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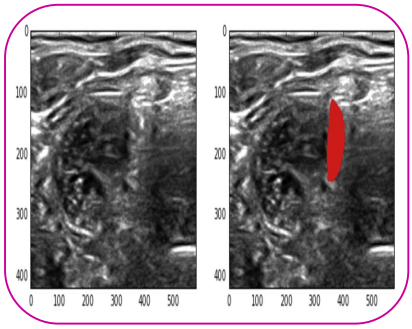
COMPARATIVE STUDY OF SEGMENTATION OF ULTRASOUND IMAGES USING KMEAN AND ACTIVE CONTOUR METHOD



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ABSTRACT—

Carotid artery disease occurs when fatty deposits known as plaques clog the blood vessels that deliver blood to your brain and head, these arteries are carotid arteries. The blockage increases your risk of stroke, a medical emergency that occurs when the blood supply to the brain is interrupted or seriously reduced. In this paper we perform a comparative study of active contour method of segmentation and k mean segmentation in order to determine which method can be employed to detect these depositions and can be further used for classification

KEYWORDS— *segmentation, k mean, active contour .*

1. INTRODUCTION

Digital technology and signals have contributed significantly in field of medical and detection imaging by ultrasound technique and its segmentation is powerfully assertive by the quality of information and continuous development of computer technology, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI), Ultrasonic Imaging (US), Infrared Thermal Imaging (Thermal Imaging), Endoscope imaging (Endoscope),micrograph imaging (Micrograph), Positron Emission Tomography (PET), Digital Subtraction Angiography (DSA) and so on Active contours have been used for image segmentation and boundary tracking since the first introduction of snakes by Kass et al. The idea is to start with first boundary shapes represented in a type of closed curves and iteratively change them by applying shrink/expansion operations according to the constraints of images. Present paper presents a comparison of two methods namely k-means method and active contour method related to image segmentation .

2. THEORY AND METHODOLOGY

Those shrink/expansion operations, called contour evolution, are done by the minimization of an energy function like fixed region based segmentation methods. Active contour evolves the segmentation using an iterative process. A mask is a binary image that specifies the initial state of the active contour. The boundaries of the object regions (white) in mask define the initial contour position used for contour evolution to segment the image. The output image is a binary image where the foreground is white (logical true) and the background is black (logical false). In traditional snakes, the energy is usually formed by internal forces and external forces is described as

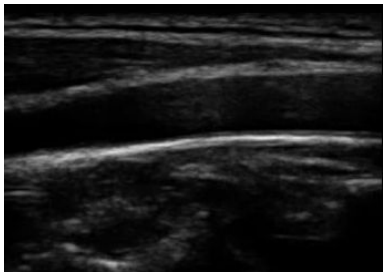
Esnake = Einternal + Eexternal

Einternal tends to elastically hold the curve together (elasticity forces) and to keep it from bending too much (bending forces).Eexternal intends to pull or push the curve towards the edges.

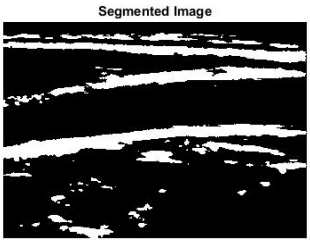
Typically, the external forces consist of potential forces
Although the traditional snakes have found many applications, they
are intrinsically weak in four main aspects.
1. They are very sensitive to parameters.
2. They have small capture range.
3. They have difficulties in progressing onto boundary
concavities.
4. The convergence of the algorithm is mostly dependent of the initial position.
K means divides the given set of data into k groups these groups are called clusters .k-means works in two phases .It calculates k clusters in the first phase and assigns data points to these clusters in second phase .After the grouping is done it recalculates the median and assigns the data point to new clusters

3. COMPARISION AND RESULTS

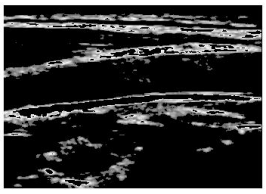
We compare the images after kmean and active contour segmentation has been performed on ultrasound images of carotid artery



The above image is the input image for both the methods



The above image is obtained through active contour segmentation process



The above image is segmented using k mean

Comparison is done with the help of confusion matrix and evaluated using the following metrices –

- Accuracy - It is the ratio of true result in the population
  (tp+tn)/total
- Specificity - It indicates how often the classifier indicates
  tn/(tn+fp)

- Sensitivity -It is the proportion of positives measured as such.
  tp/(tp+fn)
- Border Error- It is the ratio of the area covered by the XOR of segmented result (SR) and ground truth (GT) images to the area covered by GT image.
- Hammoude distance-It makes a pixel by pixel comparison enclosed by the two boundaries.
- Hausdorff distance- It finds the largest distance between the boundary points
- Elapsed time-It is the total time taken for the completion of the program

Methods	Sensitivity (%)	Accuracy (%)	Border Error(%)	Specificity (%)	Hammoude Distance	Hausdorff Distance	Elapsed Time (s)
Active contour	47.18	87.3	54.1	99.3	28.56	7.4	5.20
K mean	90.6	96.88	25.3	96.77	13.3	6.8	0.33

4.CONCLUSION

For correct classification of the deposition in carotid artery most accurate and less time consuming segmentation method is necessary before processing. As it can be observed kmean gives us a better result in terms of accuracy, sensitivity, hammoude distance, hausdorff distance and elapsed time than active contour method although future work for this paper is comparing kmean segmentation technique with other techniques for better results .

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