U-Net Neural Network for Locating Midpoint of Insertion Zone of Transcatheter Aortic Valves in CTA Images

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Abstract

Identifying the insertion zone of transcatheter heart valves can be time-consuming and suffers from variability and reproducibility problems. We present a deep leaning approach in CTA images to locate the midpoint of the insertion zone. A U-Net neural network is implemented to automatically segment the aortic valve on axial projection. The insertion zone midpoint is calculated based on the range of slices with the more concentrated area of activated pixels. We found a very low systematic error with a median computed error of 0.38mm and interquartile range of 0.15 – 0.75mm. The proposed model was shown to be a robust and powerful tool to automatically locate the insertion zone midpoint and we believe it will play a critical role on automated assessment of aortic stenosis.

1. Introduction

Aortic stenosis (AS) is a disease characterized by progressive calcification, a highly complex, regulated pathological process that leads to valve obstruction, left ventricular hypertrophy, symptom development, heart failure and death. The only available treatment is valve replacement, otherwise more than half of patients succumb 2 to 3 years after symptom onset. In many countries, there has been an increase of number of cases of AS, which is partly related to the aging of the population. In 2017, the incidence of AS reached 64 cases/100,000 individuals (20% increase in 10 years), with an estimated mortality of 102,700 patients [1].

In the past decade, minimally invasive transcatheter aortic valve replacement (TAVR) has been established as an option regarding valve intervention for patients with symptomatic severe aortic stenosis. The precise anatomic assessment of the aortic valvular complex using computed tomography angiography (CTA) is crucial for optimal sizing of transcatheter heart valves (THV) and identification of patients with increased anatomical risk for post-procedure adverse events, such as paravalvular leakage and conduction abnormalities [2]. However, the identification of the THV insertion zone (IZ) from 3D images can be time-consuming in clinical routines and suffers from considerable variability and problems of reproducibility.

Deep learning-based algorithms have shown high accuracy in several medical domains. In this paper, we present a deep leaning approach in 3D images to locate the midpoint of the IZ as a first step towards a completely automated assessment.

2. Methodology

Retrospectively, we included 164 patients (132+32 training and test set) with severe AS who underwent CTA before TAVR, from 2011 to 2020, in three centers. CTA was routinely performed in multidetector CTs (Canon, Siemens and Phillips), using a retrospective ECG-gated acquisition to assess the aortic root and the ascending aorta. Abdominal aorta and ilio–femoral arteries to the proximal part of the femoral common arteries were assessed either in the same ECG-gated acquisition or in a non-ECG-gated CTA.

An experienced radiologist manually segmented the IZ using 3D Slicer 4.1, and the resulting segmentations were considered gold standard. Figure 1 shows a manually segmented aortic valve on axial plane. 190,655 2D axial images were extracted from 132 3D images for training, where 15,138 contained the aortic valve and 175,517 did not.

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Figure 1: Thoracic axial slice showing a manual segmentation of the aortic valve by a radiologist.

3D images were resampled to 0.8 x 0.8 x 0.3 mm and 2D axial projections were extracted and resized to 256 x 256 pixels. A U-Net neural network model [1] was implemented adding batch normalization after each convolutional layer to increase numerical stability [4]. During the training, shuffled batches of 16 images (8 showing the valve and 8 not showing) fed the model to decrease the occurrence of false positives. Data augmentation was applied with random rotations and Gaussian noise to both input and output images. Hounsfield units were adjusted to a window width and center of 1000 and 400 respectively and then normalized to a range of [0, 1]. Dice similarity coefficient was used as loss function and stochastic gradient descent was used as optimizer with learning rate of 0.01. Initial number of epochs was set to 100, but training was automatically stopped after 3 consecutive epochs without improvement.

Figure 2 shows an example of the radiologist's manually segmented aortic valve from a 2D axial image (gray contour) and the U-Net contour (white contour).

After prediction, a histogram vector was created with length equal to the number of axial slices, each element representing the count of activated pixels per slice. The vector was then split into unbroken stretches of non-zero values and the densest one was used to define the start and end slices of the IZ. This procedure was needed to suppress any noise arising from false positives, even though there was no sparse activation outside the IZ range on the test set. Figure 3 shows the histogram of a predicted segmentation.

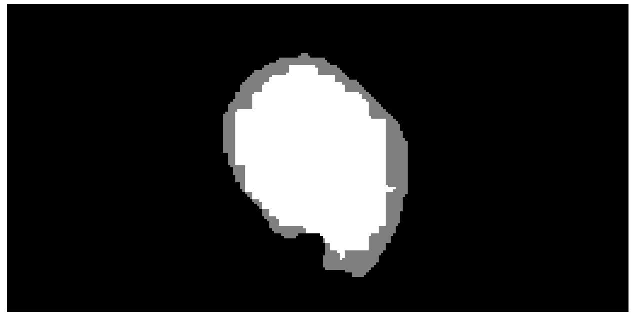

Figure 2: Aortic valve mask manually segmented by a radiologist (in gray) and the predicted aortic mask by U-Net model (in white).

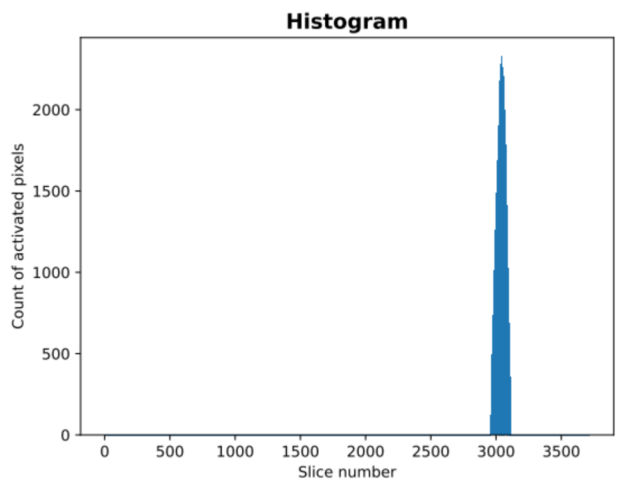

Figure 3: Histogram of predicted aortic valve masks by U-Net model. Predicted slices of IZ=[2936,3119], with midpoint=3027.

The midpoint of IZ was computed as the average of start and end slices; the IZ length was computed as the difference between end and start slices. Finally, the original 3D input image was cropped ±10cm around the midpoint on the axial projection. Figure 4 shows a coronal projection of the resulting cropped image and Figure 5 shows the complete workflow.

The model described in this paper was written for Python 3.8.10 with SimpleITK 2.0.2, Keras 2.4.3, Tensorflow 2.3.0 and executed with a Nvidia Tesla K80 graphic card on a Linux desktop with an i3 processor. Training took an average of 6 hours for up to 50 epochs and prediction took an average of 0.05 seconds per slice.

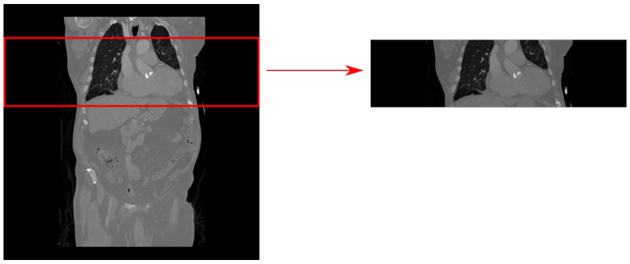

Figure 4: Thorax-Pelvis coronal projection of an image cropped ±10 cm around predicted midpoint of aortic valve.

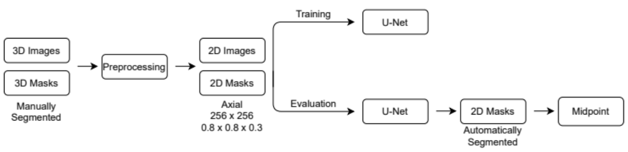

Figure 5: The complete workflow to automatically identify the insertion zone midpoint.

3. Results

We found a very low systematic error for the recognition of the midpoint with a median computed error of 0.38mm (interquartile range 0.15 – 0.75mm). All percentage errors (error divided by insertion size) were 5% or less (Figure 6), with the vast majority below 2%. There was no evidence of a significant proportional error across different IZ lengths. Table 1 summarizes the statistics of midpoint errors.

Table 1: Axial distance between gold standard and predicted IZ midpoints in mm.

Average	Std.Dev.	Median	Interquartile range
0.57	0.73	0.38	0.15 – 0.75

4. Discussion

U-Net is a well-established model for automatic medical image segmentation and, in this study with 3D CTA images, it showed excellent performance for segmenting the aortic valve in axial projections. Even though 3D segmentation models would take advantage of contextual information from the volume, yielding arguably better accuracy, to avoid sampling distortion a cropping stage would be required to provide a similar number of axial slices in each 3D volume. This study, which shows the feasibility of locating the axial midpoint of IZ, can be seen as an initial step towards complete automated assessment of aortic stenosis.

Immediate consequences of this work are:

(i) 3D segmentation of aortic valve calcification and automated calculation of valvular volume;

(ii) Identification of aortic valve inclination and extraction of images from the rotated plane;

(iii) Automated assessment of aortic stenosis severity based on calcification volume and location.

5. Conclusion

The proposed model has shown to be a consistent and powerful tool for automated determination of the IZ midpoint and could play a critical role in automated assessment of aortic stenosis.

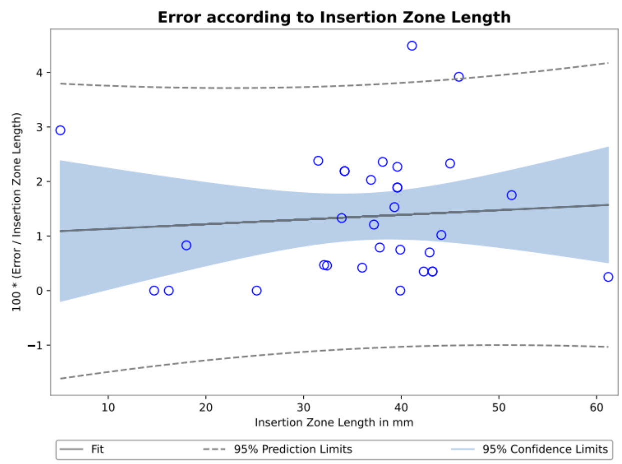

Figure 6: Model error according to patients' insertion zone length.

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