A New Image segmentation of Arterial Infundibula in Cereberal Aneurysm Patients Using Mumford-Shah Approach

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Abstract. automatic image segmentation and boundary detection of blood vessels is desirable for analysis and diagnosis of some diseases. In this paper, we introduce a new image segmentation approach in order to detect arterial infundibula at brain arteries. This new technique is a combination of a region based segmentation using Mumford-shah model and Gabor wavelet filter that applied to digital subtraction angiography (DSA) images. Gabor wavelet filter is used to outcome complicated image intensity distribution in DSA images. The proposed method is used to determine arterial infundibula in brain arteries images. This method requires no training stage and relatively is fast.

Keywords: component; image segmentation; Mumfod-Shah model; Arterial Infundibula

1. Introduction

More than thousands person worldwide suffer from Brain Arteriovenus Malformation (AVM) and Brain Aneurysm. Brain aneurysm is one cause of subarachnoid hemorrhage (SAH) result of morbidity and mortality [1]. Aneurysms are localized dilation of the vessel wall and are traditionally classified based on morphology or etiology. Based on their morphology, more common saccular and fusiform aneurysms can be distinguished. The etiologist include vessel degeneration from hemodynamic factors, pressure congenital disorder that affect the vessel wall, atherosclerosis, dissection , infection (mycotic aneurysms), vascular disease , trauma , and neoplastic invasion [2] .

There are different imaging strategies in diagnosis of brain aneurysms. Digital subtraction angiography (DSA) has historically considered the standard of reference in the diagnostic evaluation of patients acutely suspected of having intracranial aneurysms rupture. However, DSA is an invasive, resource and costly procedure, which may not be readily available on a 24-houre basis. It is also associated with a small but definite risk of complications such as stroke. On the other hand, multi-detector computer tomography (CTA) provides a fast non-invasive assessment of cerebral vessels is readily in an acute setting and be easily performed immediately after the initial diagnostic computed tomography (CT) scan. CTA allows rapid diagnosis and treatment planning and can potentially replace invasive DSA in an emergency [2].

The diagnosis of cerebral brain aneurysm, especially in the setting of sub-arachnoid hemorrhage, remains of critical importance in patient management. Angiography is considered by most practitioners to be the standard of reference in the diagnosis of cerebral aneurysm. Arterial infundibula are small, funnel-shaped dilatations of the proximal posterior communicating artery that may be considered as mimic aneurysms [3].

Extraction of information from DSA images such as vessels diameter, branch angel, vessels morphology could be useful to assess the severity of the disease. So, appropriate vessel segmentation is an important stage in this process. The manual segmentation requires trained specialists, so appropriate automatic segmentation is always desirable. Blood vessel segmentation has received much attention in recent researches and different

approaches such as vessel tracking [4], deformable model [5] and supervised classification [6, 7] are developed. In this paper, we used from a region based model which is called Mumford-shah (MS) model [7] in segmentation of DSA images from brain proximal posterior communicating arteries. A modified MS model introduced by Xiaojun [8] is used in this research which has the ability to adopt to the complicated image intensity distributions which is usual DSA images. Also, Gabor wavelet filter [9] is used to improve the results of proposed method. This approach is fast and there is no need to any type of training stage.

The organization of paper is as follows. In section II, we first describe the basis of Mumford-Shah model used in this research. Section III introduces the Gabor wavelet Transform. Section IV shows our image segmentation algorithm. Experimental results will be described in section V and we conclude paper in section VI.

2. The Mumford-Shah Model

Mumford and Shah [6] model is an image segmentation algorithm based on minimization of an energy function. This energy function is defined as

$$E(u, Z) = \int_{\Omega} |u - u_0|^2 \, dxdy + \mu \int_{\Omega \setminus Z} |\nabla u|^2 \, dxdy + \nu |Z| \tag{1}$$

where Z is the curve of segmentation; $|Z|$ is the curve length; u_0 is original image and u is smooth approximation of original image. Ω is defined as image domain and $\Omega \setminus Z$ is image domain excluding the segmentation curve. If the energy function in eq.1 minimized, the image will be segmented into regions in order to boundary of each region is as short as possible and u be a smooth approximation of u_0.

Considering eq.1, segmentation problem is reduced to the problem of finding a piecewise smooth approximation of u. The functional $E(u, Z)$ has been studied extensively and a large body of results has been obtained [10, 11]. Some alternative solutions for this problem are suggested in [12]. Chan and Vesse proposed a level set method for piecewise smooth approximation of energy function [13]. In their proposed method, approximation of image density function is done by smooth functions and MS model function is solved by three Partial Differential Equations (PDEs). PDE based proposed solution is a very time consuming approach. To solve this limitation, Chan and Vesse proposed the piecewise constant smooth approximation [14]. In their new method, the image intensity inside object regions is approximated by constants and then there is no need to solve two PDEs. In this case, the image intensity inside regions is presented by the average intensity of the object and only one PDE should be solved for segmentation curve. In addition to constant approximation algorithm, other methods such as linear approximation [15] were proposed for image segmentation, but these approaches are effective only for some special cases that image intensity distribution was simple and failed for complicated cases such as DSA images. Because of non-uniform image density distribution in DSA images used in this research, the usage of MS model fails to segment brain arteries properly.

To overcome this failure in this research we used from MS model introduced by Xiaojun and Tien [7] which is a modified version of original MS model. In this new model, the energy function is given by

$$E(Z) = \int_{\Omega \setminus Z} |F(u_0)|^2 \, dxdy + \mu |Z| \tag{2}$$

where $F(u_0)$ is the high frequency components of the original image and μ is defined as balance parameter. The new minimal energy function consists of high frequency components of regions and the length of segmentation curve. If the energy function be minimized, only low frequency components will be exists inside regions and high frequency parts are preserved in boundaries. The noise effect is suppressed by curve length constraint.

In new energy function, only the segmentation curve length should be solved. This model provides two main advantages for us to conduct brain arteries images segmentation problem. First, only one equation should be solved and then this is a fast algorithm. This advantage lets us to extract the brain arteries movement profile in a series of DSA images. Second, because no constant and linear approximations are used, the model can deal in problems with different image density distributions such as blood vessels DSA images. To improve blood vessel detection, a wavelet based filter using Gabor transform is applied. In next section, we will describe the Gabor wavelet transform used in this research.

3. Gabor wavelet

A Gabor transform consist a complex sinusoid function which is modulated by a rotated Gaussian function. Bovik et al [16] suggest the restriction of the choice of Gabor filters to those with isometric Gaussians (aspect ratio of one). The spatial-domain presentation off the corresponding Gabor function is

$$g_{u,v}(x,y) = \frac{\|k_{u,v}\|^2}{2\pi\sigma^2} e^{-\frac{\|K_{u,v}\|^2(x^2+y^2)}{2\sigma^2}} [e^{ik_{u,v}(x+y)} - e^{-\frac{\sigma^2}{2}}] \tag{3}$$

where $k_{u,v}$ is wave vector which is defined by both orientation u and scale v and defined as $k_{u,v} = k_v e^{i\psi_u}$. In equation 3, the first term in square brackets is the oscillatory part of Gabor function. The parameter σ defines the ratio of Gaussian window width and wavelength. Also we have

$$k_v = \frac{\pi}{2(\sqrt{2})^v} \tag{3}$$

$$\psi_u = \frac{\pi u}{4} \tag{4}$$

Figure 1 shows the real part of Gabor kernels with $\sigma = 2\pi$ for $v=[0,1,3]$ and $u=[0,1,2,3]$. In this research, to accelerate the speed of proposed algorithm, only imaginary parts of Gabor wavelet was used. The best value of σ is determined as $\sigma = \pi$. Also in order to accelerate the algorithm speed, only one orientation ($u = 3$) and one scale ($v = 1$) is used. Using these parameters, results are still good enough to be used as second stage on blood vessel segmentation process.

4. Image Segmentation Algorithm

In this section, proposed image segmentation algorithm will be described. Figure 2 shows the overall structure of
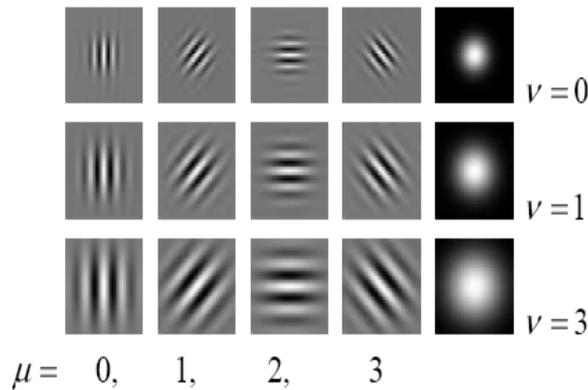

Figure 1.   Gabor Wavelets for $u \in \{0,1,2,3\}$ and $v \in \{0,1,3\}$

introduced method for segmentation of DSA images. As shown in figure2, a preprocessing stage is done to remove background image. In this stage, we first convert gray scale image to a binary image using a threshold and then subtract empty background image from it. Figure 3 shows this process. Figure 3.a shows the original DSA image. Figure 3.b shows the binary image extracted from original image. Figure 3.c shows the empty background image and finally figure 3.d shows the finally pre-processed image. In following because of non-uniform illumination in blood
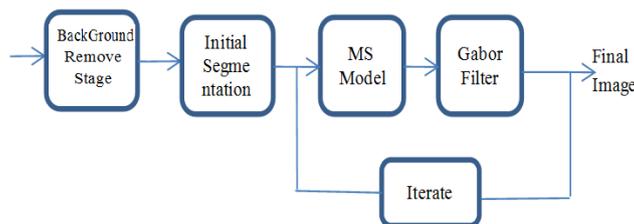

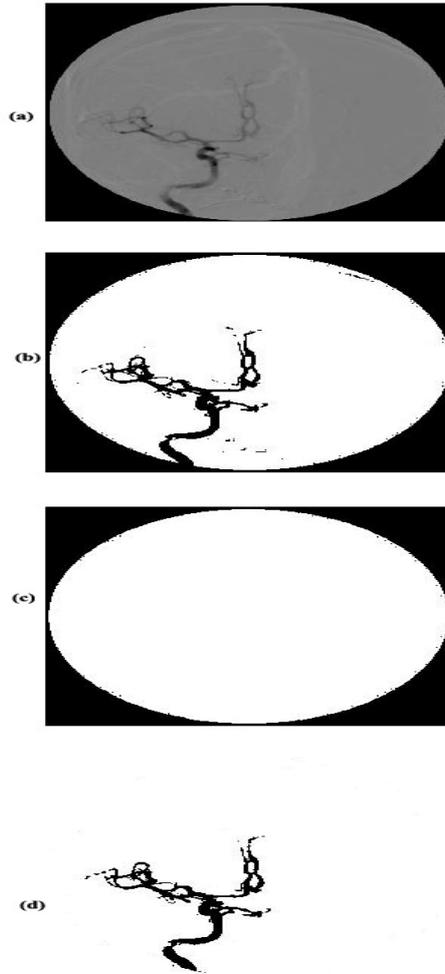Figure 2.   Overall Structure of blood vessel segmentation algorithm

Figure 3.   (a) Original DSA Image, (b) Binary Image, (c) Background Image (d) Subtracted Image

vessels, an adaptive threshold is used to create an initial segmentation. As, the results of initial segmentation are not good and there is noise in different regions, the created initial segmentation is fed into an iterative process. This process includes two stages. In first step, segmentation is done by applying MS model and the output of first step is corrected by a Gabor filter.

5. Experimental Results

A. Ultrasound Image Database

There is no benchmark database for DSA images of brain arterial infundibula. In this research, to evaluate the performance of proposed images, we constructed our database from images of 20 patient DSA images. These images are obtained from Tehran Khatam Al Anbia Hospital. Totally we collected 87 DSA images for our database.

B. Experiments

In the process of image segmentation, as described in section III, only imaginary part of Gabor filter is used in image segmentation. To accelerate the computation, in each iteration, only narrow band Gabor filter is calculated beside the segmentation curve from MS model. As a result, the segmentation process is relatively fast. Training step is the most time consuming step in image segmentation problems.

As our method needs no training step, the segmentation process is fast enough to be used in processing of DSA image series.

We tested our approach on 87 images of our database. Figure 4 shows the original DSA image, final boundary detection of brain arteries and final segmentation of blood vessels from DSA image. As shown in

figure.4, proposed algorithm has no sensivity to noise and gives us a perfect scheme from vessels morphology that could be used in diagnosis process.

6. Conclusion

In this research, we use a new image segmentation model to segment and detect boundaries of brain arteries DSA images. The proposed method is based on a modified version of Mumford-Shah model. MS model is a region based approach that uses from segmentation curves. The MS model is a good segmentation approach, but the minimization of original energy function in not a trivial task and needs an approximation stage. However, due to non-uniform image density distribution in complicated case, approximation techniques such as constant and linear methods can not deal with such cases. In used modified MS model, this problem is solved by applying new energy function that could be easily solved with one PDE and can handle with complicated cases such as brain arteries DSA images. Also a preprocessing stage is applied in order to remove background image. In order to improve segmentation results, a Gabor filter is applied after MS model. To accelerate the speed of algorithm, we used only a simplified version of Gabor filter, but results are still good and algorithm is fast relatively in comparison with other segmentation approaches. We are working now to develop an automatic recognition system to use the results of image segmentation and detect the type of brain aneurysm.
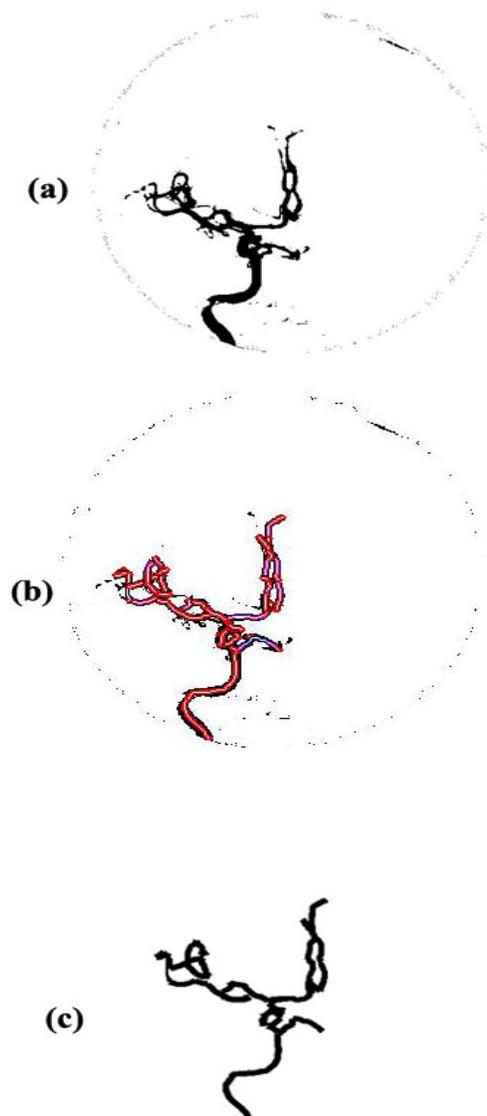

Figure 4.   (a) Original DSA Image After preprocessing, (b) Tracked Vessels, (c) Finally Segmented Image

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