority voting system for prediction of output label.

2.A. Study subjects and data acquisition

Our study consisted of 34 subjects with known chronic ischemic cardiomyopathy. By definition, these subjects were
a minimum of 3-months from any clinically recognized acute coronary syndrome. Therefore, all myocardial scar visualized by LGE imaging was reasonably assumed to be “mature” (i.e., healed). All subjects provided written informed consent and the study protocol was approved by the Research Ethics Board at Western University. All subjects underwent a standardized imaging protocol inclusive of cine imaging, contrast-enhanced coronary MRI and post-contrast 3D LGE at the Robarts Research Institute (London, ON, Canada). The latter two image datasets were acquired using a whole-heart, respiratory navigated, 3D inversion-recovery gradient echo pulse sequence performed during and 30 min following infusion of 0.2 mmol/kg Gadovist (Bayer, Toronto, ON, Canada), as previously described. The imaging hardware and pulse sequence parameters are described in Table I.

The average age and body mass of the population, who completed the imaging protocol was 51.5 ± 12.6 yr and 28.2 ± 4.7 kg/m². The mean of heart rate and the ventricle ejection fraction (LVEF) at the time of imaging was 67.1 ± 11.2 beats per minute (BPM) and 32.1 ± 12.7%, respectively. The mean volume of LV myocardium and myocardial scar in the test population was 257.43 ± 55.91 cm³ and 45.97 ± 26.41 cm³, respectively.
TABLE I. Image acquisition parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Siemens medical</td>
</tr>
<tr>
<td>Model</td>
<td>MAGNETOM Trio</td>
</tr>
<tr>
<td>Field strength</td>
<td>3 Tesla</td>
</tr>
<tr>
<td>Echo time</td>
<td>1.3 ms</td>
</tr>
<tr>
<td>Flip angle</td>
<td>$20^\circ$</td>
</tr>
<tr>
<td>Pulse sequence</td>
<td>Inversion-recovery gradient echo</td>
</tr>
<tr>
<td>Voxel size</td>
<td>$0.625 \times 0.625 \times 1.3$ mm</td>
</tr>
</tbody>
</table>

2.B. Manual segmentation for training and testing

The boundaries of myocardial and scar in all images in the dataset were manually segmented by an expert using a 3D brush in a multi-planar view in ITK-SNAP Software\(^3^4\) that took 54 and 42 min, respectively.\(^1^4\) An interactive algorithm\(^3^5\) was employed to segment the border of epicardial and endocardial as the manual delineation of myocardial tissue on the isotropic dataset was impractical. The segmentation results were then refined by an experienced radiologist. Papillary muscles, and/or mural thrombus, and valvular tissue, if present, were excluded from the segmentation.

2.C. Architecture of CMPU-Net

Figure S1 shows the architecture of the U-Nets used in this study. Each subnet was trained separately. The number of trainable parameters for each network in Myo-Net and Scar-Net was $\approx 1.9M$ and $\approx 7.8M$. Although the number of parameters for a network within each subnet was the same, the weights were different as each network was trained using slices from one of the orthogonal views. The U-Net consists of contracting and expanding paths, where pooling and up-sampling layers are used in each way that yields a U-shaped architecture. The contraction path is identical to that of standard CNN in which convolutional layers along with pooling and activation layers are applied to the input data. In expanding path, pooling layers are replaced by up-sampling layers to expand the dimension of feature space. The output of up-sampling layers is merged with appearance feature representation learned from the corresponding layer in the shrinking path to localize high-resolution features. The most important modification of this architecture is that convolutional layers are used in expanding path as well that allows learning features to propagate to the higher resolution layers.\(^2^7\) U-Net does not have a fully connected layer at the end but generates a probability output to the size of the input image.\(^2^7\)

Contraction path of our U-Net consists of five stages in each two convolutional layers of size $3 \times 3$ followed by rectified linear unit (Relu) activation layer and one max pooling layer of size $2 \times 2$ were applied. Thirty-two filters were used in the first level of Myo-Net and the number of filters was doubled in each subsequent stage. In the Scar-Net, 16 filters were employed in the first stage of the network and similarly, the number of filters was doubled in the next stages. To maintain the activation function invariant to scaling of the weights,\(^3^6\) we conducted batch normalization with a batch size of 10 after each convolutional layer. Batch normalization also leads to faster training by enabling smoother convergence in optimization.\(^3^7\) We used a dropout layer at the end of the contraction path to minimize overfitting, where neurons are randomly dropped out of the network during training.\(^3^8\) At the final stage, a convolutional layer of size $1 \times 1$ followed by the sigmoid activation layer was applied to all feature maps to generate a probability map to the size of the input image. The probability map was then thresholded such that each voxel with a probability of greater than 0.5 was labeled as the desired object (i.e., myocardium for Myo-Net and scar for Scar-Net).

2.D. Training the CMPU-Net

As the first step, a median filter of size $3 \times 3$ pixels was applied to each slice to minimize noise. Pixel intensities of the images were then normalized to a range of [0–1] using the following equation:

$$I_N = (I - \text{Imin})/(\text{Imax} - \text{Imin})$$

Image normalization was performed for all 2D slices extracted from 3D training images in axial, sagittal, and coronal directions. The 3D LGE-MR images were then divided into 18 and 16 subjects including a total of 8430 and 7250 2D slices for training and testing the networks.

We used the DSC,

$$DSC = \frac{2|A \cap M|}{|A| + |M|} \times 100\%,$$

which quantifies the spatial overlap between algorithm-generated (A) and manual segmentations (M). The DSC is used both as a loss function and evaluation metric for segmentation. The DSC as a loss function has led to fast and accurate segmentations.\(^3^9\) We used AdaDelta as the optimizer, which employs an adaptive learning rate method for gradient descent as choosing a small value for learning rate slows down the algorithm and large values cause parameters oscillation around minima.\(^4^0\)

Morphological cleaning was applied to the output segmentation map to remove false positives that are small in size. All sparse small segmented objects fewer than 100 pixels (39.06 mm$^2$) were removed from the segmented results. To reduce the sharp edges, segmented scar 3D scar volume was smoothed via mathematical erosion operation followed by dilation. Employing a combination of those removes the patchy and sharp edges, while avoiding target to become smaller.

We implemented the algorithm in Python using Keras library, on top of Tensorflow. We trained each network for 50 epochs on Intel Core i7, 2.8 GHz on a GPU-accelerated computing platform. We monitored DSC on a validation set that
was 20% of training data samples during training and saved the latest best model according to the monitored quantity. In our experiments, the best-saved model performed better compared to the models saved after 50 epochs.

2.E. Comparison of our method to alternative methods

We compared the results of our method to those of several alternative techniques, including cascaded conventional U-Net (CCU-Net), direct multiplanar U-Net (DMPU-Net), direct conventional U-Net (DCU-Net), 3D U-Net, hierarchical max-flow (HMF), FWHM, and STRM. The LV scar was segmented using those methods from the same test dataset. Out of all the alternatives, only the HMF, FWHM, and STRM methods have been previously reported for scar segmentation.

We chose the CCU-Net as an alternative method, which has been successfully applied to numerous segmentation tasks to compare uniplanar vs multi-planar networks for scar segmentation. The CCU-Nets is a fully automated pipeline in which two U-Nets were used in series to segment the myocardium and scar in a cascaded manner. In CCU-Net, the network was trained and tested using 2D slices in the axial direction.

In the manual delineation of scar from LGE-MR images, surrounding information outside the myocardial boundary influences the expert’s decisions. To investigate whether such information influences the automated algorithm to the same extent, we included direct segmentation methods in our comparison. DMPU-Net and DCU-Net are similar in network architecture to CMPU-Net and CCU-Net but have been applied to directly segment scar from LGE-MR images without using presegmented LV myocardium. Furthermore, in the DMPU-Net approach, a voxel-by-voxel summation was employed to combine the results of each orthogonal view to establish a final label prediction. In this rule, the voxel was labeled as scar when at least one of the constituent networks predicted the label of the voxel as scar.

We also used 3D U-Net to directly segment the scar. The 3D U-Net is a widely used network for segmentation, which is an extension of the U-Net architecture from Ronneberger et al. in which all 2D operations are replaced with their 3D counterparts. We used a 3D U-Net with five stages in which 16 filters of size $3 \times 3 \times 2$ were used in the first stage of the network and the number of applied filters were doubled in the four subsequent layers. As this method is computationally expensive, we ran all our experiments on images down-sampled by a factor of two. The network was trained for 30 epochs within 150 min.

We used the same dataset and the results were postprocessed similar to what was applied for CMPU-Net, where the smallest allowable size for the segmented myocardium/myocardial scar was set to 100 pixels and the boundary of segmented regions was smoothed. Identical to the evaluation of our method, the algorithm-generated results were compared to manual segmentations.

2.F. Evaluation metrics

We used region-based and volume-based evaluation metrics to assess the performance of our method for myocardial scar segmentation. Region-based metrics include DSC [Eq. (1)], accuracy, precision, and recall, where they were computed as, $\text{accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \times 100\%$, $\text{precision} = \frac{TP}{TP + FP} \times 100\%$, and $\text{recall} = \frac{TP}{TP + FN} \times 100\%$. TP, FP, TN, and FN denote true positive, false positive, true negative, and false negative, respectively, that have been computed through pixel-by-pixel comparison of algorithm-generated segmentation map with the manual delineation. The DSC, accuracy,
precision, and recall were calculated for each slice of a test image and their mean ± standard deviation (SD), 25th, and 75th percentiles values were then computed. The absolute volume difference, AVD = |VA – VM|, measures the difference between the algorithm-generated (VA) and manually computed LV scar volume (VM).

Hausdorff distance (HD) was computed between two contours generated from algorithm (A = {ai: i = 1, 2, . . . , NA}) and manual (M = {mj: j = 1, 2, . . . , NM}) segmentation. To this end, for each point in A (ai) the Euclidean distance from all points in M was computed (d(ai, M)) and the shortest distance was considered as a perpendicular distance (pi) from A to M. HD measures the maximum of this set of the minimum distances.44

\[ p_i = \min\{d(a_i, M)\}, M = \{m_j: j = 1, 2, \ldots, N_M\}, \quad \text{(3)} \]

\[ HD = \max\{p_i\}, i = 1, 2, \ldots, N_A \quad \text{(4)} \]

Region and volume-based metrics were computed for each subject in the test dataset and the average of them was reported that reflect the performance of our proposed methodology for myocardial scar delineation.

To investigate the statistically significant difference between the DSC of our method and alternatives, we used the Wilcoxon rank-sum test at a 5% significance level. This test was chosen because a normal distribution for the sample population cannot be assumed.45 We also used Bland Altman plots to study the agreement between algorithm and manually generated LV scar volumes.46

3. RESULTS

Figures 3 and 4 show the LV myocardium and scar segmentation results of the CMPU-Net for three and five subjects, randomly selected from the test dataset. The algorithm-generated segmentations closely match the manually segmented boundaries for both LV myocardium and scar. Table II shows the summary of the results of our method. The test results suggested that CMPU-Net is capable of accurately segmenting LV myocardium with a mean DSC, AVD, and HD of 85.14% ± 3.36%, 43.72 ± 27.18 cm³, and 19.21 ± 4.74 mm, respectively. In testing, our method also reported DSC, AVD, and HD of 88.61% ± 2.54%, 9.33 ± 7.24 cm³, and 17.04 ± 9.93 mm for LV scar segmentation for the test images, respectively. Once trained, the average running times required to segment LV myocardium and scar in a typical 3D LGE-MR test image were 49.96 ± 9.76 s and 120.45 ± 23.34 s, which are substantially faster than manual segmentation (54 and 42 min, respectively14).

![Fig. 4. In the first four columns, exemplary results of segmented scar tissue in different slices extracted from three-dimensional (3D) late gadolinium enhancement magnetic resonance image of five subjects are displayed. The contours computed from the CMPU-Net method and manual segmentations are displayed in red and cyan. The fifth and sixth columns indicate the 3D view of the myocardial scar regions generated by our proposed technique and expert manual segmentation, respectively. [Color figure can be viewed at wileyonlinelibrary.com)](image-url)
The volume of LV scar computed from the CMPU-Net algorithm and expert manual segmentations were compared and the \( P \) value was estimated employing Wilcoxon rank sum as 0.4856. Accordingly, we failed to reject the null hypothesis at the 5% significance level. Therefore, proposed CMPU-Net could be employed as a replacement of manual segmentation for LV scar volume measurement. This conclusion is valid considering high segmentation accuracy reported using DSC, which penalizes for the discrepancy in shape and spatial location.

Figure 5 shows the Bland Altman plots for CMPU-Net vs manual LV scar volume. In this graph, the solid blue line, upper, and lower dashed lines represent the mean value of the difference, the upper and lower limits of agreement, respectively. In comparison to manually computed volume, the average bias of our method in estimating LV scar volume was 7.58 cm\(^3\). Thus, our proposed technique slightly overestimated the LV scar volume.

We computed the Pearson correlation coefficient (\( r \)) between DSC of LV myocardium and LV scar segmentation on the test population to quantitatively assess the impact of myocardium segmentation on the final scar segmentation. To this end, the covariance of DSC of myocardial and scar was divided into the product of their standard deviations. The \( r \) value was reported as 0.503, which indicates a moderate positive correlation between those variables. Accordingly, the segmentation accuracy of myocardial boundaries somewhat influences the segmentation accuracy of scar. Moreover, we studied the effects of scar presence on myocardium segmentation. Case-by-case study of algorithm-generated segmentation showed that a decrease in myocardium segmentation accuracy is not caused by misclassification in regions where scar is observed. Therefore, using our proposed algorithm, despite potential poor segmentation outside the myocardium, the scar tissue can be correctly identified.

Our alternative methods include CCU-Net, DMPU-Net, DCU-Net, 3DU-Net, HMF, FWHM, and STRM \( >2\)SD to \( 6\)SD. Figure 6 shows the segmented LV scar for all the tested methods for a 3D LGE-MR image chosen randomly. Two-dimensional slices were selected from basal, apical, and middle level to provide a level-based visual comparison of the different algorithms as well. We included only the results for STRM \( >5\)SD as it yielded the best DSC among the STRMs. In comparison to other methods, our method segmented scar more accurately, particularly at the basal and apical slices. Table III summarizes the quantitative results. Our proposed method yielded significantly higher DSC than that of alternatives for fully automated segmentation of myocardial scar. The next best DSC was achieved using the CCU-Net technique (85.69% \( \pm \) 4.20%). Image threshold-based methods reported the most inferior DSC.

Although we had a limited number of test images, LV scar was sufficiently variable in terms of myocardial scar volume, shape, location, and signal characteristics (Fig. 7).

### 4. DISCUSSION

In this paper, we described CMPU-Net, a method to fully automatically segment LV scar by integrating information along three orthogonal planes of a 3D LGE-MR image. As compared to numerous alternative methods, our method reported significantly higher DSC. As 2D U-Net takes a single slice as input, it inherently fails to leverage context from adjacent slices. Our suggested methodology addresses this issue
by applying 2D convolutional kernels to the image slices from three orthogonal views to make segmentation predictions for a volumetric scan with a computational cost as a result of the increased number of parameters used by the model. To the best of the authors’ knowledge, this is the first attempt to fully automatically segment LV scar from 3D LGE-MR images. Case-by-case investigation of the segmented scar on the test dataset revealed that our algorithm is comparatively accurate in identifying scar description at the apex, which is a challenging task due to its small size. The comparison results demonstrate that multiplanar methods achieved a higher segmentation accuracy compared to single-plane approaches. Furthermore, the cascaded pipeline yielded higher DSC compared to those that segment scar directly from LGE-MR images.

In this work, we also developed a fully automated method for LV myocardium segmentation. Although several methods have been reported for fully automated myocardial segmentation in 3D LGE MRI, fully automated segmentation of scar in 3D LGE MRI has not been reported. Tao et al. developed an algorithm based on the global registration of the Cine-MRI and LGE-MRI volumes using a cohort of 50 subjects (25 ischemic) to segment LV myocardium from 3D LGE-MRI.\textsuperscript{47} Their method yielded the DSC of 81% ± 7% and 83% ± 9% for the two observers who manually segmented the LV in LGE-MR images. Kurzendorfer et al. utilized a two-step registration-based method to delineate the LV myocardium and evaluated their proposed method on 30 clinical 3D LGE-MRI datasets from individual subjects obtained at two different clinical sites, which reported DSC of 83% and 80% for the endocardium and epicardium, respectively.\textsuperscript{48} We used a majority voting system for final label prediction from three orthogonal views that result in more confident prediction. This is particularly useful in ambiguous cases, where suppression of false-positive errors can be achieved. Our results demonstrated that multi-planar slice extraction not only helps to maintain spatial consistency across adjacent slices but also increases the number of extracted 2D slices for training. Combining this architecture with the cascaded U-Net model further improves the localization accuracy for segmentation tasks.

Our study has several limitations. All images were from a single institution retrospective cohort, which may introduce bias to our results. Validation within a multi-center cohort is desirable. Additionally, the manual segmentation was done by a single expert cardiac imager, so a remaining step of this work would be to study the interobserver variability of manual segmentation to provide assurance of this measure as an appropriate gold standard for algorithm training. Although multi-planar slice extraction increases LV scar delineation accuracy, it inherently slows segmentation efficiency.

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**Fig. 6.** Exemplary results of three-dimensional (3D) scar segmentation methods applied for an example of 3D late gadolinium enhancement magnetic resonance image, presented in orthogonal views (Column 1–3) and using a surface rendering. The last column indicates the 3D view of the myocardial scar regions. Results of each method are shown in the corresponding row. [Color figure can be viewed at wileyonlinelibrary.com]
compared to other methods where conventional feature learning approaches are employed. Furthermore, as we used cascaded U-Nets to segment scar within segmented LV myocardium, incorrect segmentation of LV myocardium will adversely influence the segmentation accuracy of scar.

### 5. CONCLUSIONS

In conclusion, we describe a deep learning-based method for fully automated segmentation of LV scar from 3D LGE-MR images without any user interaction. Through
simultaneous delineation of global myocardial architecture and scar, this paradigm is relevant to the clinical translation of image-guided therapeutics that are reliant upon the reproducible representation of scar distribution for their success.

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CONFLICT INTEREST

The authors of this paper have no conflict of interest to disclose.

REFERENCES


SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure S1. Block diagram of the Myo-Net and Scar-Net for left ventricle myocardial and scar segmentation.