Reconstruction of Patient-Specific Cerebral Aneurysm Model through Image Segmentation

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Abstract. The diagnostic assessment of cerebrovascular disease makes use of computational simulation as a predicting tool to determine hemodynamics factor contributing to the disease from patient-specific models which imitate the actual shape of the object of interest. However, the patient-specific models are generally reconstructed from the medical images subjectively. Image segmentation is commonly performed to produce object of interest with high visualization. In order to produce patient-specific anatomical model, a systematic adjustment on image intensity was performed in this study. This paper tends to present the reconstruction of three-dimensional (3D) patient-specific cerebral aneurysm model through systematic image segmentation by using threshold coefficients, C_{thres} of 0.2, 0.3, 0.4, 0.5 and 0.6. 25 models were extracted from digital subtraction angiography (DSA) images. The results show that there is an obvious physical change of geometry on the models reconstructed with C_{thres} of 0.5 and 0.6 especially on the artery branch. The models reconstructed with C_{thres} of 0.2 to 0.4 are considered sufficient in term of arterial geometry configuration and they would be opted for further computational study.

Keywords: Cerebral Aneurysm, Model Reconstruction, Segmentation, Threshold Coefficient.

1 Introduction

The application of medical imaging in the diagnosis of cerebrovascular diseases has provided an abundance of information in terms of physiological and pathological conditions on particular cerebrovascular system [1]. Besides, the analysis of hemodynamics in the cerebrovascular system can be acquired more accurately and specifically through computational study on the anatomical model. The information acquired from the hemodynamics analysis can be used as a reference in medical studies, treatment planning and surgical intervention. There has been research reported that the circumferential enhancement along the aneurysm wall (CEAW) which deals with the model configuration is highly associated to the analysis of aneurysm hemodynamics factor [2]. In other words, the analysis of hemodynamics is strongly depending on the model configuration, therefore it is crucial to obtain anatomically realistic model which does not compromise the actual structure or shape of the object [3–7].

In order to obtain the anatomically realistic model, image segmentation is performed by extracting the object of interest from digital and medical images. The image segmentation is a common image processing technique and has been used widely in medical [8–10], agricultural [11, 12], archaeological [13] and construction [14, 15] sectors for research, demonstration as well as device intervention purposes. However, there is lack of information in the research community concerning on the model reconstructed with image segmentation based on threshold image intensity other than the boundary condition set-up for conducting simulation [16–18].

The commercial software packages that are available nowadays provide automatic adjustment on image intensity [9, 19–24], aiding users in model extraction and reconstruction at fast pace and also eliminating the complex process to remove image noise. With the automatic feature, the model might not be segmented consistently since it is extracted by trial and error [22–24] and this technically has an impact on the hemodynamics analysis [25]. The medical image resolution is an uncontrollable factor affecting the wall shear stress distribution (WSS) especially on the complex flow region [26]. Therefore, the extracted model configuration has to be maintained as precise as possible to minimize the error arisen from the model configuration.

In this paper, the image segmentation was performed systematically on the digital subtraction angiography (DSA) images by adjusting the threshold image intensity calculated through threshold determination method [21]. The models extracted with five different threshold coefficients, C_{thres} of 0.2, 0.3, 0.4, 0.5 and 0.6 were reconstructed and compared. Some differences in term of geometry configurations have been identified.

2 Methodology

This study uses 768 slices of DSA images from a patient diagnosed with internal carotid artery (ICA) aneurysms. The images are stored as a DICOM file. The image segmentation was performed by using AMIRATM 2019.3. Before image segmentation was performed, the DSA images were exported to ImageJ and presented in 8-bit depth with 256 x 256 acquisition matrices. Then, a line probe was constructed at the representative cross-section of the proximal artery as shown in Fig. 1 to measure the image intensity. A profile curve of the image intensity was generated according to the line probe across the artery as shown in Fig. 2.



Fig. 1. Line probe at representative cross-section of proximal artery.



Fig. 2. Profile curve along the line probe.

In the present data, the image intensity ranged between 7.56 and 7997.27. The minimum and maximum values of the image intensity along the line probe, I_{min} and I_{max} were obtained. They were then used to determine the threshold image intensity, I_{thres} with different threshold coefficient, C_{thres} such as 0.2, 0.3, 0.4, 0.5 and 0.6 by using the formula defined in the threshold determination method [21] as shown in Eq. (1). The calculated values of I_{thres} as listed in Table 1 were then used for image segmentation.

$$I_{thres} = C_{thres}(I_{max} - I_{min}) + I_{min}$$
(2)

Table 1. Values of threshold image intensity with respective threshold coefficient.

Threshold coefficient, C _{thres}	Threshold image intensity, Ithres
0.2	1605.501
0.3	2404.473

0.4	3203.444
0.5	4002.415
0.6	4801.386

The three-dimensional (3D) patient-specific cerebral aneurysm models were extracted according to the calculated values of threshold image intensity, I_{thres} . Moreover, the arteries or branches which were out of the region of interest would be removed manually to protect the actual geometry configuration of the object of interest. There were 25 segmented vascular models created in total from five different cases of ICA aneurysm. A smoothing procedure with standardized smoothing factor of 0.5 was performed to reconstruct the models with good surface finishing and without compromising the local or global geometry configuration. The overall process flow for the present study is shown in Fig. 3.



Fig. 3. Methodology flowchart for the present study.

3 Results and Discussion

Fig. 4 to Fig. 8 show the 3D patient-specific cerebral aneurysm models reconstructed with respective C_{thres} from the DSA images. By comparing among the models, there is no significant change in term of geometry except for the model reconstructed with C_{thres} of 0.5 (Case 4) and 0.6 (Case 1, 2, 3, 5 and 6). There are dislocation and disappearance of the artery or branch where bifurcation exists as indicated in the red box for every case. Furthermore, it can be noticed that the arteries after bifurcation become narrower and the smaller arteries disappear as the C_{thres} increases. This might be due to the vasculature adherence to the object of interest, the patient-specific cerebral aneurysm model with arteries reduces as the C_{thres} increases and thus, causing some important parts to be marked out unconsciously.

According to the previous research, it was reported that the geometry configuration of reconstructed model has high impact on the aneurysmal hemodynamics especially in computational simulations [2, 3, 8]. Some researchers also claimed that small arteries can be neglected for physiological analysis as compared to the large arteries which have high visualization [23]. However, the reconstructed models would not be neglected as long as they contain the actual arterial geometry configuration.

Among all the models which have been created at the first phase investigation, the models reconstructed with C_{thres} of 0.2 to 0.4 are considered sufficient for further use since the actual arterial configurations are contained. From the current obtained results, it is confirmed that the model reconstructed based on threshold image intensity has noticeable impact on model configuration. However, further investigation has to be conducted to explore the effect of image segmentation with different threshold image intensity on the reconstructed models in more details such as blood flow behavior, WSS distribution and velocity flow field through computational study.



Fig. 4. Reconstruction of case 1 using threshold coefficient, C_{thres} of 0.2 to 0.6 (left to right). The red box indicates the dislocation and disappearance of artery or branch.



Fig. 5. Reconstruction of case 2 using threshold coefficient, C_{thres} of 0.2 to 0.6 (left to right). The red box indicates the dislocation and disappearance of artery or branch.



Fig. 6. Reconstruction of case 3 using threshold coefficient, C_{thres} of 0.2 to 0.6 (left to right). The red box indicates the dislocation and disappearance of artery or branch.



Fig. 7. Reconstruction of case 4 using threshold coefficient, C_{thres} of 0.2 to 0.6 (left to right). The red box indicates the dislocation and disappearance of artery or branch.



Fig. 8. Reconstruction of case 5 using threshold coefficient, C_{thres} of 0.2 to 0.6 (left to right). The red box indicates the dislocation and disappearance of artery or branch.

4 Conclusion

From the present data, the patient-specific cerebral aneurysm models reconstructed with C_{thres} of 0.2 to 0.4 would be used for further computational study and analysis due to the preserved geometry configuration with minimal difference. The noticeable difference on the models reconstructed with different threshold image intensity is the primary evidence from the current study proving that the systematic image segmentation based on image threshold intensity without post processing editing has revealing impact on the model configuration. However, more data would be obtained to maintain the consistency of justification. Besides, the effect of geometry configuration on aneurysmal hemodynamics is yet to be investigated.

Acknowledgement. The support from Universiti Malaysia Pahang under grant RDU190153, Ministry of Higher Education (MOHE) under FRGS grant (FRGS/1/2018/TK03/UMP/02/23) and MedEHiT are gratefully acknowledged.

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