Automated heart segmentation using a convolutional neural network accelerates 3D model creation for cardiac surgery

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Introduction: Improvements in cardiovascular imaging have contributed to the accurate diagnosis and treatment of cardiovascular diseases. In recent years, we can find a new demand from surgical departments, i.e., 3D heart models of patients for preoperative simulations. However, a 3D surgical model needs a detailed segmentation of heart structures from clinical images because these details are essential for achieving accurate polygon data of an exact 3D model. Thus, in most cases, manual segmentation is required for complicated heart shapes such as the chamber wall, valves, and papillary muscles, which causes a prolonged duration time.

Purpose: We aim to achieve an automated heart segmentation using a convolutional neural network (CNN) trained using deep learning techniques for the rapid creation of 3D surgical heart models of individual patients.

Methods: We constructed our original CNN program based on the latest artificial intelligence techniques and trained it to extract shapes of the heart from cardiac computed tomography (CT) images. The training data was 361 slices selected from CT scans of 10 patients. We used data augmentation to increase the amount and diversity of the data into 24,052 slices. The training result with the best Intersection over Union (IoU), one of the evaluation metrics used in deep learning, was saved. Finally, we used the best-trained CNN to construct 3D polygon data of two surgical cases of hypertrophic obstructive cardiomyopathy (HOCM) for preoperative assessments.

Results: The IoU attained 0.85 after deep learning. The time required to complete the 3D polygon data for the first HOCM case was 5 minutes for segmentation by the trained CNN and 3 hours for data correction by a human operator. Similarly, the time required for the second case was 5 minutes for segmentation without manual correction. We had to correct the segmentation for the first case because we needed an exact 3D model for the preoperative assessment (Fig. 1). According to our records of the other eight 3D heart models in the lab, the work for a 3D polygon shape from CT images needs a median 30 hours (quartiles 23-50 hours) when the procedure is fully manual and non-continuous with breaks in between.

Conclusion: The CNN-based segmentation aided the constructing heart shapes from cardiac CT images of preoperative patients. Although the performance, reaching IoU of 0.85, was insufficient for fully automatic segmentation, the methodology can shorten the process duration from several hours to several minutes for detailed segmentation of heart structures.

We previously applied the CNN-based segmentation to the aorta, aortic stenosis valves, and atheromatous plaque in clinical images, demonstrating adequate segmentation performance. The proposed methodology can be applied as a fundamental technology of cardiovascular imaging for obtaining the actual structures of a target object as 3D coordinate values or a 3D model within a reasonable duration time.

Abstract Figure 1