A Machine Learning-Based Approach for Automatic Coronary Sinus Vein Segmentation and Anatomy Reconstruction

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Abstract

The purpose of this study was to develop an approach for reconstructing the anatomy of coronary sinus veins using the proprietary cardiac computer tomography (CT) protocol. The method used in this study is based on a state-of-the-art neural network (NN) for medical image segmentation called Swin-Unet and the 5-fold cross-validation ensemble. The trained NNs were fuzzed using the mean ensemble and the final quality was estimated. The results of the study indicate that the neural network ensemble achieved a quality of 0.76 *in terms of the dice score. Furthermore, the study confirmed the efficiency of the proposed cardiac CT protocol for the reconstruction of CS veins in patients with chronic HF and a reduced LV ejection fraction (LV EF 50%).*

1. Introduction

One of the types of heart dyssynchrony is the left bundle branch block (LBBB), the occurrence is estimated to be about 0.1% of the population [1], for example, in a large French population of 69,186 aircrew members examined for fitness assessment in an aeromedical center was 0.08% [2], but if consider patients with acute myocardial infarction (AMI), the left bundle branch block can be found in 2.7% of AMI < 65 years of age and in 10.5% in those > 75 years old [3].

The leading approach to correcting heart dyssynchrony is an implantation device for cardiac resynchronization therapy (CRT)[4]. Regarding CRT, the critical point is to know the anatomy of the left ventricle (LV) venous tree, represented by a coronary sinus (CS) and its tributaries. In routine clinical practice, the structure of veins is evaluated in the operating room with direct invasive contrast. Frankly, getting information on the venous structure would have been helpful already at the outpatient stage of preoperative planning. Hence, it would allow determining in advance the choice of surgical approaches, the set of tools to avoid fruitless implantation of LV lead and unnecessary costs of the health insurance system afterward. Currently, preoperative visualization of LV venous anatomy is performed using computer tomography (CT)[5–7]. The optimal phase to contrast a cardiac vein should be performed in diastole at 30-50% intervals between the R-R waves of the synchronized electrocardiography recording. The best image quality is obtained at 40% of the R-R interval[5]. The easiest way to achieve this is to use CT scanners with at least 64 slices. After recording the raw tomography data, the question arises about extraction, i.e., segmentation of the CS and its tributaries from the whole heart image. Without extraction of these data, it is unrealistic to demonstrate to the surgeon the anatomy of the CS branches in the required radiological projections (LAO, RAO) because the other heart structures interfere with visualization. We analyzed all well-known manufacturer cardiac imaging post-processing packages in a routine clinic. In general, there is no special software that allows automatic segmentation of the heart veins. Therefore, the focus of our work is to develop a technique that would allow automatic segmentation of CS and its branches for clinical practice.

The current study is an extension of the previously reported investigation [8].

2. Related work

Recently, deep learning-based approaches have replaced conventional methods in the fields of cardiac image segmentation. To address such problems, there are many ML-based solutions. Most CNN-based works for vessel segmentation are based on U-Net, as mentioned by Ronneberger et al. [9]. Other studies provided by Peng et al.

[10] introduced a new CDNet neural network formed on U-Net. In addition, Al-Diri et al. [11] suggested a hierarchical Deep Network for Vessel Segmentation. Furthermore, in the work [12] by Zhao et al. authors proposed a method based on hybrid region information. Additionally, several solutions for whole heart CT-based segmentation have been reported [13, 14].

In addition, In recent years, several solutions for vessel segmentation have been reported, for example, Dang et al. [15] described a patch-based segmentation model for brain vessels; He et al. [16] and [17] tried to improve the results of large cardiac vessel segmentation by centerline extraction.

The most close task and solution related to CS segmentation were presented by Lohendran Baskaran et al. in [18] and Shiyang Lu et al. [19], but the definition of CS does not include the medium and small veins of CS, which are critically important for the main purpose of developing technology, as a potential target position for the implantation of CRT lead.

3. Materials and Methods

3.1. Dataset

To provide a proof-of-concept for the developed workflow, we studied 100 consecutive patients scheduled before the implantation of the CRT device. Age at enrollment was 65 (37; 81) – median (min; max) years. Eighty subjects examined had sinus rhythm, 16 subjects atrial fibrillation without high frequency during the study, and 4 subjects with a pacing via the right ventricle lead. Written informed consent was obtained from each patient before the procedure. The local Ethics Committee of the Almazov National Medical Research Centre approved the study (reference ID 203 from 19th of November 2018).

The CT acquisition method used in this study is based on the CT scan protocol of the CRT-DRIVE clinical study, which is specifically designed to examine the anatomy of the heart and the cardiac venous system in patients with heart failure (HF) and a reduced LV ejection fraction (LV EF $< 50\%$). (ClinicalTrials.gov ID: NCT05327062)

In the current study, cardiac CT (Somatom Definition 64, Siemens AG, Germany) was utilized. Next, each image was labeled by a radiologist and independently validated by two cardiologists. The acquired data set was divided into 70/30 rate (70 and 30 cases) for training and test purposes. Furthermore, the training subset was utilized for validation purposes within the 5-fold validation procedure.

3.2. Segmentation model

The proposed reconstruction method is based on a combination of a state-of-the-art neural network (NN) for medical image segmentation called Swin-Unet [20] and the 5-fold cross-validation ensemble. The model was built with the following configuration:

- Input and output image shape: $96 \times 96 \times 96$.
- Number of input channels: 1.
- Number of output channels: 2 (background, coronal sinus).
- Size of the feature space: 48.
- Gradient checkpoint was used to reduce memory usage.

Due to the heterogeneous spatial resolution of the data set, and necessity to normalize pixels' intencity we used we following preprocessing pipeline:

1. Cast image orientation to the next 3D orientation: (Left, Right), (Posterior, Anterior), (Inferior, Superior)
2. Resample 3D image to resolution $0.5 \times 0.5 \times 1.0$. Resolution was chosen on the basis of target sizes of anatomical structure and original dataset parameters.
3. The scale intensity ranges from $[0, 800]$ Hounsfield to $[0, 1]$ with values clipping.

Additionally, because of the comparably small possible resolution of the neural network, a sliding-window approach was used. For quality estimation we used an overlap 0.5 and two types of window: constant, which gives equal weight to all predictions, and Gaussian, which gives less weight to predictions on the edges of windows with $\sigma = 0.125$. During the training procedure, we used a random cropping approach with balancing based on central pixel class.

For better generalization, we used a well-known training-time data augmentation approach. Namely, we used the random shift of intensity with a 0.10 offset.

For neural network training, AdamW optimizer [21] with initial learning rate $1.5e-4$ and weight decay $1e-5$ was used. For better parameter tuning, multistep learning rate reduction was used. The learning rate was scheduled to be reduced in the 60, 120, 300, and 600 epochs with multiplier 0.1. As a loss function, we used a TverskyLoss [22], as shown in equation 1 with the following parameters: $alpha = 0.3$ and $beta = 0.7$ to balance an extremely unbalanced dataset. The parameters were chosen on the basis of recommendations from the original paper.

$$S(X, Y, \alpha, \beta) = \frac{|X \cap Y|}{|X \cap Y| + \alpha|X \setminus Y| + \beta|Y \setminus X|} \quad (1)$$

where X is the predicted mask and Y the ground truth mask, respectively, and $X \cap Y$ denotes the relative complement of Y in X,

For quality evaluation, we used the Dice score:

$$Dice = \frac{2|X \cap Y|}{|X| + |Y|} \quad (2)$$

where X is the predicted mask and Y the ground truth mask, respectively.

The training procedure was performed sequentially 5 times accordingly to 5-fold cross-validation procedure. Finally, the trained NNs were fuzed using the mean ensemle, and the final quality was estimated.

4. Results

As shown in the Table 1, the results of the study indicate that the basic NN achieved a quality of 0.744 ± 0.02 ($mean \pm std$) in terms of the dice score during the 5-fold cross-validation procedure. The final quality of the ensemble estimated using the test subset was 0.76 in terms of the dice score using the mean ensemble with Gaussian window.

The findings are exceptionally promising, highlighting that in clinical practice, physicians place considerable emphasis on identifying the optimal vein for LV lead implantation prior to the CRT procedure. Within this context, large or middle-sized CS veins emerge as the predominant focus of clinical interest before the operation. These outstanding results underscore the significant potential and applicability of our approach in enhancing preoperative planning. However, we anticipate improvements in the visualization quality for smaller veins with the augmentation of the training dataset. In figure 1 is possible to compare the automatic segmentation to the ground truth complex, previously segmented by expert cardiologists. It is clearly observable that there are some gaps and interruptions according to the recognition of CS system. These imperfections will be addressed through a coherent post-processing step, aiming to enhance the quality of the segmentations. To evaluate the NN results applied to the validation subset, Dice score has been calculated and shown in figure 2.

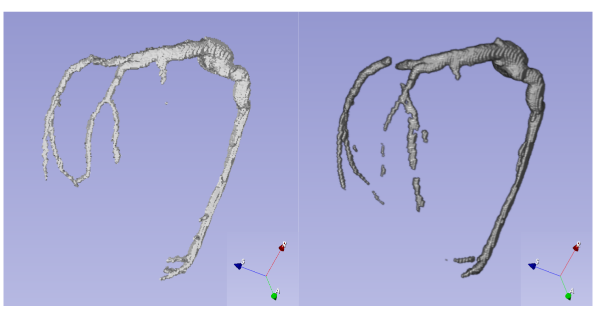

Figure 1. Expert manual segmentation (left side), NN automatic segmentation (right side) of CS veins belonging to a test set patient.

5. Conclusion

The study accomplished a high quality of CS anatomy reconstruction, and a high-quality dataset was amassed. Significantly, this represents one of the world's first results

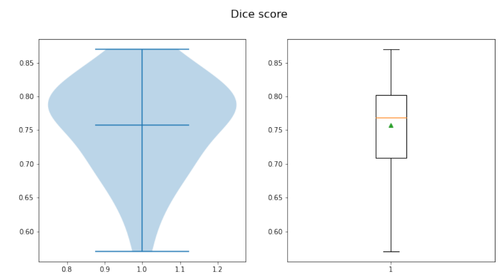

Figure 2. Boxplot and ditribution of Dice score across validation dataset.

Table 1. Validation scores of CS segmentation.

Model	Mean Dice
Base model. Fold 1	0.74
Base model. Fold 2	0.77
Base model. Fold 3	0.72
Base model. Fold 4	0.76
Base model. Fold 5	0.73
Mean Ensemble Const Win	0.757
Mean Ensemble Gauss Win	0.764

with complete automatic segmentation of CS veins, marking an outstanding and excellent breakthrough for routine clinical practice and the implementation of traditional CRT. The efficiency of the proposed cardiac CT protocol for reconstructing CS veins in patients with chronic HF and reduced LV EF was further confirmed by the study. The promising nature of these findings is underscored by the outstanding possibilities they present. Moreover, the results showcased can be further enhanced through the introduction of a larger dataset and an additional step in the pretraining used, leveraging a neural network based on an extensive CT data corpus.

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