Analysis of B-Mode Transverse Ultrasound Common Carotid Artery Images using Contour Tracking by Particle Filtering Technique

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Abstract- **In the recent past, object segmentation plays a vital role in medical image analysis for taking subjective decisions by physicians. Segmentation of the common carotid artery (CCA) images using particle filtering is presented in this paper. Noninvasive B-mode transverse ultra sound images of CCA are used for segmentation. Normally, Ultra sound images are affected by speckle noises. For effective segmentation, the noises are to be removed using preprocessing techniques. An edge preserving anisotropic diffusion filter is used for speckle reduction. In the proposed technique, seed points have been initialized to start the segmentation of the contour. The intensities of the pixels lying inside and outside the contour have been used for obtaining likelihood function of the particle filter. This method is highly effective for images that are affected by speckle noises. The proposed method is suitable for segmentation of CCA wall and diagnosis of atherosclerosis and cardiovascular diseases.**

Keywords – Particle filtering, Image Segmentation, Ultrasound image, Medical imaging.

I. INTRODUCTION

In medical image analysis, the problem of segmenting the images into meaningful regions is a challenging and time consuming process. Segmentation is a process of partitioning a digital image into multiple objects. The objective of the segmentation is to change the representation of an image so that it is more meaningful and is easier to analyze. In images, boundaries of the objects such as lines and curves are located using image segmentation.

Particle filtering concepts were applied for images with homogeneous foreground and background. An optimal contour path was determined using local and global constraints by tracking [1]. The structure of a scene was estimated from number of scenes using multi resolution concepts with particle filter [2]. For medical diagnostics and treatment, Monte Carlo algorithm for extracting lesion contours in ultrasound medical images was applied. An efficient multiple model particle filter has been used for contour extraction of medical images [3]. Segmentation of coronary arteries using Bayesian filter based approach has been discussed for successive planes of the vessels as a sequential process [4]. Spatial Kalman filter based tracking approach has been used for the estimation of boundary of CCA without employing any numerical optimization procedure [5]. A method for analyzing noisy medical images has been discussed with Principle Component Analysis based particle filtering for better clinical decision making [6]. Computation complexity of the particle filters have been reduced by Kalman particle filter. Information obtained from the current frame has been used for reducing the number of particles and hence computational complexity [7]. A robust augmented particle filters have been used for visual tracking with fewer particles. Current observations are considered for obtaining proposal distribution. Maximum likelihood shape inference based particle filtering has been used to locate multiple objects with nonlinear gray value variations in images like vertebra in spine radiographs, lung field in thorax X rays and myocardium of the left ventricle in MRI slices. Tracking of moving and deforming objects has been done using particle filter with geometric active contours [5]. An adaptive Gaussian particle filter has been proposed for tracking the contour of human head. Improvement in tracking has been achieved using particle number and noise adaption [10].

Contour tracking is done by edge based methods and region based methods. Edge based methods use gradient to detect the edges. But they do not give closed contour and require post processing. The region based methods use regional features such as pixel intensity. Particle filters use multiple hypotheses so that different possible contours are taken and best possible one is chosen. The main advantage of the particle filter is that it can cope up with nonlinear and non-Gaussian process. Hence particle filter has been considered for segmenting the CCA images.

II. PARTICLE FILTERING

The contour to be extracted from the given image is denoted by $x_{o:n} \equiv (x_o, x_1, \ldots x_k \ldots x_n)$ [8]. Let y be the observed image and all the measurements are taken only from the image. The posterior density $p(x_{k+1} \mid x_{1:k})$ is used to obtain the new contour point x_{k+1} from the observations $y_{1:k} \equiv (y_1, y_2, \ldots. y_k)$ The sequence $x_{o:k}$ is expanded to $x_{0:k+1}$ by adding a new point x_{k+1} based on the prior dynamics $p(x_{k+1} \mid x_{0:k})$ using the measurement data y. The posterior density $p_{k+1}(x_{0:k+1} \mid y)$ is used to obtain x_{k+1}.

$$p_{k+1}(x_{0:k+1} \mid y) \;\alpha\; p(y \mid x_{k+1})\, p(x_{k+1} \mid x_k)\, p_k(x_{0:k} \mid y) \qquad (1)$$

k=0,1…n-1

The posterior density cannot be computed analytically [11]. However it can be approximated by the sequential Monte Carlo frame work. The posterior p_k is approximated by a finite set $\{x_{o:k}^{(m)}\}$ m = 1, 2…..N. Where N is the number of particles or sample paths. The samples are generated from $p_{k+1}(x_{0:k+1} \mid y)$ in two steps. In the first step, prediction is done and updation is done in the second step [9]. In the prediction, the path $x_{o:k}^{(m)}$ is added one point x_{k+1} by sampling the proposal density function $p(x_{k+1} \mid x_k^m)$. In the updation step, the weights are assigned to each particle based on likelihood.

$$w_{k+1}^{(m)} \;\alpha\; w_k^{(m)}\; p(y(\tilde{x}_{k+1}^{(m)})) \qquad (2)$$

The posterior $p_{k+1}(x_{0:k+1} \mid y)$ is approximated by weighted contours $\{\tilde{x}_{o:k+1}^{(m)}, \tilde{w}_{k+1}^{(m)}\}$, m=1, 2…..N. $\tilde{w}_{k+1}^{(m)}$ are the normalized weights and is given by

$$\tilde{w}_{k+1}^{(m)} = \frac{\tilde{w}_{k+1}^{(m)}}{\sum_{m=1}^{N} w_{k+1}^{(m)}} \qquad (3)$$

In sequential importance sampling particle filter, degeneracy occurs after few iterations. When the effective sample size N_{eff} falls below N_{thres}, all but one particle will have negligible weight [9]. The estimate $\hat{N}_{eff}$ of N_{eff} is given by

$$\hat{N}_{eff} = \frac{1}{\sum_{m=1}^{N} (\tilde{w}_k^{(m)})^2} \qquad (4)$$

If $\hat{N}_{eff} < N_{thres}$, sequential importance resampling is applied and weights are replaced with $w_{k+1}^{(m)} = \frac{1}{N}$

The estimate of the best contour path at step k+1 is obtained by finding the mean [3]

$$(\hat{x}_{0:k+1} \mid y) \approx \sum_{m=1}^{N} \tilde{w}_{k+1}^{(m)}\; \tilde{x}_{0:k+1}^{(m)} \qquad (5)$$

III. METHODS

Flow diagram of the proposed contour segmentation procedure is shown in figure 1.

A. Image Acquisition

The B-mode ultrasound images have been acquired using Aloka Prosound Alpha-10. A multi-frequency linear transducer with a frequency range of 5-10 MHz has been used for recording the arterial movements. The transducer is operated at a frequency of 7.5 MHz to obtain the arterial movements and the movements are recorded using video recorder. The recorded video is converted into frames employing OSS video decompiler. The converted frames are stored as still images in a PC for further processing.

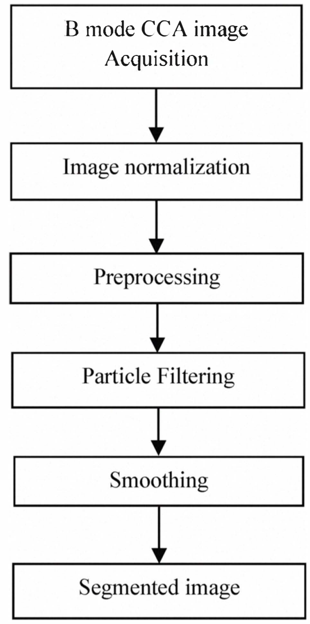

Fig 1. Flow Diagram

B. Image Normalization

The intensities of the pixels are not distributed over the entire dynamic range due to different gain settings, different operators and different machines used. Image normalization attempts to spread the pixel intensities over the entire range of intensities. To perform image normalization average histogram of all images has been carried out first and then the histogram peak of each image is adjusted to align with average histogram. Thus the brightness of all pixels are modified to fit into the entire dynamic range from 0 to 255.

C. Image Despeckling

The ultrasound images are highly corrupted by speckle noise. The ultra sound images have got vital information like intima media, media adventitia interfaces. Hence these information are to be preserved while reducing speckle noises in preprocessing. The speckle noise present in the CCA image can be reduced by adding Gaussian noise and despeckled with Speckle reducing anisotropic diffusion (SRAD) technique. It is shown in the following equation:

$$I_o(x, y) = I(x,y) + \sqrt{I(x,y)n(x,y)} \qquad (6)$$

Where $I_o(x, y)$ is the observed image, I(x,y) is the initialized image and n(x,y) is the Gaussian noise with zero mean. The modeled images have been despeckled using SRAD [10]. It is an efficient nonlinear technique for simultaneously performing contrast enhancement and noise reduction. In the speckle reduction process, homogeneous regions of the image are smoothened and edges are retained. The main concept of an anisotropic diffusion is the introduction of a function that inhibits smoothing at the image edges. This function is called diffusion coefficient. The diffusion coefficient is chosen to vary spatially in such a way to encourage intra-region smoothing in preference to inter-region smoothing. The Partial Differential Equation (PDE) approach to remove speckles in the Ultrasound images is referred as SRAD.

D. *Particle Filter for Common Carotid Artery*

The boundary of the carotid artery resembles circular shape and the all the edges can be viewed from the center of the lumen area. In this algorithm, circular nature of the common carotid artery has been exploited. Figure 2 shows the contour extraction method followed in the proposed algorithm. Contour extraction starts with initialization of two seed points manually. First point x_c is selected in the middle of the lumen area and all the radial distances and angles are measured with respect to this point. The second point is marked on the contour to be extracted from the image. The vector [r θ]' uniquely defines a point on the contour in polar coordinate. At step k, the distance between the seed point x_c and the edge point estimated is $r_{(k)}$ and the corresponding angle is $\theta_{(k)}$. At step k+1, the point $[r_{(k)}\ \theta_{(k+1)}]$ is obtained by moving in radial direction from $[r_{(k)}\ \theta_{(k)}]$ by an angle Δ θ. N Particles are generated along the radial line at angle $\theta_{(k+1)}$ about $r_{(k)}$ based on Gaussian distribution. As the measurement area is between $r_{(k)}$ - L_{min} and $r_{(k)}$ + L_{max}, the particles generated outside this range are assigned to boundaries. The values of L_{max} and L_{min} can be chosen and changed according to the size of the image.

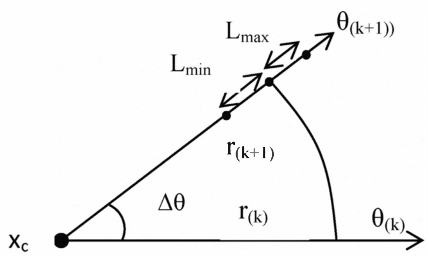

Fig 2. Contour extraction method

The distance and angle of the particles are given by

$$R_{k+1} = r_k + w_{k+1} \tag{6}$$

$$\theta_{k+1} = \theta_k + \Delta\theta \tag{7}$$

where w_{k+1} is the white Gaussian noise with zero mean and variance σ_d^2. Where Δ θ =360/n. For calculating particle weights in (2), the following likelihood [3] is used.

$$p_{on}(\tilde{x}^{m}_{k+1}) \propto G(\tilde{x}^{(m)}_{k+1})^2 \exp\left[-\frac{(\tilde{d}^{(m)}_{k+1} - d_{\max})^2}{2\sigma_e^2}\right] \tag{8}$$

where p_{on} is the likelihood of the pixel x_k, if it belongs to the contour. $d_{\max}$ is the distance between the seed point x_c and the edge point with maximum magnitude. d_k is the radial distance between x_c and the sample point considered

$$G(x_k) = \sqrt{G_x(x_k)^2 + G_y(x_k)^2}$$

$G_x(x_k)$ and $G_y(x_k)$ are the gradient in x and y directions

The radial distance of the contour point estimated in step k+1 is $r_{(k+1)}$ and is used as radial distance for step k+2 for generating particles.

E. Algorithm: Particle filter segmentation

Step 1: Initialize the seed points.
Step 2: N particles are generated at angle Δ θ
Step 3: The weights associated with each particle are calculated based on likelihood measurement.
Step 4: Weights are normalized
Step 5: When the effective sample size *Neff* falls below N_{thres} resampling is performed to avoid possible degeneracy.
Step 6: Best path is obtained by taking the mean
Step 7: Steps 2 to 6 are repeated for 'n' times to estimate n contour points.

F. *Smoothing*

The particle filter algorithm estimates the contour points at n places about the boundary. As the boundary of the CCA image is not clear in few locations, the estimated contour deviates from the actual contour at those locations. Hence the estimated contour is smoothened by using curve fitting.

IV. RESULTS AND DISCUSSION

The B-mode transverse mode ultrasound image of common carotid artery considered for segmentation is shown in figure 3. The figure 4 shows CCA image with two seed points initialized. The speckle noise is removed by anisotropic edge preserving diffusion filter. The preprocessed image is shown in figure 5. The segmented contour wall of the common carotid artery is given in figure 6. The figure 7 shows the macro view of the segmented contour of CCA.

Particle filtering algorithm for segmenting contours in B-Mode ultrasound images is proposed in this method. The circular shape of the CCA images is considered and is exploited for obtaining measurement area. This method is capable of segmenting contours with high accuracy in the presence of speckle noise. Hence this method can be applied for segmentation of CCA wall and it will help physicians in diagnosis of atherosclerosis and cardiovascular diseases.

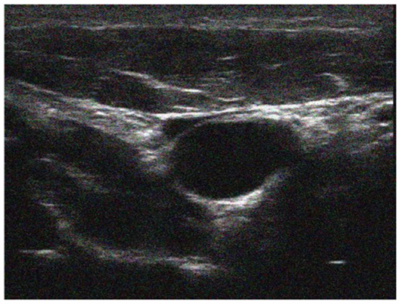

Fig. 3 Input B-Mode CCA image

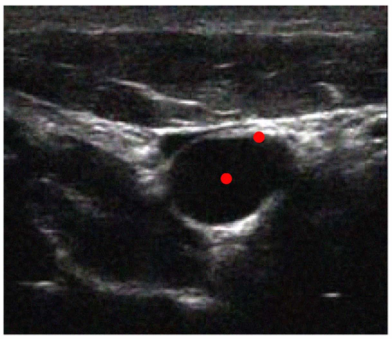

Fig. 4 B-Mode CCA image with seed points initialized

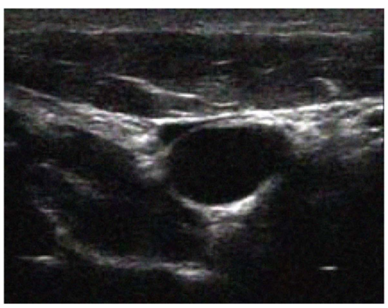

Fig. 5 Preprocessed B-Mode CCA image

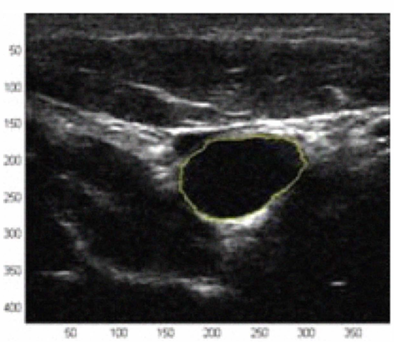

Fig.6 Segmented B-Mode CCA Image

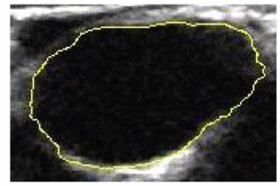

Fig.7 Macro view of the segmented contour

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