IMPROVED THREE-DIMENSIONAL RECONSTRUCTION OF PATIENT-SPECIFIC CAROTID BIFURCATION USING DEEP LEARNING BASED SEGMENTATION OF ULTRASOUND IMAGES

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Abstract:

Clinical examination is crucial during diagnostics of many diseases, including carotid artery disease. One of the most commonly used imaging techniques is the ultrasound (US) examination. However, the main drawback of US examination is that only two-dimensional (2D) cross-sectional images are obtained. For a more detailed analysis of the state of the patient's carotid bifurcation it would be very useful to analyze a three-dimensional (3D) model. Within this study, an improved methodology for the 3D reconstruction is proposed. US images were segmented by using deep convolutional neural networks and lumen and arterial wall regions are extracted. Instead of using a generic model of the carotid artery as the basis that is further adapted to the particular patient with individual US cross-sectional images, in the presented approach the longitudinal cross-sectional US image of the whole carotid bifurcation is used to extract the shape of the whole geometry, which ensures more realistic 3D model. Computer AI-based 3D reconstruction of patient-specific geometry could ensure more complete view of the carotid bifurcation, but also this geometry could be further used within numerical simulations such as blood flow simulation or simulation of plaque progression, that could provide additional quantitative information useful for clinical diagnostics and treatment planning.

Keywords: deep learning, image segmentation, 3D reconstruction, finite element mesh

1. Introduction

Computer-aided systems for automated detection and classification based on artificial intelligence have been presented in literature [1,2]. Machine learning and deep learning techniques have been applied for segmentation of medical images [3,4]. Clinical examination may have a crucial role in diagnosis of many diseases, including carotid artery disease. Within this particular examination, several imaging techniques are applied in order to analyse the state of patient's arteries and to detect possible atherosclerotic lesions. Imaging techniques include computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound (US) examination. US imaging is fast, noninvasive and inexpensive and is, therefore, in most cases the first method applied in diagnostics. However, the main drawback of US examinations is that only two-dimensional (2D) cross-sectional images are obtained. In order to perform a more detailed analysis of the state of the patient's carotid bifurcation, it would be very useful if a three-dimensional (3D) model were available. For this purpose, the 3D reconstruction was performed in literature by using the available 2D cross-sections [5]. Within this approach, the US images were segmented by using U-Net [6] based deep convolutional neural networks (CNN). The accuracy of this approach was validated against clinically measured parameters [7]. However, the main drawback of the presented method is that it uses a generic carotid bifurcation model as the basis and then the available segmented data is attached onto this model to adapt it to the specific patient. This method is further expanded within this study by segmenting US images that contain whole carotid bifurcation and also by including more US transversal cross-sections. In this way, a more detailed 3D geometry of the patient-specific carotid bifurcation is obtained and this geometry can be further used for both simple visual analysis and quantitative analysis of blood flow parameters obtained in numerical simulations. The paper is organised as follows. Details of the applied improvements of the reconstruction methodology are discussed in Section 2. Results for the 3D reconstruction of a particular patient are presented in Section 3, together with an illustration of the benefits of the presented improvements. Section 4 concludes the paper.

2. Materials and Methods

The methodology for 3D reconstruction using US images segmented with deep learning techniques is described extensively in literature [5,7]. In this paper, only the basic idea will be described. Deep learning techniques are used to segment US images and extract the lumen and wall of the carotid bifurcation. The data from transversal US images are used to define the cross-sections of the appropriate branches of the carotid artery (internal carotid artery (ICA), external carotid artery (ECA) and common carotid artery (CCA)). The data from longitudinal US images are used to define the shape of the arterial branches. Segmented data are preprocessed to create B-spline curves that are then projected onto the trihedron normal-binormal plane [8] along the centerline of each branch. In this way, the NURBS surface [8] is generated and further used to generate the 3D finite element mesh of the reconstructed geometry.

2.1 Deep learning segmentation

Similarly to the previous studies [5,7], a clinical data set is used to train the CNNs. The clinical data set consisted of both longitudinal and transversal US images. The difference from previous studies is that in this case, the dataset contained longitudinal images where the whole carotid bifurcation was visible. Also, the dataset included a larger number of transversal images, instead of only 3 that were available in the previous studies. The CNNs were trained and later used to segment both lumen and arterial wall from both types of images. The clinical dataset for one particular patient is shown in Figure 1A. The segmented data obtained from the deep learning module is shown in Figure 1B.

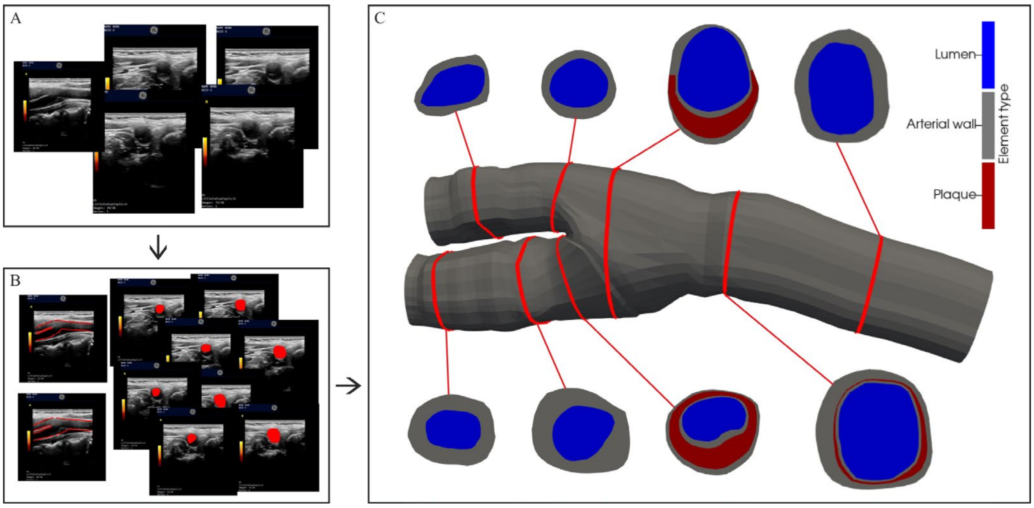

Fig. 1. Proposed methodology for 3D reconstruction; A - Original US images; B - Segmented data using deep learning module; C - Reconstructed model.

2.2 Improved three-dimensional reconstruction

Within cited literature [5,7], the generalised model of the carotid artery is adapted to the particular patient, by using the longitudinal US image only for the ICA branch. As already mentioned in Section 2.1, within this study the longitudinal US images contained the whole carotid bifurcation. Hence the segmented data included lines of the lumen and wall for all three branches, as illustrated in Figure 1B. These lines are then used to define the shapes of all three branches. Instead of using a single transversal US image for the definition of cross-sections for the whole branch, which was the case in the previous model, now the transversal cross-sections were inserted in the appropriate place along the carotid bifurcation, by matching the values of diameter from longitudinal and transversal US images.

3. Results

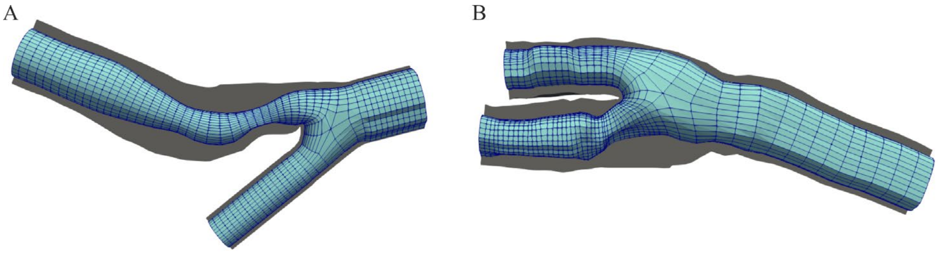

Fig. 2. Comparison of two reconstructed carotid bifurcations; A – reconstructed geometry using the generic model as the basis, as shown in [5]; B –reconstructed geometry using the improved methodology presented in this study.

Figure 1 shows the reconstruction process. The obtained reconstructed 3D finite element mesh for the patient is shown in Figure 1C. The cross-sections of the reconstructed geometry are shown together with extracted plaque components. A comparison of the patient-specific reconstructed mesh using the previously proposed approach [5,7] and the approach presented in this study is shown in Figure 2. Both models are shown in the sectioned arterial wall, in order to illustrate the shapes of lumen and arterial wall. As it can be observed, the shape of the ECA and CCA branches is no longer generic and straight, but adapted to the patient. Also, the exact orientation, i.e. the angle between the branches, is now patient-specific instead of generic as in the previous model. It is obvious that the changes introduced within the methodology provide a more detailed and realistic model of the carotid bifurcation.

4. Conclusions

A detailed analysis of the state of patients' arteries is a crucial step in the diagnostics. Computer AI-based models could be a very useful tool that could help determine and plan the most appropriate treatment. The 3D reconstruction of patient-specific geometry could ensure a better view of the carotid bifurcation, but this geometry could be further used within numerical simulations such as blood flow simulation or simulation of plaque progression, that could provide additional quantitative information. The improved reconstruction methodology presented within this study is a step towards a more broad application of AI-based computer models in clinical practice.

Acknowledgment: The research presented in this study was part of the project that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 755320 - TAXINOMISIS. This article reflects only the author's view. The Commission is not responsible for any use that may be made of the information it contains.

References

[1] Sun T et al., Comparative evaluation of support vector machines for computer aided diagnosis of lung cancer in CT based on a multi-dimensional data set. Comput. Method Programs Biomed. 111 (2):519-524, 2013.

[2] Shi J, Su Q, Zhang C, Huang G, Zhu Y, An intelligent decision support algorithm for diagnosis of colorectal cancer through serum tumor markers. Comput. Method Programs Biomed. 100 (2):97-107, 2010.

[3] Shen D, Wu G, Suk HI, Deep learning in medical image analysis. Annual review of biomedical engineering 19:221-248, 2017.

[4] Ravì D et al., Deep learning for health informatics. IEEE journal of biomedical and health informatics 21(1):4-21, 2016.

[5] Djukic T, Arsic B, Koncar I, Filipovic N, 3D reconstruction of patient-specific carotid artery geometry using clinical ultrasound imaging. Workshop Computational Biomechanics for Medicine XV, 23rd International conference on Medical Image Computing & Computer Assisted Intervention (MICCAI), October 4-8, 2020

[6] Ronneberger O, Fischer P, Brox T, U-net: Convolutional networks for biomedical image segmentation, in Lecture Notes in Computer Science, 2015.

[7] Djukic T, Arsic B, Djorovic S, Koncar I, Filipovic N, Validation of the machine learning approach for 3D reconstruction of carotid artery from ultrasound imaging, IEEE 20th International Conference on Bioinformatics and Bioengineering (BIBE), October 26-28, 2020

[8] Vukicevic AM et al, Three-dimensional reconstruction and NURBS-based structured meshing of coronary arteries from the conventional X-ray angi-ography projection images. Sci. Rep.8:1711, 2018.