Towards ultrasound-based navigation: Deep learning based IVC lumen segmentation from intracardiac echocardiography

Hareem Nisar[a,b], Patrick K. Carnahan[a,b], Djalal Fakim[c], Humayon Akhuanzada[c], David Hocking[c,d], Terry M. Peters[a,b,c], and Elvis C. S. Chen[a,b,c]

[a]Robarts Research Institute, Canada
[b]School of Biomedical Engineering, Western University, Canada
[c]Schulich School of Medicine and Dentistry, Western University, Canada
[d]London Health Sciences Centre, London, ON, Canada

ABSTRACT

Vascular navigation is a prerequisite to transcatheter cardiac interventions. The current standard approach to catheter navigation relies on real-time fluoroscopy, while this technique utilizes ionizing radiation and it places the interventionalist at risk for eye cataracts and cancer. The shielding equipment needed to mitigate these risks is associated with spinal issues and neck and back pain which has led towards the coining of the term "interventionalist's disc disease". A proposed alternative is to have an ultrasound-guided vascular navigation system where a catheter-based ultrasound probe scans the vessel and reconstructs the vascular roadmap, which can then be navigated by tracked guidewire or catheter. One of the major challenges here is the segmentation of the vessel lumen from the ultrasound images. In this study, we address this challenge using a deep learning based approach. We acquired inferior vena cava (IVC) images from an animal study performed using a radial, forward-looking Foresight™intracardiac echocardiography (ICE) ultrasound probe. The ground truth was established using manual segmentations and validated by an expert clinician. We use the MONAI platform to train a U-net architecture on our dataset to perform vessel segmentation. The images are cropped to retain only the central 300 pixels as the traversed vessel will always appear central to the radial ICE image. Data augmentation was performed to enhance the number of images available for training. After post-processing, the segmentation output, a 90 % accuracy was achieved as indicated by the Dice coefficient. We plan on integrating this vessel segmentation pipeline in an image-guided surgical navigation system.

Keywords: vessel segmentation, inferior vena cava, IVC, cardiac interventions, deep learning, intracardiac echocardiography, ICE

1. INTRODUCTION

Recently the focus for intracardiac procedures has shifted away from open-heart and trans-mural approaches to transcatheter interventions, due to the adoption of minimally invasive techniques, which allow for shorter hospital stays and lower procedure-related morbidity. During these percutaneous procedures, the heart may be accessed from a trans-arterial or transvenous approach, depending on the goal of the procedure. Where access to the left side of the heart is necessary, a transarterial approach is generally employed, wherein access is typically obtained via the radial artery, femoral artery, or occasionally the brachial artery. Conversely, where access to the right heart is needed, access is commonly achieved via the femoral vein or internal jugular vein. Access via the femoral vein requires traversal of the IVC in order to reach the heart. Regardless of the path chosen to access the heart, vessel navigation is a necessary component of endovascular cardiac interventions and is currently performed under fluoroscopy guidance. In some cases, pre-operative CT is used for planning and guidance using fusion techniques. An alternative to these radiation-based modalities is to employ ultrasound imaging to generate a vascular roadmap, referred to as vessel reconstruction.

Vessel reconstruction typically has two major components – vessel lumen segmentation from the ultrasound images and stitching the segmentations together to form a vessel skeleton in a 3D coordinate system. The lumen

Send correspondence to H.N.: hnisar3@uwo.ca

segmentations can be combined or stitched using tracking-based techniques and the pullback method. Regardless of the stitching technique used during vessel reconstruction, a common denominator has been the segmentation of the vessel lumen from the ultrasound images. Vessel segmentation has been an ongoing challenge since the early 1990s.[1] Various solutions have been proposed in the literature, both based on conventional image processing techniques[2–4] and using artificial intelligence (AI).[5–7] The segmentation of vessels from ultrasound (US) images remains challenging because of their variable and complex appearance, which largely depends on the type of ultrasound transducer and imaging parameters used during a procedure, as well as the composition of the vessel and the surrounding tissue.

Many different ultrasound transducers can be used for the purpose of vessel reconstruction. Hand-held ultrasound probes such as a trans-thoracic echocardiogram (TTE) display the vessels either as circular, disk-like objects with a continuous vessel boundary or as tubular shapes with well-defined boundaries. Several methods have been described for such vessel segmentation.[5,8] On the other hand, catheter-based ultrasound images are more likely to demonstrate a complex appearance of a vessel, showing calcification and intraluminal buildup. High-frequency intravascular ultrasound (IVUS) images are a vital component of many percutaneous procedures as they display the full vessel boundary and the different layers of the vessel. Vessel segmentation in IVUS images can be performed using conventional image processing techniques and artificial intelligence (AI) as well.[7,9–11] Intracardiac echocardiography (ICE) is another catheter-based ultrasound imaging method with applications in transcatheter cardiac interventions. ICE technology can be either side-firing or radial in nature, with a spinning transducer producing circular images (Fig. 1). Vessel appearance in radial ICE images is much more complicated than the hand-held US or IVUS, since the vessel wall does not always appear as a closed, circular shape, but rather has a c-shaped appearance with a discontinued vessel wall boundary. ICE provides a larger field of view for imaging, can visualize anatomy more clearly, and has Doppler imaging capability. Figure 1 shows a comparison of vessel appearance under different ultrasound probes as well as the variance in the appearance of vena cava (IVC) under ICE. However, segmenting vessel lumina from ICE images remains a challenge, and while deep learning has outperformed many conventional segmentation techniques and continues to improve the domain of medical image segmentations,[12] vessel segmentation from ICE images using machine learning is a road less traveled. We sought to apply deep learning techniques to the unique challenges of ICE as we believe it provides a stepping stone for a novel catheter guidance that may decrease reliance on ionizing radiation.

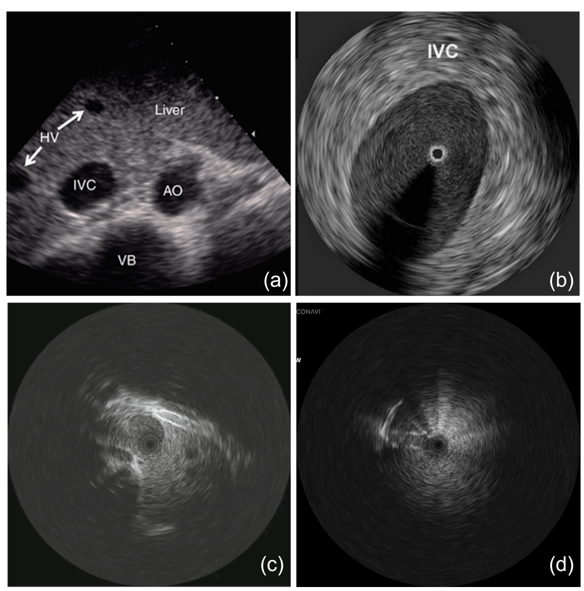

Figure 1. Various forms of ultrasound imaging technology and appearance of the vessel lumen. (a) Transthoracic ultrasound showing multiple small vessels. (b) Intravascular ultrasound (IVUS) depicts the vascular structure of the vena cava in detail. (c,d) Intracardiac ultrasound (ICE) imaging of the vena cava shows complex shapes of the vessel lumen and surrounding structures.

ICE is often used clinically to guide transseptal punctures, atrial septal defect closure, catheter ablation procedures and to guide tool positioning during a number of cardiovascular interventions.[13] During such procedures, it is imperative that the tools are navigated from the groin to the chest via the IVC (i.e. trans-femoral access) or through a trans-jugular or trans-radial access. Apart from vena cava navigation, many endovascular and cardiovascular procedures such as aneurysm repair, stent placement, IVC filter placement, and aortic valve repair involve a more complex vascular path, as well as intricate vessel anatomy. In such cases, navigating the vessels become a challenge. Currently in clinical practice, vessel navigation is performed under fluoroscopic guidance, which exposes the patient and the medical staff to ionizing radiation. This harmful exposure places the interventionalists at risk of developing health complications such as cataracts[14] and cancer.[15] The heavy lead shielding used by the medical staff is reported to have caused spinal issues, disc herniation, and neck and back pain, collectively coined as the "interventionalist's disc disease".[16–18]

A viable alternative for fluoro-guided vascular navigation can be to use a catheter-based ultrasound probe such as ICE to navigate and scan the vessel and reconstruct a road map to be followed by the surgical tools and catheters. An ultrasound-based vascular navigation system eliminates the potential health risks associated with radiation exposure and may improve the safety of the patient and the medical staff. In order to implement this image-guided system vessel segmentation is required but remains a challenge because the vessel appearance varies significantly as it passes through the different regions of the abdomen. To our knowledge, there is no existing AI-based technique for segmenting vessels from complex background anatomy on radial ICE images. There is therefore an unmet need for an accurate real-time vessel segmentation algorithm that works with radial ICE images. Such a technique would pave the way towards the clinical implementation of radiation-free or radiation-reduced, ultrasound-guided vessel navigation during transcatheter interventions.

In this study, we take a deep learning-based approach towards the challenge of vessel segmentation in ICE imaging. A U-net architecture[19] is trained using the IVC images of swine, where data augmentation is used to expand the existing training dataset. IVC was selected for this study since it is larger in size and fairly consistent, and the training data were readily available. We use Dice and other spatial overlap metrics to evaluate the trained U-net model. This segmentation approach, when combined with tracking technology, will facilitate the development of ultrasound-only transfemoral navigation during interventions.

2. METHODS

2.1 Data Acquisition

A single-element, radial, forward-looking Foresight™ICE probe by Conavi Medical Inc. (North York, Canada) was used for ultrasound data acquisition. The ICE images were acquired during experiments performed on Yorkshire swine, approximately 40 kg in weight, under a protocol approved by Sunnybrook Research Institute's Animal Care Committee and provided to our research group by Conavi Medical Inc. The dataset comprised ICE images of the inferior vena cava (IVC) from two different animal subjects. The complete dataset included 88 2D images. Based on the 80:20:20 rule, 70 images were kept for training the network, 9 for validation, and 9 for final testing. Ground truth labels were generated by manually segmenting the IVC from the ICE images. The manual segmentations were corrected and verified by an experienced interventional radiologist at the London Health Sciences Centre (London, Canada).

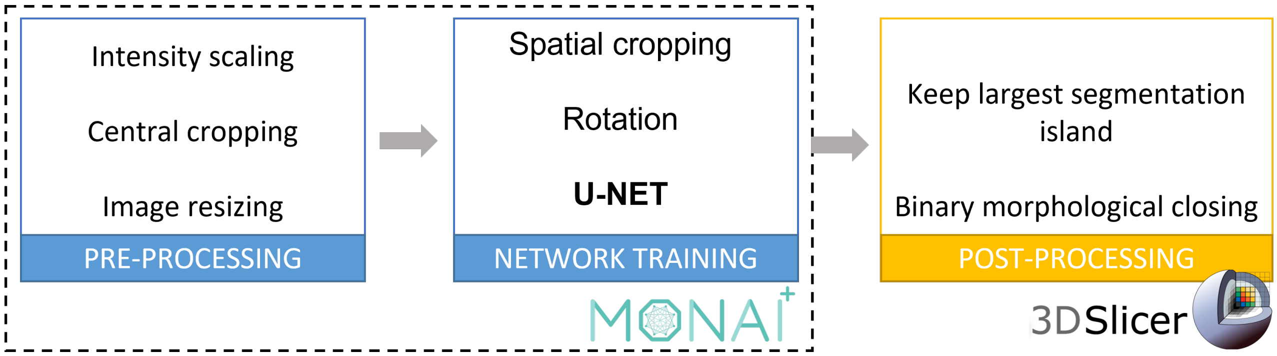

Figure 2. The overall workflow for methods - Intracardiac ultrasound (ICE) imaging dataset is pre-processed and used to train a U-net model via the MONAI framework. Segmentation labels generated by the U-net are processed via 3D Slicer to produce the final segmentation output.

2.2 Pre-processing

We use the MONAI framework to pre-process, train and validate our neural network. MONAI[*] is an open-source platform for implementing deep learning-based solutions in the medical imaging and healthcare domain. The training dataset, present in NIfTI format, was first loaded as two-dimensional images, which were then cropped to the central 300×300 pixels (approximately 6 cm) to acquire the region of interest with vessel lumen. Since the ultrasound probe used in this study was transcatheter and radial in nature, we can safely establish that the probe resides within a vessel and that the vessel lumen will always lie somewhat central to the image. This was followed by normalizing the image intensity to lie within the range of 0 and 1 across all datasets. Finally, the images were resized to 256×256 pixels. The validation and testing datasets also underwent all these pre-processing steps before they were used during the training and final evaluation phase.

2.3 Deep Learning based Segmentation

U-net architecture has been used successfully for medical image segmentation tasks, even when the training dataset is small. In our study, we performed data augmentation during the training phase to increase the robustness of our neural network. Additional training images were generated by randomly cropping to 96×96 pixels based on the label value and applying random rotation by 90° with a 0.5 probability.

A U-net was trained using our dataset to perform the task of 2D lumen segmentation from ICE images. The U-net architecture included 5 layers with 16, 32, 64, 128, and 256 channels respectively, and trained in batches of 2 for 400 epochs using the Adam optimizer. Following training, the output model was evaluated using a spatial overlap metric (i.e. the Dice coefficient).

2.4 Post-processing

Due to the small size of the training data for the U-net, and given the complexity of vessel appearance, we added a post-processing pipeline to enhance the final output. The post-processing and evaluation step was performed using the open-source 3D Slicer[20] platform. Only the cropped region for all the images, labels, and segmentations was imported. The segmentations output by the trained U-net model were refined by applying a binary morphological closing filter (8×8 pixels kernel), followed by only keeping the largest island of segmentation for each image. The resultant segmentations were labeled as the final output of our segmentation algorithm and pipeline.

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[*]MONAI: https://monai.io/

2.5 Evaluation

The final post-processed segmentation outputs were evaluated by comparing them to the manually annotated ground truth segmentations. The output accuracy was measured using the Dice score, volumetric differences, and the false-positive, false-negative, true-positive, and true-negative spatial overlap metrics. Since the images were captured as a screenshot of the console screen, there was no header information provided about the image spacing. As such the distance-based metrics do not convey the true measurements in millimeters. However, we do evaluate our segmentation pipeline in terms of average Hausdorff Distance (HD), measured by the number of pixels.

3. RESULTS

The results from the deep learning based segmentation performed on the test dataset showed that the average Dice coefficient was 0.86. Figure 4 shows representative images of our trained U-net model where the ground truth labels are qualitatively compared to the segmentation output by the U-net model. Figure 4 also compares the ground truth to the final output after the post-processing steps. The qualitative evaluation shows that postprocessing steps greatly reduced the over-segmented regions. The final segmentation output had a 90 % accuracy with only an 8.8 % average volumetric difference with the ground truth. Additional spatial overlap metrics are provided in Table 1, where true-positive represent the regions correctly segmented as the vessel and overlap with the ground truth. Similarly, true-negative is the correctly identified background region, false-positive represents the region incorrectly identified as a vessel lumen, and false-negative represents the region incorrectly identified as the background while the ground truth shows it to be a part of a vessel lumen.

The distance between the contours of the U-net output segmentation and the ground truth was evaluated in terms of HD. The 95 % confidence interval HD was observed to be 26 pixels. This number was reduced to 4 pixels when the post-processed output was compared to the manual segmentations. Overall, the final output had an average HD of 1 pixel and a maximum HD of 17 pixels. The distribution of average HD before and after the post-processing steps can be seen in Figure 3.

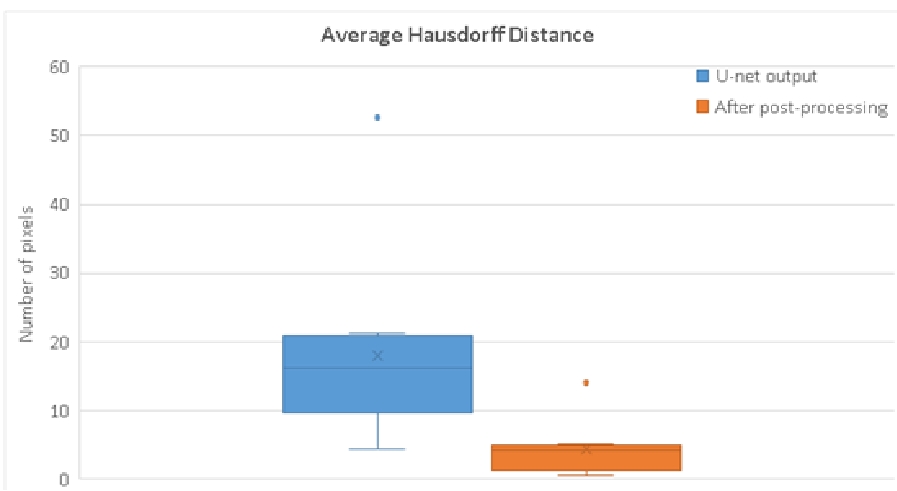

Figure 3. Comparison of average Hausdorff distance calculated for the output of our U-net model (in blue) and the output of the complete segmentation algorithm including post-processing steps (in orange).

Spatial overlap	U-net output comparison	After post-processing
Dice coefficient	0.86	0.90
True positives (%)	16.45	57.80
True negatives (%)	77.54	31.06
False positives (%)	3.66	6.04
False negatives (%)	2.35	5.11
Volumetric difference (%)	13.66	8.8

Table 1. Spatial overlap metrics to evaluate the performance of our trained U-net model and complete segmentation pipeline in comparison to the manually segmented ground truth.

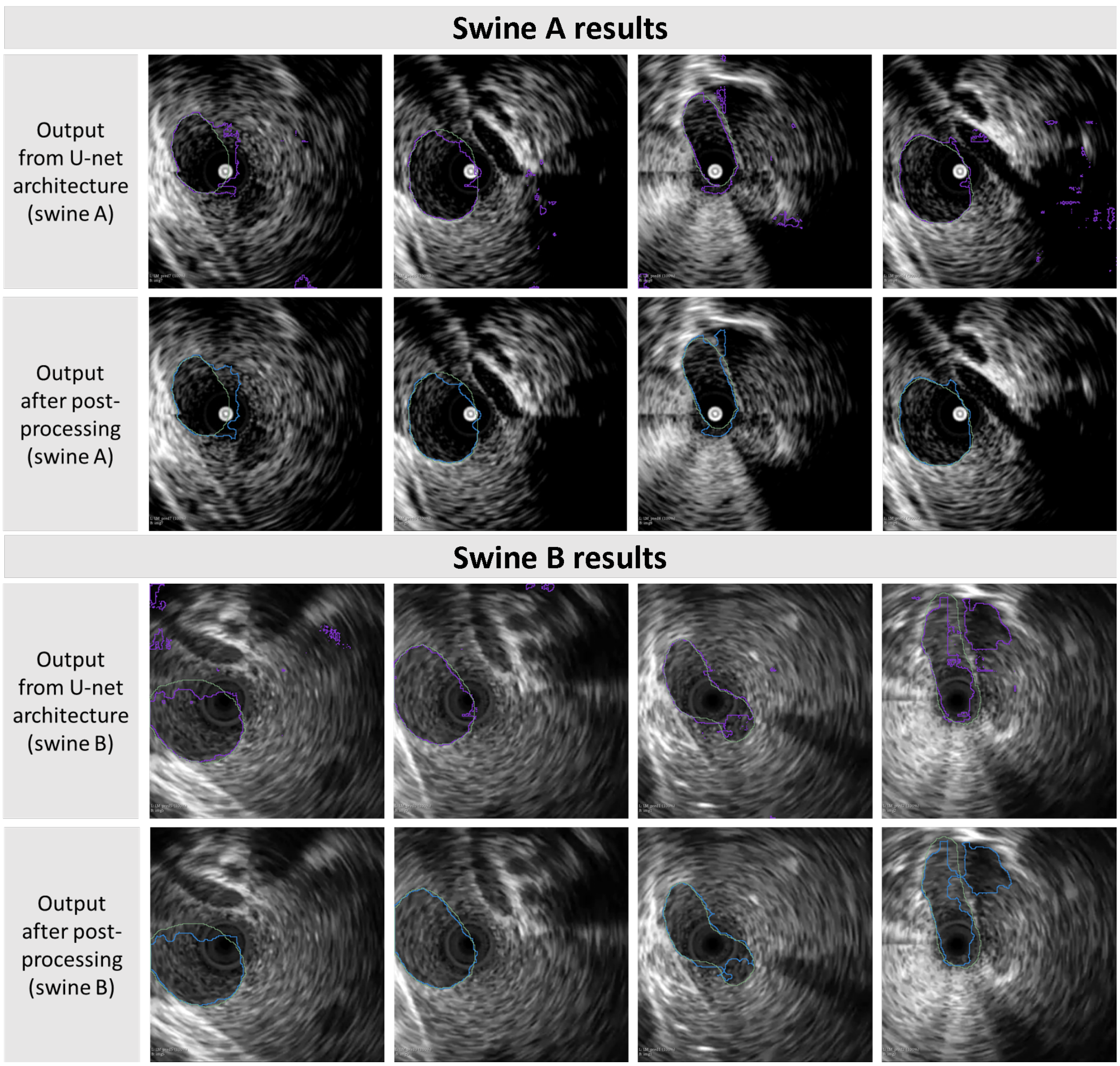

Figure 4. Qualitative assessment of trained U-net model outputs (first/third row) as well as the output after the post-processing steps (second/fourth row) performed on swine A and B test dataset. The green outline in both cases represents the contours of the ground truth labels. The purple and blue lines represent the segmentation output from the U-net model and the complete post-processing pipeline respectively. The bright white circle (swine A) or the completely black circular region (swine B) present in the center of the image represents an artifact inherent to the radial ultrasound probe.

4. DISCUSSION

While vessel segmentation in general may be an imaging problem that has been extensively studied, the identification and segmentation of the vessels from radial ICE imaging remains a challenge. In this work, we present the first deep learning-based method for vessel segmentation compatible with radial ICE imaging. For this study, a novel forward-looking ICE probe was used to acquire images of the IVC, which has been used as a surrogate to develop a real-time vessel segmentation from radial ICE images. We presented a deep learning based algorithm to segment complex vessel lumina from the ICE ultrasound images. Our pipeline utilizes the U-net architecture implemented within the MONAI framework and enhances the output using traditional image processing techniques. On the basis of the Dice coefficient, the result of this segmentation pipeline is 90 % accurate compared to expert manual segmentation.

The overarching goal for developing a vessel segmentation algorithm compatible with ICE imaging is to design a guidance system to assist the transfemoral navigation of tools and catheters during percutaneous endovascular and cardiac interventions. The image-guidance system will utilize a catheter-based ultrasound and electromagnetic tracking technology, and will facilitate the navigation stage of the interventions by first generating a vascular roadmap using a tracked ultrasound probe, which can then be traversed by tracked tools or guidewires. We demonstrate this idea of a vascular roadmap in Figure 5. A vessel phantom was imaged using the Foresight ICE probe. Our deep learning based algorithm (trained on animal images) was used to segment the vessel lumina from the phantom ultrasound images. A vessel skeleton was generated by placing each segmented lumina in its respective position in 3D space using the tracking information. Finally, some image processing techniques were applied to reconstruct the 3D vessel surface.

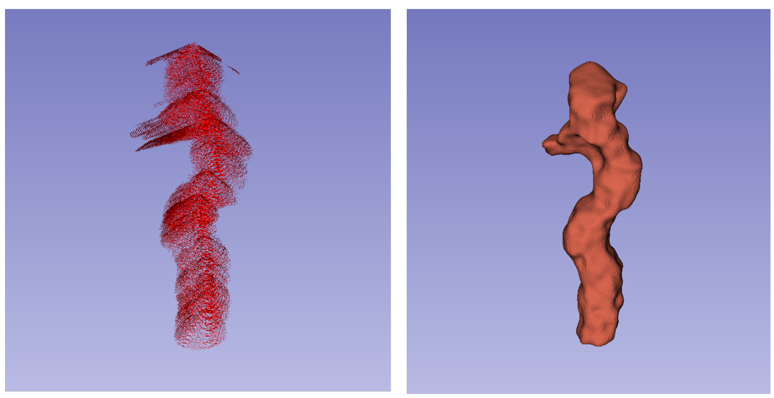

Figure 5. (Left) A vessel skeleton generated by applying tracking information to vessel lumina segmented from ICE imaging of a vascular phantom, using our segmentation pipeline. (Right) A reconstructed vascular roadmap.

During the development of our segmentation pipeline, we observed that the performance of the neural network alone was suboptimal. The initial results showed the over-segmentation of the vessel lumina, where random dark regions in the background were also falsely segmented as part of the vessel. This inaccuracy can be seen in Figure 4 where the U-net output (in purple) includes small noisy segmentation regions. We attribute the inaccuracy of the U-net model to the small size of the available training dataset. The performance of the neural network can potentially be improved by using a larger and versatile imaging dataset, acquired via multiple ICE probes at varying imaging parameters, and more importantly including the ultrasound imaging of multiple vessels of varied anatomy and background structures.

To reduce this noise from the U-net output and improve the accuracy of the segmentation, we introduced conventional imaging processing at the end of our segmentation pipeline. By doing so, the results, in terms of spatial overlap, improved from 86 % to 90 % accuracy. The numerical improvement may appear small; however, the enhanced quality of segmentation and visual appearance of the segmented vessel is appreciable. Not only does post-processing improve the visibility of the vessel, but also allows for a smoother vessel reconstruction. To demonstrate the need for the post-processing steps, another example of vessel reconstruction is shown in

Figure 6. In this example, the vessel lumina from phantom ICE imaging is extracted using only the U-net model, without any post-processing steps. A significant amount of background noise can be seen on either side of the vessel skeleton. In such a case, the task of vessel surface reconstruction becomes a challenge. Visually, at some angles, the noisy segmentations can hinder the understanding of the vessel size and geometry (Figure 6 (right)). The vessel surface reconstruction is not included for this case as the technique failed to produce a meaningful structure through such a noisy input. This highlights the importance of the post-processing steps implemented in our segmentation algorithm.

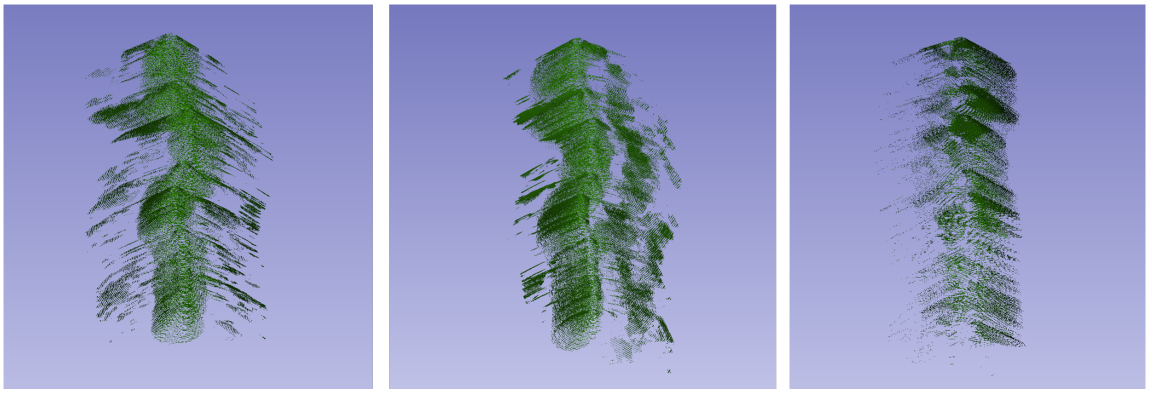

Figure 6. Multiple views of the vessel skeleton generated by applying tracking information to vessel lumina segmented from ICE imaging of a vascular phantom, without using any post-processing step.

Direction for future development of this work involves the implementation of the entire pipeline on a single, open-source platform. Currently, the post-processing steps are implemented in 3D Slicer† but we plan on leveraging the MONAI framework to include them. This integrated Slicer module will be made publicly available on GitHub‡ to be used by the community.

The study presented in this paper is limited in its application, mainly due to the available imaging dataset. Navigation of many vessels, such as the tortuous aorta, is much more complex than the navigation of vena cava. The technique presented in this project is the first of its kind, which unconventionally utilizes an ICE probe for vascular imaging and segments the vessel lumina. This study will pave the way towards the development of segmentation techniques for more complex anatomy. Future work can involve improving the accuracy of the existing segmentation algorithm by including a dataset with more varying vessel imaging. Another aspect will be to evaluate the performance of our segmentation pipeline in other vessels like the iliac and femoral vein, the aortic arch, and the superior vena cava. Given the opportunity and more imaging datasets, we would like to retrain our network with images of other venous structures. We are also interested in looking at the performance of other neural networks known for either medical image segmentation such as V-net or networks designed for high-frequency IVUS imaging.

5. CONCLUSION

In this work, we present a deep learning-based pipeline to segment the complex vessel lumina from ICE ultrasound images. The results show that U-net architecture has sufficient potential to undertake this task, however, the segmentation output can benefit from a larger training dataset. This vessel segmentation, combined with electromagnetic tracking technology, will enable a fluoro-free image-guided system to guide tools and catheters through the vasculature during transcatheter cardiac interventions.

ACKNOWLEDGMENTS

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†3D Slicer: https://www.slicer.org/

‡Code will be made available at https://github.com/hareem-nisar upon submission of the final version of the manuscript

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