



A Method Towards Cerebral Aneurysm Detection in Clinical Settings

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Abstract. Cerebral aneurysms are among most prevalent and devastating cerebrovascular diseases of adult population worldwide. The resulting sequelae of untimely/inadequate therapeutic intervention include subarachnoid hemorrhage. Geometric modeling of aneurysm being the first step in the treatment planning, the scientists therefore focus more on segmentation of aneurysm rather than its detection. A successful aneurysm detection among the bunch of vessels would certainly facilitate and ease the segmentation process. In this work, we present a novel method for aneurysm detection; the key contributions are: contrast enhancement of input image using stochastic resonance concept in wavelet domain, adaptive thresholding, and modified Hough Circle Transform. Experimental results show that the proposed method is efficient in detecting the location and type of aneurysm.

Keywords: Cerebral aneurysm · Detection · Hough transform

1 Introduction

Brain aneurysms can happen to anyone at any age and the frequency increases with age. If aneurysms are detected and treated before a rupture occurs, some of the strokes caused by brain aneurysms can be prevented [1]. A brain aneurysm is a weak or thin spot on a blood vessel wall in the brain that balloons out and fills with blood; serious consequences can result if it bursts (ruptures) in the brain spilling blood into the surrounding tissue leading to subarachnoid hemorrhage. Most cerebral aneurysms go unnoticed until they rupture or are detected by brain imaging because of the complexity of brain vasculature anatomy and they always do not occur in a specific region Fig. 1. It is imperative for the patient to be screened by different modalities such as CT with CTA (Computed Tomography with Angiography). CTA images are created by injecting an iodine-based dye into the vein of the arm. As it passes from the vein to the heart and then pumped to the brain, X-rays are passed through the head and images are created. If the clinician does not find the aneurysm and the patient complains again; the

patient might need to go through CT again exposing him to the repeated radiations exposing the patient to X-ray radiation and iodine which in some patients can lead to an allergic reaction. In order to address this problem, an automatic method for cerebral aneurysm detection would certainly help the clinician find the aneurysm at a go. CTA is performed on multi-detector helical CT scanners that allow multi-planar reformats, sub-millimeter slice thickness, and 3D reconstructions. Several investigators have demonstrated that current multidetector scanners have a spatial resolution that can reliably diagnose aneurysms greater than 4mm with nearly 100% sensitivity [2]. For aneurysms 3mm and smaller, early CT technology has been shown to be inadequate, with sensitivity numbers as low as 84% from four-channel multi-row detector CT scanners [3]. Similarly, there are different level of sensitivities, however, the problem of aneurysm is serious since it directly impacts on the nerve system and therefore, it needs to be tackled sensibly. The two main options are endovascular treatment (performed through catheters inserted into arteries under X-ray guidance) and open surgery. The selection of the option depends on many factors: aneurysm location, size, patient condition, patient preference, and local expertise. However, it is important to accurately determine the size, morphology, location, and rupture status of a cerebral aneurysm and/or to identify specific imaging characteristics that may portend a higher risk of rupture so that potential treatment can be guided more accurately. In this paper, we present a novel method by application of Modified Hough Circle Transform & Peak Trekking technique on the image extracted from Computed Tomography with Angiography (CTA). The proposed method is divided into three broad stages: (1) contrast enhancement of input images, (2) adaptive thresholding, (3) template matching, and aneurysm detection by Peak Trekking.

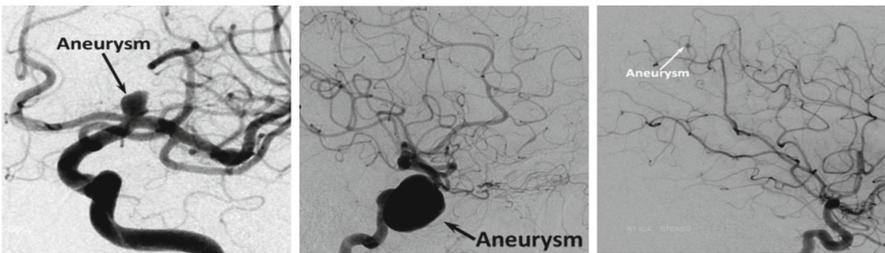


Fig. 1. Samples of brain aneurysm images.

2 Related Work

Over the years, several methods tackle the noisy and cluttered medical images mostly by filtering that leads to degradation in the image quality, therefore in our approach, we utilize the noise in a constructive manner instead. One of the

efficient approaches that utilize noise to enhance the contrast of low contrast input image is Stochastic Resonance (SR) [5]. Apart from a few attempts e.g. [4], SR is yet to get the full attention of the image processing community. In this paper, we have applied SR for the image enhancement followed by an adaptive thresholding for image segmentation. SR occurs if the Signal-to-Noise Ratio (SNR) and input/output correlation have a well marked maximum at a certain noise level. Unlike very low or high noise intensities, moderate ones allow the signal to cross the threshold giving maximum SNR at some optimum noise level. In the bistable SR model, upon addition of zero mean Gaussian noise, the pixel is transferred from weak signal state to strong signal state that is modeled by Brownian motion of a particle placed in a double well potential system. In the context of this paper, the double well represents the contrast of an image and the position of particle as the intensity values. The state, at which performance metrics are found optimum, can be considered as the stable state that provides maximum SNR. Some researchers have attempted to use SR in Fourier or spatial domains [4], however we have chosen the wavelet transform domain as explained in the following section.

We use adaptive thresholding that is a function of local property in a neighborhood centered at a pixel location, pixel intensity and pixel location. The literature is quite rich on this [7–9]. However, most of methods are application specific; since we are dealing with medical images, cerebral aneurysm, and the intensity distribution is complex, we have proposed a new method as described in the next section.

Detection of CA from different modalities is a new domain, and has got much to be explored although there have been attempts [11–14]. While McKinney et al. [12] reveal that the combination of DSA with 3D RA is currently the most sensitive technique to detect untreated aneurysms and should be considered in suspicious cases of SAH where the aneurysm is not depicted by 64 multi-slice computed tomography angiography (64 MSCTA), because 64 MSCTA may occasionally miss aneurysms less than 3–4 mm size. Our proposed method makes use of Auto-Thresholding along with Modified Hough Circle Transform & Peak Trekking technique for the accurate detection of CA.

3 Materials and Methods

3.1 Data

The datasets used to test the proposed segmentation algorithm have been obtained from Hamad Medical Corporation in Qatar. On average, each dataset consisted of 400 slices acquired along the long axes of the subjects. The proposed segmentation algorithm is tested on these datasets with average slice thickness of 0.29 mm, pixel spacing of $0.29 \text{ mm} \times 0.29 \text{ mm}$, and matrix size 512×512 .

3.2 Contrast Enhancement Using Stochastic Resonance

In this methodology, 2-D discrete wavelet transform is applied to the $M \times N$ size image I . Applying SR to the approximation and detail coefficients, the

stochastically enhanced (tuned) coefficient-sets in DWT domain are obtained as $W_{\psi}^s(l, p, q)_{DSR}$ and $W(l_0, p, q)_{DSR}$. The SR in discrete form is defined as:

$$\frac{dx}{dt} = [ax - bx^3] + B \sin \omega t + \sqrt{D}\xi(t) \quad (1)$$

where $\sqrt{D}\xi(t)$ and $B \sin \omega t$ represent noise and input, respectively; these are replaced by DWT sub-band coefficients. The noise term is the cause in producing SR; the maximization of SNR occurs at the double well parameter a . The (1) is solved as in [6] before SR implementation on digital images. The low contrast image may be viewed as a noisy image containing internal noise due to lack of illumination. This noise is inherent in its DWT coefficients and therefore, the DWT coefficients can be viewed as containing signal (image information) as well as noise. The final stochastic simulation is obtained after some pre-defined number of iterations. Given the tuned (enhanced and stabilized) set of wavelet coefficients ($X_{\phi}(l_0, p, q)$ and $X_{\psi}^s(l, p, q)$), the enhanced image $I_{enhanced}$ in spatial domain is obtained by inverse discrete wavelet transform (IDWT) given as:

$$\begin{aligned} I_{enhanced} &= \frac{1}{\sqrt{MN}} \sum_p \sum_q X_{\phi}(l_0, p, q) \phi_{l_0, p, q}(i, j) \\ &+ \frac{1}{\sqrt{MN}} \sum_{s \in (H, V, D)} \sum_{l=l_0} \sum_p \sum_q X_{\psi}^s(l, p, q) \psi_{l_0, p, q}^s(i, j) \end{aligned} \quad (2)$$

This is the enhanced image after n iterations. The double well parameters a and b are determined from the SNR by differentiating SR with respect to a and equating to zero; in this way, SNR is maximized. This leads to $a = 2\sigma_0^2$ for maximum SNR, where σ_0 is the noise level administered to the input image. The maximum possible value of restoring force ($R = B \sin \omega t$) in terms of gradient of some bistable potential function $U(x)$,

$$R = -\frac{dU}{dx} = -ax + bx^3, \quad \frac{dR}{dx} = -a + 3bx^2 = 0 \quad (3)$$

resulting $x = \sqrt{a/3b}$. R at this value gives maximum force as $\sqrt{\frac{4a^3}{27b}}$ and $B \sin \omega t < \sqrt{\frac{4a^3}{27b}}$. Keeping the left term of this expression to its maximum value and B as unity, $b < \frac{4a^3}{27}$. In this way, the input image is contrast enhanced. An adaptive thresholding method is applied on the contrast enhanced image.

3.3 Adaptive Thresholding

Dynamic statistical parameters are used for estimating the threshold that separates two regions [15]. The dynamic statistical parameters set a low threshold value for high intensity region and a high threshold value for low intensity region. In addition, a change detection technique [16] is used to estimate the position,

where the change in intensity occurs. Both methods are combined together forming an adaptive technique to obtain the boundary pixels. In order to discriminate the particles owing to different regions, the individual dynamic statistical parameters viz., mean, standard deviation (σ) and third moment (M) of all the pixels are calculated. The new pixels encountered in the vector update the statistical parameters automatically indicating the change in regions. After each sample pixel, a deciding function DF_f is calculated: $\beta_f = k_1 (\sigma_f + M_f)$. Threshold (E) is updated continuously on the basis of the deciding function and is calculated: $E_f = E_{f-1} - k_2 (\beta_f - \beta_{f-1}) E_{f-1}$, where constants k_1, k_2 are determined empirically. In this way, we get as many threshold values as the number of pixels are present. In order to confirm the correct threshold value at the desired location, CUSUM (cumulative sum) [16] is applied. It traps the position of a significant change in amplitude. The boundary pixel is thus given by: $X = \min \{f : d_f \geq j\}$ and $X = \min \{f : D_f \geq r_f + j\}$, where D_f is the log likelihood function and $r_f = \min_{1 \leq l \leq f} D_l$. The threshold is compared with the adjacent values to deny any deviation of X from the actual position and the pixel corresponding to both threshold value and X is the *boundary pixel*. In this way, with this process is repeated for all orientations and all the boundary pixels are determined forming a region of pixels enclosed.

3.4 Template Matching

Hough Transform (HT) is a template matching technique that locates shapes in images. HT computation requires a mapping from the image points into an accumulator space or Hough space. Hough transform for circles is chosen as our preferred method of shape extraction since aneurysms are in general of saccular or balloon type. Midpoint Circle Algorithm [10] has been proved to be one of the most efficient algorithms to calculate the pixel positions around a circular path centred at the coordinate origin (0, 0) with a given radius r . A circle function $f_{circle}(x, y)$ is therefore defined in this connection which can be applied in this method is: $f_{circle}(x, y) = x^2 + y^2 - r^2$.

This generated circle can then be shifted to proper screen position by moving its centre to (x_c, y_c) . Modified Hough Circle Transform (MHCT) maps binary image points in I to a 3D parameter space defined as Hough Hierarchy, \mathcal{H} . The mapping function for our MHCT algorithm also attributes as Votes casted at co-ordinate point (x, y) is defined as:

$$v(x, y) = \sum_{r=1} \left[\frac{|\delta\Omega_r(x, y) \cap I|}{|\delta\Omega_r(x, y)|} \right] \quad (4)$$

The cardinality operator is used to find the number of pixels. Hough Hierarchy, is generated by the accumulation of the casted votes for all pixel positions within the image: $\mathcal{H} = \left\{ (x, y) \in (X \times Y) : \bigcup_{\forall(x, y)} v(x, y) \right\}$. The co-domain of the function $v(x, y)$ and upper limit of relation \mathcal{H} is given by:

$V = \{0, 1, 2, \dots, \text{Heirarchy height}\}$, where $v(x, y) \in V$ and

$$\max(\mathcal{H}) = \{(x, y) \in (X \times Y), v(x, y) \in H : \max[v(x, y)]\} \quad (5)$$

Hough Hierarchy associates to every pair (x, y) in $X \times Y$ an element $v(x, y)$ in V . This makes the graph of \mathcal{H} a ternary relation between X , Y and V . Hence, Hough Hierarchy is a 3D parameter space. Hough Hierarchy 3D parameter space resembles a mountain range, therefore, we perform a reverse mapping of the 3D local mountain from the mountain range to a 2D binary region. This process of region detection and region subtraction is iterated till the condition $\max(\mathcal{H}) \geq \text{Peak depth}$ is violated. Peak Depth decides whether the height of the post processed Hough Hierarchy, 3D parameter space is sufficient for the regions being called as mountain any more

The complete workflow of cerebral aneurysm detection is as follows:

1. The input image if first contrast enhanced.
2. The enhanced image is then segmented using adaptive thresholding method.
3. Hough Circle transform is then applied on the segmented image generating Hough Hierarchy 3D parameter space.
4. Based on the peak, area and compactness, the aneurysm region is detected.

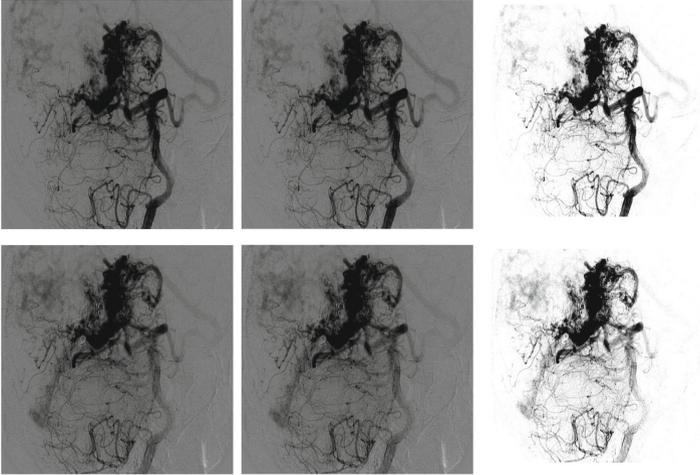


Fig. 2. (a–f) Contrast enhancement of input brain aneurysm images.

4 Results and Discussion

We have tested each stage of the algorithm and included the results although we are not able to accommodate all the results due to page constraints. The

results of contrast enhancement are provided in Fig. 2. The results of adaptive thresholding, Hough space, and detection of aneurysms are given in Fig. 3. The average time required by MATLAB R14 to perform segmentation is 2 m for one subject (without optimization). Experimental results have shown satisfactory results for meshes with either simple or complicated model. To evaluate the performance of the approach; performance metrics such as sensitivity, specificity and accuracy are calculated; they are found as 89%, 90%, and 92% respectively. From the Fig. 3, the aneurysm looks like a saccular type. The determination of aneurysm type could assist the clinician in deciding the type of treatment that can be offered to the patient. Although, we have not compared our method with other methods to check its potential level or rank, however, the detection is found quite satisfactory in clinically setting.

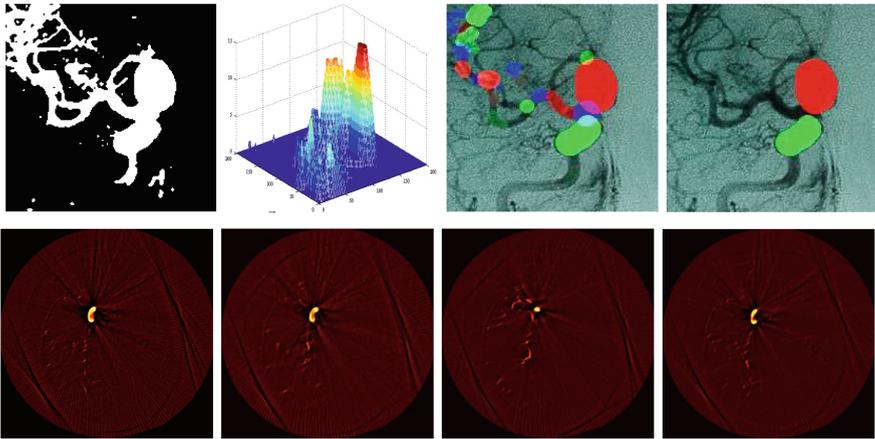


Fig. 3. (a) Simple segmentation by adaptive thresholding. (b) Hough Hierarchy 3D parameter space. (c) Possible aneurysm regions. (d) Final detected aneurysm regions. (e–g) Detected aneurysms.

5 Conclusion

The brain vascular anatomy is huge and complex. Therefore, location and detection aneurysm is paramount before segmentation. Otherwise, the process would be time consuming and there would be higher probability to miss smaller aneurysms that could be present in vascular sub-branches. We have presented a method to detect brain aneurysm in this paper using SR theory, adaptive thresholding, and modified Hough transform. The results are quite satisfactory and promising. In future, we plan to test this method on large database and with other state of art aneurysm detection methods.

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