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[d], Terry M. Peters[a], and Elvis C. S. Chen[a,b]

[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, especially traversing the inferior vena cava (IVC), is a prerequisite to many transcatheter cardiac interventions. By clinical standards, the vessels are navigated by the catheters under fluoroscopy, which places the interventionalists at the risk of eye cataracts, cancer, and fetal congenital defects. The shielding equipment is also known to cause spinal issues and neck and back pain which has led towards the coining of the term "interventionalist's disc disease". An alternative is to have an ultrasound-guided vascular navigation system where an intracardiac (ICE) probe scans the IVC, reconstructs the vascular roadmap which can then be travelled by tracked guidewire or catheter. One of the biggest challenges here is to segment the IVC lumen from the ICE images. In this study, we address this challenge using a deep learning based approach. We acquired IVC images from an animal study performed using a radial, forward-looking Foresight™ ICE 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. Preliminary results indicate an 85 % accuracy of the spatial overlap as indicated by the Dice coefficient. We plan on improving this accuracy and integrating this vessel segmentation pipeline in a tracked image-guided environment.

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

1. INTRODUCTION

Vessel surface 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 space. The lumen segmentations can be combined using tracking-based techniques or acceleration-based techniques such as the pull-back method. Regardless of the stitching technique used during vessel reconstruction, a common denominator is the segmentation of the vessel lumen from the ultrasound images. Vessel segmentation is an ongoing challenge since the early 1990s [1]. Many solutions have been proposed proposed in the literature, both based on conventional image processing techniques [2] and using artificial intelligence (AI) [3]. The segmentation of vessels from ultrasound (US) remains challenging because of the variable and complex appearance of ultrasound images, which largely depends on the type of ultrasound transducer 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 transthoracic echo (TTE) display the vessels either as circular, disk-like objects with a continuous vessel boundary or as tubular shapes with a well-defined boundary. Several methods exist in the literature for such vessel segmentation [3,4]. On the other hand, catheter-based ultrasounds are more likely to have a complex appearance of a vessel lumen. High-frequency intravascular ultrasound (IVUS) images display

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

the full vessel boundary and even display the different layers of the vessel. IVUS is a vital component of many percutaneous abdominal procedures. As such there are many existing solutions for vessel segmentations in IVUS images using conventional image processing techniques and artificial intelligence (AI) as well 5. Intracardiac echocardiography (ICE) is another catheter-based ultrasound imaging method with applications in transcatheter cardiac interventions. ICE technology can either be side-firing or radial in nature, with a spinning transducer producing circular images. Vessel appearance in radial ICE images is much more complicated than the hand-held US or IVUS. 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. Segmenting vessel lumena from ICE images remains a challenge. Deep learning has outperformed many conventional segmentation techniques and continues to improve the domain of medical image segmentations 6. However, vessel segmentation from ICE images using AI is a road less traveled.

ICE is often used clinically to guide transseptal punctures, atrial septal defect closure, catheter ablation procedures and to guide tool positioning during several cardiovascular interventions 7. During such interventions, it is imperative that the tools are navigated from the groin to the chest via the inferior vena cava (IVC) (i.e. trans-femoral access) or through a trans-jugular or trans-radial access. Currently, in clinical practice, IVC navigation is performed using fluoroscopy, which exposes the patient and the medical staff to X-radiation. This harmful exposure places the interventionalists at risk of developing several issues such as eye cataracts 8 and cancer 9. 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" 10.

A suitable alternative for fluoro-guided vascular navigation is to use a catheter-based ultrasound probe such as ICE to navigate and scan the IVC and reconstruct a vascular road map to be followed by the surgical tools and catheters. An ultrasound-based vascular navigation system eliminates the adversities of the X-rays, and improves the safety of the patient and the medical staff. However, to implement this image-guided system, vessel segmentation remains a challenge, especially because the IVC appearance in ultrasound varies significantly as it passes through the different regions of the abdomen. This varying and complex nature of IVC imaging makes the task of vessel segmentation quite challenging. To our knowledge, there is no existing AI-based literature for segmenting complex IVC vessels from radial ICE images. Currently, there is an unmet need for an accurate real-time vessel segmentation algorithm that works with radial ICE images of IVC.

In this study, we take a deep learning-based approach towards the challenge of vessel segmentation in ICE imaging. A U-net architecture 11 is trained over the IVC images of swine. Data augmentation is used to expand over the existing training dataset. We use DICE and spatial overlap metrics to evaluate the trained U-net model. This segmentation approach, when combined with tracking technology, will lead to the development of ultrasound-only transfemoral navigation during interventions.

2. METHODS

A single-element, radial, and 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 as a courtesy of Conavi Medical Inc. The dataset comprised ICE images of the inferior vena cava (IVC) from two different pigs. 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 University Hospital (London, Canada). U-net architecture has been used in literature for medical image segmentation tasks, especially when the training dataset is small. In such a case, data augmentation can help generate variants of the training image and improve the output model. In our study, we performed data augmentation by randomly cropping to 96x96 spatial size based on the label value and by randomly rotating the image by 90 degrees with a 0.5 probability. We use the MONAI platform to train and evaluate our network. In our deep learning pipeline, we first load the images as two-dimensional, crop the image to the central 300x300 pixels, normalize the image intensity and resize the image to 256 pixels. This is followed by data augmentation as described earlier. The

U-net architecture includes 5 layers with 16, 32, 64, 128, and 256 channels respectively. It was trained in batches of 2 for 400 epochs using the Adam optimizer. After training the output model was evaluated using spatial overlap metrics including the Dice coefficient.

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 output. The segmentations acquired as a result of testing are imported into 3D Slicer. Only the cropped, region of interest for all the images, labels, and segmentations are imported. The segmentations are refined by applying a binary morphological closing filter (8x8 pixels kernel), followed by only keeping the largest island of segmentation. The pre-processed segmentation outputs were re-evaluated. We are still in the process of refining the deep learning method pipeline. For the complete paper, we aim to produce a more accurate model and a more comprehensive evaluation using Hausdorff distance (HD). We will potentially eliminate the post-processing step if the network model can deliver highly accurate results.

3. RESULTS

The preliminary results show that the Dice coefficient was 0.86 for the output of the U-net model on test data. Figure 1(a) shows the performance of the DL-based pipeline. The green outline represents the contours of the ground truth labels, whereas the purple outline represents the segmentation output by the U-net model. More spatial overlap metrics are provided in Table 1. Figure 1(b) compares the ground truth to the algorithm output after the post-processing steps.

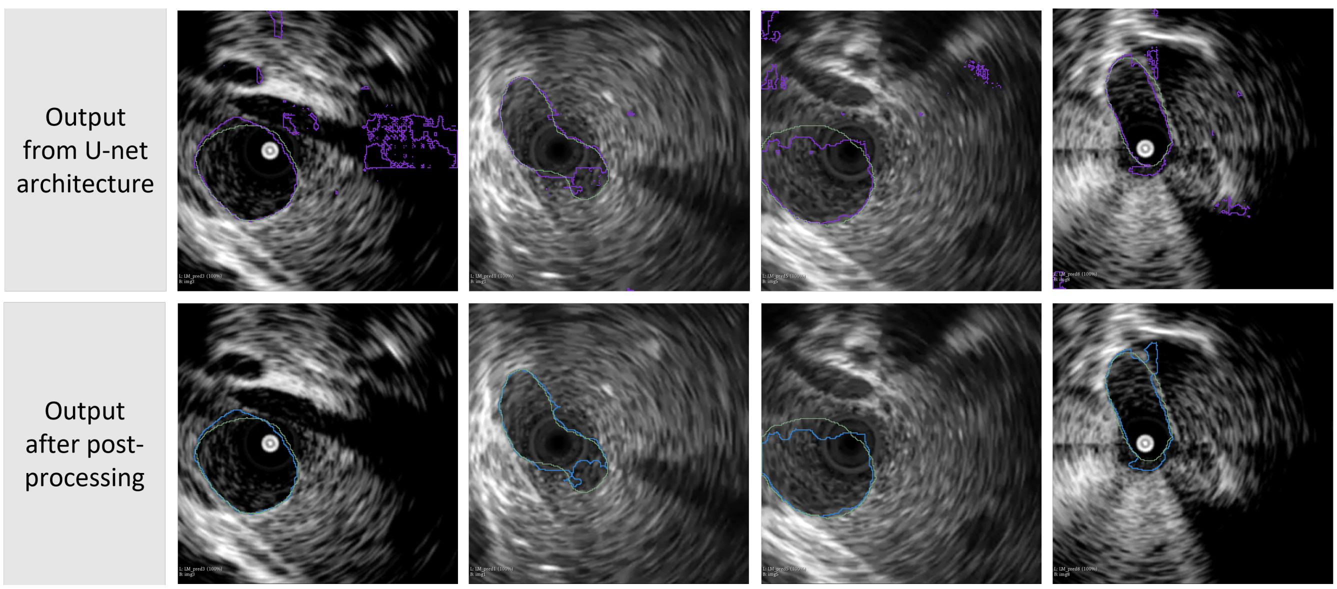

Figure 1. Qualitative assessment of trained U-net model outputs (first row) as well as the output after the post-processing steps (second row). The green outline in both cases represent the contours of the ground truth labels. The purple and blue lines represent the segmentation output from the U-net model and from the complete post-processing pipeline respectively.

	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 the post-processing steps as well.

4. NEW AND BREAKTHROUGH WORK TO BE PRESENTED

While vessel segmentation in general may be an imaging problem that has been extensively studied, the identification and segmentation of the IVC from radial ICE imaging remain a challenge. In this work, we present the first deep learning based method for vessel segmentation compatible with radial ICE imaging of vena-cava. A novel forward-looking ICE probe was used to acquire the imaging of IVC which is characteristic of complex shape and appearances under ultrasound. A planned work to be completed by end of September is expected to be listed here.

5. CONCLUSION

In this work, we present a deep learning based pipeline to segment complex vena cava vessels from the intracardiac ultrasound (ICE) 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 IVC during transcatheter cardiac interventions.

REFERENCES

[1] Sonka, M., Zhang, X., Siebes, M., Bissing, M. S., DeJong, S. C., Collins, S. M., and McKay, C. R., "Segmentation of Intravascular Ultrasound Images: A Knowledge-Based Approach," *IEEE Transactions on Medical Imaging* **14**(4), 719–732 (1995).

[2] Noble, J. A. and Boukerroui, D., "Ultrasound image segmentation: A survey," *IEEE Transactions on Medical Imaging* **25**, 987–1010 (aug 2006).

[3] Mishra, D., Chaudhury, S., Sarkar, M., and Soin, A. S., "Ultrasound Image Segmentation: A Deeply Supervised Network With Attention to Boundaries," *IEEE Transactions on Biomedical Engineering* **66**, 1637–1648 (jun 2019).

[4] Groves, L. A., VanBerlo, B., Veinberg, N., Alboog, A., Peters, T. M., and Chen, E. C. S., "Automatic segmentation of the carotid artery and internal jugular vein from 2D ultrasound images for 3D vascular reconstruction," *International Journal of Computer Assisted Radiology and Surgery 2020 15:11* **15**, 1835–1846 (aug 2020).

[5] Yang, J., Tong, L., Faraji, M., and Basu, A., "IVUS-Net: An Intravascular Ultrasound Segmentation Network," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* **11010 LNCS**, 367–377 (jun 2018).

[6] Hesamian, M. H., Jia, W., He, X., and Kennedy, P., "Deep Learning Techniques for Medical Image Segmentation: Achievements and Challenges," *Journal of Digital Imaging* **32**, 582–596 (aug 2019).

[7] Ali, S., George, L. K., Das, P., and Koshy, S. K., "Intracardiac echocardiography: Clinical utility and application," (may 2011).

[8] Jacob, S., Boveda, S., Bar, O., Brézin, A., Maccia, C., Laurier, D., and Bernier, M.-O., "Interventional cardiologists and risk of radiation-induced cataract: Results of a French multicenter observational study," *International Journal of Cardiology* **167**, 1843–1847 (sep 2013).

[9] Roguin, A., Goldstein, J., Bar, O., and Goldstein, J. A., "Brain and neck tumors among physicians performing interventional procedures.," *The American journal of cardiology* **111**, 1368–72 (may 2013).

[10] Ross, A. M., Segal, J., Borenstein, D., Jenkins, E., and Cho, S., "Prevalence of Spinal Disc Disease Among Interventional Cardiologists," *The American Journal of Cardiology* **79**, 68–70 (jan 1997).

[11] Ronneberger, O., Fischer, P., and Brox, T., "U-Net: Convolutional Networks for Biomedical Image Segmentation," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* **9351**, 234–241 (2015).