Automatic Cerebral Aneurysm Segmentation Using Contourlet Transform and Hidden Random Field Model Template

Yousra Regaya[1], Abbes Amira[1], Sarada P. Dakua[2], Noor Al-Maadeed[1], Julien Abinahed[2]

[1] Computer Science and Engineering Department, Qatar University, Doha, Qatar

[2] Hamad Medical Cooperation, Doha, Qatar

1. Abstract

Cerebral Aneurysm (CA) is a vascular disease that affects almost 1.5 - 5% of the general population, mostly adults. Sub-Arachnoid Hemorrhage, caused by a ruptured CA, has high morbidity and mortality rates. Therefore, radiologists aim to detect and diagnose this disease at an early stage to prevent or reduce its consequential damages.

This work contributes to the CA segmentation field by proposing a novel automated algorithm. Precisely, the contourlet transform, as a multiresolution technique, and Hidden Markov Random Field with Expectation Maximization, as a statistical technique, are the two main adopted approaches. The first technique helps in extracting images features not apparent in the normal image scale; while the second technique segments images in the contourlet domain based on the spatial contextual constraints. The proposed algorithm reveals promising results on the tested Three-Dimensional Rotational Angiography (3D RA) datasets, where both an objective and a subjective evaluation are carried out.

2. Introduction

Cerebral Aneurysm (CA) is an abnormal inflammation that formulates within the brain blood vessels, more precisely at the branching point of the arteries. It is detected more commonly after the age of forty as it takes several years to develop. Per [1], 1.5 - 5% of the general population are affected by this disease, where the mortality and morbidity rates of these affected people are 30 - 40% and 35 - 60% respectively.

While the causes and the consequences of aneurysm formulation are known, its detection remains challenging as the traditional manual procedure handled by the experts suffers from various disadvantages (e.g. the bias results depending on the radiologist' s experience, the significant increase in the number of images to be analyzed which increases consequently the probability of the analysis error, the time consumption, and the number of needed labors, etc). Due to the aforementioned reasons, different computer-aided diagnosis algorithms, known as Medical Image Segmentation (MIS) algorithm, come into the picture to overcome the limitations of the manual process and provide the experts with a robust second opinion. Hence, many researchers are tackling CA segmentation research area by proposing different automatic or semi-automatic approaches, in 2D or 3D domain, and adapted for different medical images modalities (e.g., MRA, CTA, DSA, or RA).

Many semi-automatic approaches are proposed, where human intervention is expected at some point during the running time of the algorithm. This interactivity is laborious and prone to inter/intra-operator variability, which affects directly the final segmentation accuracy. Therefore, some researchers avoid this interactivity by developing fully automatic approaches. Some of these automatic algorithms are customized either to segment only a specific type of CAs (e.g. saccular Cas) or to segment CAs that appear in a specific location. These kinds of customization reduce the complexity of the task; however, they limit their applicability in real clinical practices. Moreover, the accuracy of the proposed automatic CA segmentation algorithms varies considerably across different datasets.

Accordingly, this work contributes to the field by proposing a novel automatic and robust algorithm to segments CAs regardless of their shapes, locations, or sizes using a multiresolution statistical approach, where the Contourlet Transform (CT) in conjunction with Hidden Markov Random Field with Expectation Maximization (HMRF-EM) are used to segment 2D images in the contourlet domain based on the pixels' relationships with their neighbors. The rest of this paper is organized as follow: The proposed methodology is presented in section 3. The objective and subjective evaluation are carried out in section 4. Finally, a conclusion is given in section 5.

3. Methodology

A series of 2D images for a certain patient is fed to the proposed CA segmentation algorithm. These images represent the Region of Interest (ROI) which consists of a CA and some surrounding vessels (i.e. the ROI selection from the entire cerebral vasculature is done manually). Later, three consecutive phases are performed on each 2D image separately, as presented in sections 3.1, 3.2, and 3.3 respectively. Finally, all images are reconstructed to visualize the 3D volume of interest. Fig. 1 summarizes and illustrates the overall proposed algorithm.

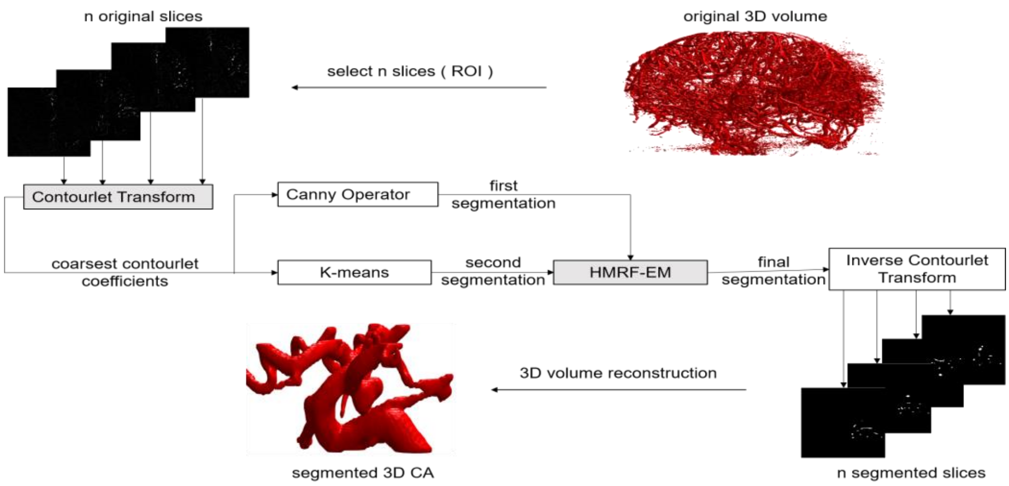

Figure 1: Flowchart of the proposed segmentation

3.1. First Phase: Contourlet Transform

During the first phase, CT [2] is applied to extract features from a 2D image $a_0[n]$ by decomposing it into a lowpass subband $a_j[n]$and several bandpass directional subbands $c^{L_j}_{j,k}[n]$ c^{L_{j}}_{j,k}[n]$, which are referred as the contourlet coefficients. This process can be expressed mathematically by the Eq. 1 and 2 respectively.

$$a_j[n] = f, \theta^{(L)}_{j,k,n} \rightarrow \theta^{(L)}_{j,k,n} = \sum_{n \in Z^d} g_k[n]\, \phi_{j,k}(t) \quad (1)$$

$$c^{L_j}_{j,k}[n] = f, \rho^{(L)}_{j,k,n} \rightarrow \rho^{(L)}_{j,k,n} = \sum_{n \in Z^d} d_k[n]\, \varphi_{j,k}(t) \quad (2)$$

, where $\theta^{(L)}_{j,k,n}$ is the LP basis function used for scale decomposition and $\rho^{(L)}_{j,k,n}$ is the DFB basis function used for directional decomposition. The parameters $j, k, d,$ and n, used in the two above equations, are defined respectively: number of levels/scales, number of directions in each level, dimensionality, and a scale parameter along the frequency axis.

After the decomposition is done, only the last produced lowpass subband image $a_j[n]$ is selected, which consists of the coarsest produced coefficients, since they are considered as the best representatives of all the produced coefficients to perform on them the remaining steps.

3.2. Second Phase: Hidden Markov Random Field model with Expectation Maximization

In order to apply the second phase of the proposed segmentation algorithm, which is the HMRF-EM [3], two prior steps need to be performed. **The first step** is to obtain a constrained image by applying a Canny edge detection operator to highlight the image's edges; this operator produces thicker edges compared to the second derivative edge detection operator (e.g., LP). As for **the second step**, an initial segmentation along with its parameters, which are mainly the means and standard deviations, need to be initialized. Due to the over-segmentation of the HMRF-EM framework, a technique with under-segmentation is preferable to complement it. Accordingly, k-means clustering is selected and applied.

After getting all the needed inputs (the initial segmentation $\hat{x}^{(0)}$ along with the initial parameters $\theta^{(0)}$ obtained by the k-means clustering technique, the constrained image $ce_j[n]$ obtained by the Canny edge operator, and the lowpass subband image $a_j[n]$ obtained by the contourlet decomposition),

HMRF-EM algorithm starts by iterating between the Expectation Step (E-Step) and Maximization Step (M-Step) to update the initial segmentation (Eq. 3) and the parameters (Eq. 4 and 5) until a certain pre-fixed number of iterations is reached.

$$\hat{x} = \arg\min(\, U(y|x) + U(x)) \quad (3)$$

$$\mu = \frac{\sum_{i \in S} P^{(L)}(l|y_i) y_i}{\sum_{i \in S} P^{(L)}(l|y_i)} \quad (4)$$

$$\sigma = \sqrt{\frac{\sum_{i \in S} P^{(L)}(l|y_i)(y_i - \mu)^2}{\sum_{i \in S} P^{(L)}(l|y_i)}} \quad (5)$$

3.3. Third Phase: Inverse Contourlet Transform

Finally, the Inverse Contourlet Transform (ICT) is applied to reconstruct the decomposed 2D image and turn it back to its original size. Here, the extracted lowpass subband image $a_j[n]$ in phase one is replaced by the final segmented image $\hat{x}$. The ICT process is achieved using the same LP and DFB functions used in the decomposition phase but in the reverse order, where the DFB function is applied first followed later by the LP function.

4. Evaluation

The proposed CA segmentation algorithm is evaluated objectively and subjectively on four 3D RA datasets provided by Hamad Medical Corporation (HMC). Each dataset is a series of 385 2D slices/images of a certain patient in the Digital Imaging and Communications in Medicine (DICOM) format of size 512 x 512 each, where it comes along with its ground truth data in the STL format. Fig. 2 depicts one of the used datasets before and after applying the segmentation of the volume of interest (VOI).

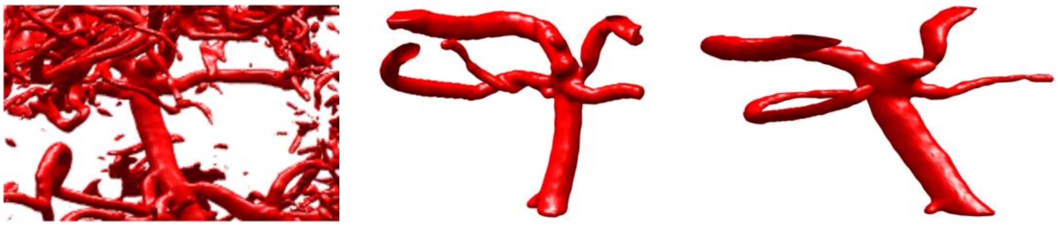

Figure 2: Dataset 4 (a) Original VOI (b) Segmented VOI (c) Ground Truth VOI

For the objective evaluation, six performance metrics are used to measure the effectiveness of the proposed segmentation which are: Dice Similarity Index (DSI), sensitivity, specificity, accuracy, False Positive Ratio (FPR), and False Negative Ratio (FNR). Table 1 reports the average obtained results for the 4 datasets. As for the subjective evaluation, each dataset is accessed visually by five observers, where one of them is an expert and the others have some medical background. A rate, between \$0\$ and \$5\$, is assigned by each observer; where \$5\$ means that the ground truth volume and the segmented volume are identical. While \$0\$ means that the two volumes are completely different. Table 2 reports the observations' average for the 4 datasets.

(%)	Accuracy	DSC	FPR	FNR	Sensitivity	Specificity
Average	99.86	93.58	0.08	5.27	94.73	99.92

Table 1: Objective Evaluation Results

(Out of 5)	Observer 1 (Expert)	Observer 2	Observer 3	Observer 4	Observer 5
Average	4	4.25	4.5	4.25	4.25

Table 2: Subjective Evaluation Results

5. Conclusion

Cerebral aneurysm (CA) has serious consequences leading to high morbidity and rates. Therefore, detecting and diagnosing CAs at an early stage is imperative. This work contributes to this research field by proposing a new automatic CA segmentation approach using the contourlet transform (CT), as a multiresolution technique, and the hidden Markov random field model with expectation maximization (HMRF-EM), as a statistical technique. This algorithm reveals promising results on the tested datasets without requiring any long training or human interactivity. Nevertheless, more testing needs to be done to guarantee its applicability in clinical practices.

6. References

[1] R. T. Higashida, "What you should know about cerebral aneurysms," Pamphlet. American Heart Association Cardiovascular Council, 2003.

[2] M. N. Do and M. Vetterli, "Contourlets: a directional multiresolution image representation," in Proceedings. International Conference on Image Processing, 2002.

[3] Y. Zhang, M. Brady and S. Smith, "Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm," IEEE transactions on medical imaging, vol. 20, no. 1, pp. 45--57, 2001.