International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Region-Growing based Hough Transform for Localization of Carotid Artery

[1]Tulika Mandal, [2]Vrishank Mishra, [3]Prof. Anitha M., [4]Prof. Arbind Kumar Gupta

Submitted: 08/01/2024 **Revised**: 13/02/2024 **Accepted**: 23/02/2024

Abstract—Shape recognition is one of the most important tasks in image processing and pattern recognition. A prominent technique employed for circular shape recognition is the Circular Hough Transform algorithm, which is utilized to localize the carotid artery to discern the potential onset of Atherosclerosis disease. In this research, we present a novel multi-seeded iterative region growing based on circular Hough's transform algorithm to locate the center of the carotid artery using ultrasound images to measure the diameter of the artery. The uniqueness of our algorithm is underscored by the automatic selection of multiple seed points randomly, which is then utilized for the region- growing process. Post-processing, the Circular Hough transform is employed to discern the pertinent carotid region. Further, the radius is measured for the diagnosis of Atherosclerosis disease is a cardiovascular disease engendering from plaque buildup in the carotid artery, consequently decreasing its diameter.

Keywords: *uniqueness, Atherosclerosis, plaque, cardiovascular, carotid*

Introduction

Detection of circular objects is one of the common feature extraction tasks in pattern recognition in various fields of computer vision [7]. Many applications, such as iris detection [1], cell counting [2], cell shape identification [10], and bolts [3], use circle-based object detection techniques. Various techniques have been continuously developed to achieve better computational performance and accuracy [7], [1].

In this paper, we propose region-based CHT to localize the carotid artery to monitor the progression of Atherosclerosis disease. Further, this helps prevent Cerebrovascular stroke, a common cause of many deaths worldwide. Cerebrovascular stroke is characterized by the obstruction of blood flow due to the narrowing (stenosis) of the carotid artery. This narrowing is caused due to the formation of plaque in the near and far walls of the carotid artery, leading to Atherosclerosis disease. Detecting circles in ultrasound images poses significant challenges due to noise, low contrast, distortion, and blurred boundaries. These issues arise from the image sensor settings and poor lighting conditions, leading to excessive irrelevant feature extraction, incomplete and distorted circle contours, and a higher incidence of false positives. To tackle these challenges, we suggest a novel strategy involving the utiliza- tion of circular Hough's transform-based iterative multi-seeded region-growing algorithms.

Various techniques were suggested to enhance the efficiency of the Hough Transform (HT). [6], [4]. An improved HT was presented by Yao Z [9], which used a dynamic voting mech- anism for circle detection aided with a curvature technique. Similarly, Xavier [8] used internal tangent angle variance to improve the performance of conventional HT. However, when detecting objects among many multiple circular objects, these methods tend to give inaccurate results. Illingworth et al. [4] introduced the concept of employing adaptable

[1]*Dept. of CSE DSCE Bengaluru, India*
[2]*Dept. of CSE DSCE Bengaluru, India*
[3]*Dept. of CSE DSCE Bengaluru, India*
[4]*Dept. of CSE DSCE Bengaluru, India*
tulikamandal08@gmail.com
vrxshxnk@gmail.com
anitha-cs@dayanandasagar.edu
arbindgupta@dayanandasagar.edu

parameter windows within the Hough Transform, enabling it to identify circle centers and radii in two distinct stages. Ioannou et al. [5] proposed a two-step technique, utilizing a bisection-based 2D Hough Transform to detect circle centers initially, followed by radius histogramming to extract the radii. [5]. These methods reduced storage requirements and computational time by employing a 2D Hough Transform, as opposed to the 3D approach utilized in other methodologies. Most of these algorithms only worked with acceptable results in special cases, while their robustness and universality are insufficient. Moreover, the processing speeds of these algorithms are affected due to the random selection of false pixels, leading to inaccurate results.

Proposed Solution: Multi-Seeded Iterative Region-Growing Segmentation Algorithm And CHT

A. Step 1: Multi-Seeded Iterative Region-Growing Segmenta- tion

The primary objective of our research was to employ Circular Hough Transform-based multi-seeded iterative region- growing algorithm for the purpose of segmentation, with the aim of isolating and identifying the carotid artery. Traditional region growing faces major challenges, such as the manual assignment of a seed point to initiate the algorithm. This approach is suboptimal as it relies on user judgment, which may not always yield the precise seed point necessary for accurate image segmentation.

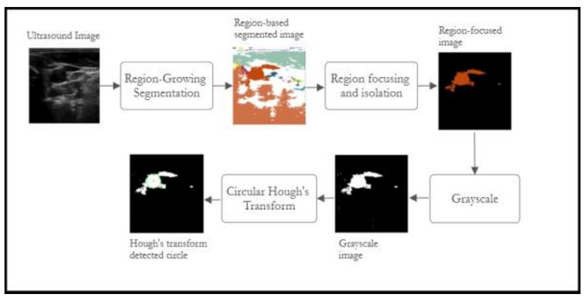


Fig. 1. Block diagram illustrating the sequence of image-processing for localization of the carotid artery

Furthermore, it exhibits limitations in noisy regions, especially in ultrasound images, which are characterized by a lot of speckle noise, creating multiple short regions and leading to inaccurate segmentation. To address these challenges, we propose a novel alternative in the form of an iterative-based multi-seeded region-growing algorithm, which will be elabo- rated upon in the following section. The proposed algorithm operates over a finite range of iterations denoted as N , where N is the frequency of the number of times the region-growing algorithm is applied to segment the ultrasound image. Unlike conventional region-growing methodologies, it omits the necessity for the user to choose a seed point manually to start the segmentation process. Our methodology embod- ies a multi-seeded technique wherein multiple seed points are automatically identified based on the various intensities identified in the ultrasound image. It then groups the other pixels within close proximity into isolated regions based on the similar intensity of the selected seed points. In this manner, our algorithm facilitates the division of the image into discrete regions based on the various intensities in the image.

The algorithm can be illustrated as follows:

Consider an input image (IM) of size $(h,\ w)$ where h and w are the height and width of the image, respectively. A 2D array of the same image size, VIS, is used to track if each pixel is visited or not. We generate a list of random seed points, denoted as random seeds, where each seed point $(x_i,\ y_i)$ is selected based on image dimensions and shuffled.

$$\text{Shuffle}(\{(x_i, y_i) | 1 \leq i \leq m, 0 \leq x_i < h, 0 \leq y_i < w\})$$

In this representation, Shuffle() denotes the operation of shuffling the order of elements in the set, ensuring that the selected seed points are randomly ordered within the image dimensions.

Step 1: Generate the multi-seed pixels randomly. Consider the initial seed pixel (x0, y0) in the image, push (x0, y0) onto the stack, and initialize the region count to 0.

Step 2: Check all the neighboring pixels using the stack, which stores all the visited pixels as follows:

If the stack is not empty, pop (x, y) from the stack and apply the Breadth-First Search (BFS) algorithm by calculating the similarity measure Sim(x, y) by calculating the variance among the region starting at (x0, y0).

Step 3: If Sim(x, y, x0, y0) is below the predefined threshold, mark (x, y) as part of the region.

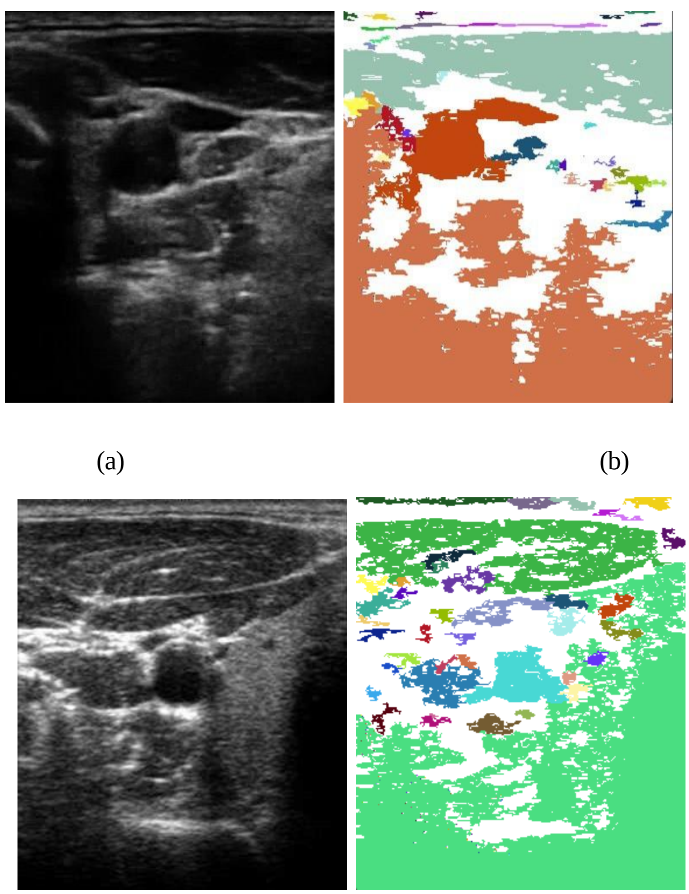
Step 4: After the new pixel is added to the region, update the variance var of pixel intensities in the region generated and then increment the region count.

Step 5: If the region count is too small, it is removed, and a new seed is chosen randomly within a small neighborhood. The process continues from step 2 again until all the pixels are visited using the VIS array.

Step 6: Based on each pixel tracked by VIS contains val which represents a particular region. Each region is assigned a color based on val to identify the segmented regions.

In this representation, $Rg(i, j)$ represents one of the classified regions at pixel (i, j) in the original image I, and $(255, 255, 255)$ denotes a white color (or any other background color) for unclassified regions. Fig. 2(a), and Fig. 2(b) show the original grayscale carotid artery image and the hierarchy-

Consider a circle in the image space. It can be represented by the equation:



(a) (b)

(c) (d)

Fig. 2. Ultrasound images of carotid artery upon undergoing multi-seeded region growing

$$(x - a)^2 + (y - b)^2 = r^2 \quad (1)$$

where (x, y) are the edge points on the circle, (a, b) are the coordinates of the circle centers, and r is the circle radius. Equation (1) establishes a relationship where each point (x, y) lying on the circle's edge in the image space corresponds to a conic surface in the (a, b, r) parameter space, with (a, b) denoting the circle centers and r representing the circle radius. These intersecting conic surfaces converge at (a, b, r), illustrated in Fig. 3.

Upon applying the Hough Transform (HT) to the edge image, a three-dimensional array (a, b, r) is employed to cap- ture the voting outcomes in the (a, b, r) parameter space. [7]. Every transformation of an edge point to the based multi-seeded iterative region-growing-based segmented most prominent

circle = arg max

image, respectively. A similar result has been illustrated for another Ultrasound image in Fig. 2(c) and Fig.2(d).

Following the region-growing segmentation process applied to the ultrasound image, we proceed to the identification and isolation of the largest region representing

B. Step 2: Circular Hough Transform

parameter space increments the corresponding accumulator by 1. Following the processing of all edge points in the image space, the three- dimensional parameter space is constructed. Subsequently, the circle detection task becomes synonymous with identifying local maxima within the 3D parameter space.

A set of detected circles is stored in a 3D array called `circles`, where each circle C_i is stored along with its center coordinates (x_i, y_i) and radius R_i.

We can select the most prominent circle, denoted as the most prominent circle, based on the radius R_i. This can be expressed mathematically as:

$(xi,yi,Ri) \in \text{Circles}$

R_i (2)

the carotid artery. We plan to use Circular Hough's transform (shown in Fig. 4(a) and Fig.4(b)) since its shape-based feature enables helps to recognize the circular region of the carotid artery easily and ignore the remaining smaller regions.

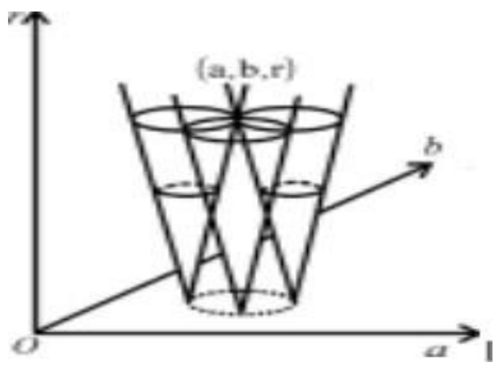


Fig. 3. Circular hough's transform cubic cones intersection

The computation and storage of HT become larger as the number of edge points increases. The region-growing step helps in reducing smaller regions caused by the speckle noise present in ultrasound images. This helps in reducing pro- cessing time and avoiding smaller circular regions, ultimately highlighting the carotid artery from the other regions.

Results:

To evaluate the effectiveness of the proposed method, evalu- ation experiments are performed using a publicly available SP lab carotid artery database. The images used in the experiment are grayscale images containing the transverse view of the carotid artery. The experiment is carried out on a PC with a 2.67 GHz Intel core i10 processor and 8GB RAM.

The output of the proposed method is the identification of the center of the carotid artery and measuring the diameter. We also compared our method with the Standard Hough Transform (SHT) method. Fig. 4(c) and 4(d) show multiple circles detected with SHT. Fig. 4(a) and Fig.4(b) show the results of some of the CA locations identified by the proposed method. The experimental results, as in Fig. 2, show that the proposed algorithm has better performance compared to normal HT. The algorithm accurately located the center of CA 925 US images out of a total of 971 US images, giving a success rate of 95 percent.

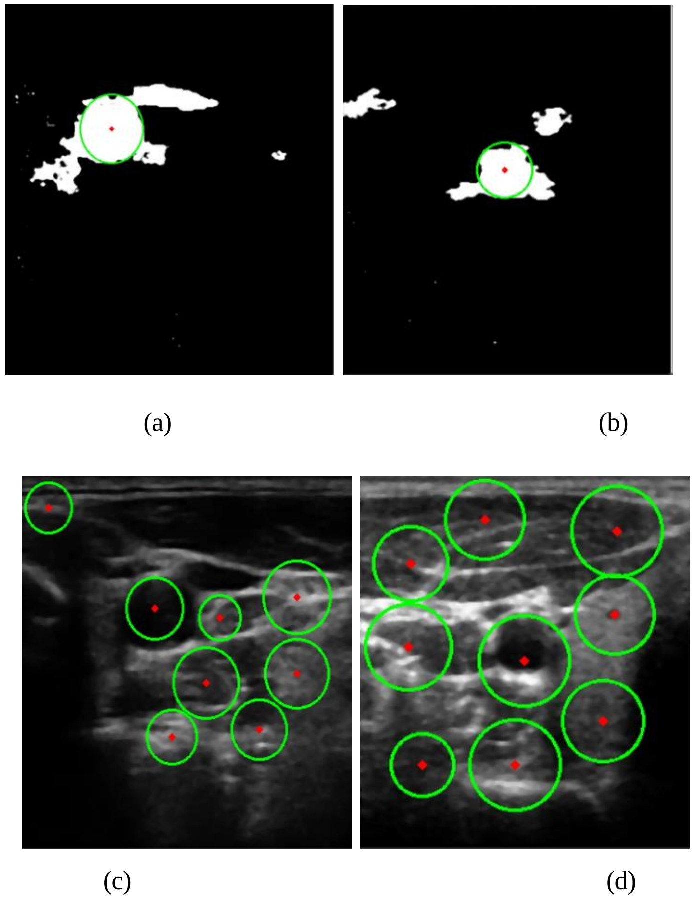


Fig. 4. Fig. (a) and (b) show the localized carotid artery upon applying our proposed algorithm, while (c) and (d) show multiple circles detected by SHT

Conclusion

This paper has presented an algorithm for the automatic detection of the circular shape of the carotid artery even in the presence high SNR of speckle noise in an ultrasound image with a simple region growing based CHT. Based on the experiment results, the proposed method can easily locate the carotid artery since the noisy regions are removed before the CHT is applied. Moreover, the proposed method gives a stable performance and accurate results compared to the other methods. The high computation time can be reduced by parallel processing of the voting process, which can be considered as future work. The possibility is facilitated by the mapping process for each edge pixel, where each is in- dependent. Thus, parallel processing may not create conflicts. The parallelization chances can save time compared to the computation time and can prove to be valuable for localizing the carotid artery for real-time application of monitoring the progression of the disease.

References

[1] Cuneyt Akinlar and Cihan Topal. Edcircles: A real-time circle detector with a false detection control. *Pattern Recognition*, 46(3):725–740, 2013.

[2] JM Bewes, N Suchowerska, and DR McKenzie. Automated cell colony counting and analysis using the circular hough image transform algorithm (chita). *Physics in Medicine & Biology*, 53(21):5991, 2008.

[3] Young-Jin Cha, Kisung You, and Wooram Choi. Vision-based detec- tion of loosened bolts using the hough transform and support vector machines. Automation in Construction, 71:181–188, 2016.

[4] John Illingworth and Josef Kittler. The adaptive hough transform. IEEE Transactions on Pattern Analysis and Machine Intelligence, (5):690– 698, 1987.

[5] Dimitrios Ioannou, Walter Huda, and Andrew F Laine. Circle recogni- tion through a 2d hough transform and radius histogramming. Image and vision computing, 17(1):15–26, 1999.

[6] Lianyuan Jiang. Efficient randomized hough transform for circle detection using novel probability sampling and feature points. Optik, 123(20):1834–1840, 2012.

[7] Richard Szeliski. Computer vision: algorithms and applications. Springer Nature, 2022.

[8] Joao Xavier, Marco Pacheco, Daniel Castro, Anto´nio Ruano, and Urbano Nunes. Fast line, arc/circle and leg

detection from laser scan data in a player driver. In Proceedings of the 2005 IEEE International Conference on Robotics and Automation, pages 3930–3935. IEEE, 2005.
[9] Zhenjie Yao and Weidong Yi. Curvature aided hough transform for circle detection. Expert Systems with Applications, 51:26–33, 2016.
[10] Johan Zakrisson, Staffan Schedin, and Magnus Andersson. Cell shape identification using digital holographic microscopy. Applied optics, 54(24):7442–7448, 2015.