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Ultrasound Image Segmentation Using Sequential Monte Carlo Method

Sreepriya P
Research Scholar,
School of Research and Innovation

***Abstract- In* this paper, a Monte Carlo algorithm for extracting lesion contours in ultrasound medical images is proposed and also a method for effectively denoising the extremely corrupted image by fixed value impulse noise using robust estimation-based filter are proposed. The proposed denoising algorithm classifies the pixels of localized window in to "corrupted" or "uncorrupted" and removes only corrupted pixels by robust estimation or by median of the processed neighboring pixels. An efficient multiple model particle filter for progressive contour growing (tracking) from a starting point is developed, accounting for convex, non-circular forms of delineated contour areas. The driving idea of the proposed particle filter consists in the incorporation of different image intensity inside and outside the contour into the filter likelihood function. The filter employs image intensity gradients as measurements and requires information about four manually selected points: a seed point, a starting point, arbitrarily selected on the contour, and two additional points, bounding the measurement formation area around the contour. The filter performance is studied by segmenting contours from a number of real and simulated ultrasound medical images. The performance of the proposed filter in the preservation of edges and details is better even at noise levels as high as 95%.**

Keywords: Ultrasound (US) image segmentation · Robust estimator · Contour tracking · Bayesian inference · Sequential Monte Carlo methods · Particle filter (PF) · Speckle noise.

1. INTRODUCTION

Image processing can take the output of marginally acceptable image acquisition system and make it qualitatively suitable for diagnostic purpose. On the other hand ima:ge processing can also render use less the output of an excellent image acquisition device. Image processing must be done right in order for the complete imaging system to be clinically useful, but right can have different meanings for different application. Image processing of medical image volumes (3D, 4D, 5D), requires a completely new approach compared to standard images (2D).

Object segmentation in medical images is an actively investigated research area. Segmentation techniques are a valuable tool in medical diagnostics for cancer tumours and cysts, for planning surgery operations and other medical treatment. Automated or semi-automated contour extraction is one of the most challenging image processing tasks, pertaining to a great variety of applications. In particular, a segmentation method that could accurately delineate the lesion contours in medical images is of significant importance for diagnostics, image-guided interventions and therapy. Due to the relatively low quality of clinical images, the task of contour segmentation is rather complex. This motivates the considerable interest in segmentation of medical images.

CT and MRI scans are limited in their ability to characterize masses reliably as malignant or benign. Necrotic scan or inflammatory tissue often cannot be differentiated from malignancy based on anatomic imaging alone. Anatomic imaging detects structural abnormalities. Ultrasonography has a special place amongst medical imaging techniques. While it may provide less anatomical detail than techniques such as CT or MR, it has several advantages which make it suitable for numerous applications: imaging the fetus, abdominal organs, heart, breast, muscles, tendons, arteries and veins. It is very safe to use and does not appear to cause any adverse effects. Ultrasound imaging is relatively inexpensive and quick to perform. It is very safe to use and does not appear to cause any adverse effects. Ultrasound imaging is relatively inexpensive and quick to perform.

The aim of this work is to develop an approach for US image segmentation, possessing high estimation accuracy achievable at reasonable computational cost. A powerful approach, avoiding many drawbacks of the optimization procedures, consists in consecutively growing (tracking) of a contour from a starting point according to a certain criterion of efficiency. Our choice of the Bayesian methodology is motivated by its power to solve problems with uncertain-ties, high level of noises and ability to account for the prior information. In this paper proposed a semi-automated approach, motivated by the necessity of real-time applications to a broad range of contour segmentation problems. The positions of four manually selected points are required: a seed point, a starting point and two additional points, bounding the measurement formation area around the contour. In order to reduce the effect of speckle noises and to improve the image contrast, median filtering, smoothing and other pre- filtering techniques are an inherent part of many segmentation approaches for ultrasound medical images.

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Particle filters (PFs) afford maintaining multiple hypotheses in a very compatible and simple manner. Also, constraints on curvature and features of the application can be incorporated into the tracking framework in an easy and natural way.

Particle filtering implements recursive Bayesian estimation via sequential Monte Carlo methods, based on plain sequential importance sampling. This algorithm can be used in any nonlinear system which can be expressed with dynamic state space models, and the precision can approach to optimal estimation. For each time step we then loop with has 3 phases:

- Prediction: take each particle and add a random sample from the motion model. The resulting distribution of particles approximates the prior distribution.
- Update: take the sensor measurements and assign each particle a weight that is equal to the probability of the observing the sensor measurements from that particle's state. Those weights are then normalized so that they sum to 1.
- Resample: A new set of particles are chosen so that each articles survives n proportion to its weights. Resulting distribution is posterior distribution.

Particle filters are also called sequential Monte Carlo methods, bootstrap filters, condensation algorithms, interacting particle approximations and survival of the fittest.

The potential of the robust particle filtering algorithm is called JetStream.. JetStream is a general tool for designing contour tracking algorithms in different application areas. The designer has the freedom to choose appropriate task oriented ingredients: dynamics and measurement models, likelihoods or likelihood ratios and constraints. The authors suggest an oriented particle spray to deal with sharp contour angles. They design a directional probability density function that is better able to control the evolution of the contour.

This paper develops a new segmentation algorithm for ultrasonic images and at the same time extends some of the capabilities of JetStream for efficient and reliable US segmentation. The new elements of the proposed algorithm, compared with JetStream, include:

(1) A multiple model structure that captures the prior dynamics, and governs the growing process of the predicted contour;

(2) A combined likelihood is proposed involving the intensity gradients along *x, y* axes and the radii, projected from the seed point towards the contour;

(3) Incorporation of constraints accounting for the contour convexity.

II.CONTOUR EXTRACTION

Let y as the observed image, which is a source of all measurements, available to the contour estimator. Consider a state vector x, containing point' s x_k in the image plane. Any ordered sequence $x_{O:n} \equiv (x_0|,\ldots, x_k,\ldots, x_n)$ **defines uniquely the contour being tracked.**

Given a prior dynamics $e(x_{k+1} \mid x_{O:k})$, modelling the expected evolution of the contour, the aim is to enlarge the sequence $x_{O:k}$, using the measurement data y.

This can be achieved by recursively calculating the posterior state probability density function (pdf)

$$e_{k+1}(x_{0:k+1} \mid y) \propto e(y \mid x_{k+1}) e(x_{k+1} \mid x_k) e_k(x_{0:k} \mid y) \qquad (1)$$

k = 0, 1, ..., n − 1, where e(y | x_{k+1}) corresponds to the data model. $y(x_k)$ is the gradient norm | ∇ I (x_k)| of image intensity. The starting point x_0 can be chosen manually or automatically.

Then the contour extraction problem, expressed as a minimisation of the function.

$$J_n(x_{0:n}, y) \equiv -\log e(x_{0:n} \mid y) \qquad (2)$$

can be **solved by** finding **the maximum a posteriori** (MAP) estimate of the posterior state pdf. The recursion can not be computed analytically. With in the sequential Monte Carlo frame work, the posterior probability density function $e_k(x_{0:k} \mid y)$ is approximated by a **finite** set $\{x_{0:k}^{(j)}\}, j = 1,\ldots, N$ of N sample paths (particles).

The generation of samples from $e_{k+1}(x_{0:k+1} \mid y)$ is performed in two steps of prediction and update.

At the prediction step, each path $x_{0:k}^{(j)}$ is grown of one step $x_{0:k+1}^{(j)}$ by sampling from the proposal density function $p(x_{k+1}|x^{(j)}_k)$.

At the step of update, each sample path is associated with a weight, proportional to the likelihood of the measurements

$$w^{(j)}_{k+1} \propto w^{(j)}_k e(y(x^{(j)}_{k+1})) \qquad (3)$$

The resulting set of weighted paths $\{x\sim^{(j)}_{O:k+1}, w\sim^{(j)}_{k+1}$ **} ,j=1,…, N with** normalized weights

$$W\sim^{(J)}_{K+1} = W^{(J)}_{K+1} / \sum_{J=1}^{N} W^{(J)}_{K+1} \qquad (4)$$

provides an approximation to the distribution $e_{k+1}(x_{0:k+1} \mid y)$. When an estimate of the effective sample size N

$$N_{eff} = 1/\sum_{j=1}^{K} (W\sim^{(J)})^2 \qquad (5)$$

falls below a threshold N_{thresh}, resampling is realized to avoid possible degeneracy of the sequential importance sampling.

In the resampling step N paths $\{X^{(J)}_{0:K+1}, W^{((J))J}_{K+1}\}$, J, ... Nare drawn with replacement (j)

posterior state pdf $e_{k+1}(x_{O:k+1} \mid y)$), an estimate of the "best" path (contour) at step k + 1can be obtained. The mean

$$D(x_{O:k+1} \mid y) \approx \sum_{j=1}^{N} W\sim^{(J)}_{K+1} X\sim^{(J)}_{O:K+1} \quad (6)$$

represents a Monte Carlo approximation of the posterior pdf expectation. This technique provides sample based approximations of posterior distributions with almost no restriction on the ingredients of the models.

III. PARTICLE FILTER ALGORITHM DESIGN

The models of prior dynamics and measurement data should provide growing of a contour, avoiding slowing down and interruption of the process. This is closely related with the selection of a variable that is analogous to the time variable, since the notion of time is associated with the successive contour **growing. It is natural to assume a fixed time analogue:** for an arc length or for an angle and the choice of a step is application dependent. The measurement data are usually characterized by greylevel distributions and/or intensity gradients (and higher derivatives). The formation of the measurement space is constrained by the probabilistic gating procedure, applied in tracking techniques. In the present paper, the gate space is imposed on the image plane by hard constraints. The **details of filter design are given below.**

Here all contour points can be seen from a seed point inside the lesion cavity. If n equispaced radii are projected from the seed point towards the contour, then an appropriate variable, analogous to the time step is the angle between **the adjacent radii $\Delta\beta = 2\pi/n$. Since** the delineated are a can have an arbitrary (noncircular) shape, a multiple model (hybrid) dynamics is adopted, **describing the contour evolution from angle β_k** to angle $\beta_{k+1} = \beta_k + \beta$, $k = 0,..., n$. Let $x^s = (x^s, y^s)$'be the location of the seed point in the Cartesian coordinate frame, centered at the left and low corner $x^c_0 = (x^c_0, y^c_0)$'of the **image . Let d = (d,β)'**be the location of an arbitrary image point in the relative polar coordinate system, centered at the seed point.

The following discrete angle jump Markov model

$$d_{k+1} = Fd_k + Gu_{k+1}(N_{k+1}) + Bw_{k+1}(N_{k+1}) \quad (7)$$

can describe the contour where $d_k = (d_k, \beta_k)$' is the base (continuous)state vector ,representing contour **point coordinates along the radius, determined by β_k** ,

F is the state transition matrix and u_k is a known control input. The process noise w_k $(m_k)$is a white Gaussian sequence with known variance: w_k **$N(0,\sigma^2_d$** (m_k)).The modal (discrete) state m_k $S \equiv \{1, 2,..., s\}$,

characterizing different contour behavior modes, is evolving according to a Markov chain with known

initial and transition probabilities

$$\pi_{ij} \equiv P_r\{N_{k+1} = j \mid N_k = i\}, (i, j \in S) \quad (8)$$

The control input $u_k(m_k) = (\Delta d_k(m_k), \Delta\beta)$'is **composed of the distance increment $\Delta d_k(m_k)$** and **sampling angle $\Delta\beta$.** In the present implementation the **set of modes S contains three models (s = 3). The first mode (m = 1) corresponds to zero increment ($\Delta d_k = 0$).** It models the "move" regime along the circle. The non-zero increments **(Δd_k** >0for m = 2) and **(Δd_k** < 0for m = 3) are constants corresponding to distance increase or decrease, respectively. The process noise wk models per turbations in the distance increment. The matrices F, G and B have a simple form

$$F = G = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \text{ and } B = (1\ 0)' \quad (9)$$

In this model, the state vector $x_k = (x_k, y_k, d_k, \beta_k)$ contains both the Cartesian coordinates of a contour point with respect to the left down image corner and the polar coordinates with respect to the internal seed point.

IV. PROPOSED SYSTEM

The proposed segmentation algorithm is implemented in three steps of preprocessing, particle filtering and smoothing.

A. Preprocessing

The nonlinear estimation techniques have been gaining popularity in image denoising problems. But they fail to remove noise in high frequencies regions such as edges in the image. To overcome this problem a nonlinear estimation technique has been developed based on robust statistics.

Robustness is measured using two parameters; influence curves and breakdown point. The influence curves tell us how an infinitesimal proportion of contamination affects the estimate in large samples. The breakdown point is the largest possible fraction of observations for which there is a bound on the change of the estimate when that fraction of the sample is changed without restrictions.

A novel method for effectively denoising the extremely corrupted image by fixed value impulse noise

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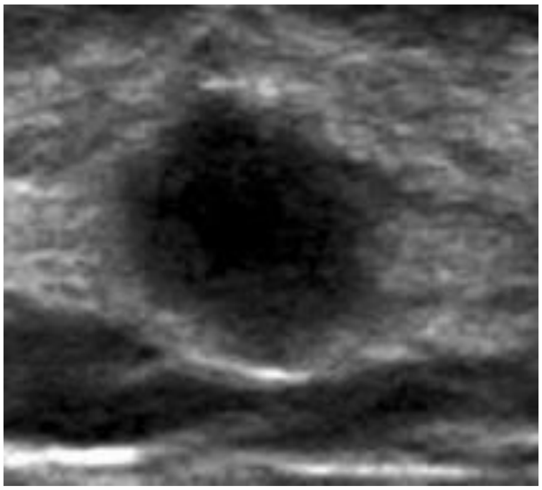
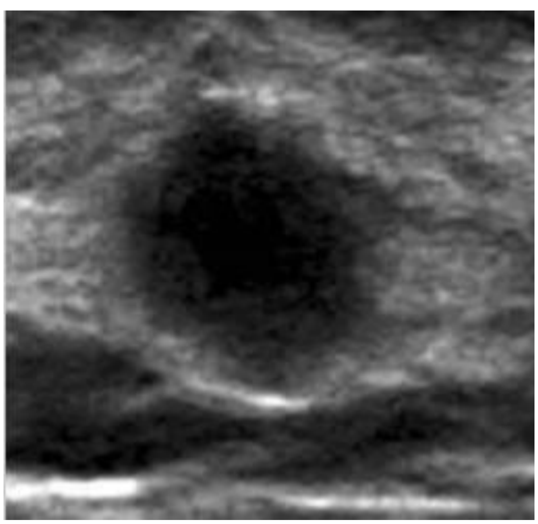
the processed neighboring pixels. This filter effectively removes the impulse noise while preserving the good image quality. The visual and quantitative results prove that the performance of this filter in the preservation of edges and details is better even at noise level as high as 95%. The robust estimation based filter is proposed to remove low to high density impulse noise by using maximum of 7 x 7 window size, which avoids the blurring effect in image.



(a)



(b)

Figure1: Simulated image (a) before and (b) after preprocessing.

B. *Particle filtering*

Particle filtering implements recursive Bayesian estimation via sequential Monte Carlo methods, based on plain sequential importance sampling. This algorithm can be used in any non-linear system which can be expressed with dynamic state space models, and the precision can approach to optimal estimation.

A particle filter (PF) is realised having the particularity that each particle is a contour. With the recursive implementation $k = 0, 1, \ldots, n$ the number of points in each contour $\boldsymbol{x}^{(j)}_{0:k}$, $j = 1, \ldots, N$ increases consecutively, and hence increasing in this way the execution time. It is important to keep a minimum sample size N, achieving the minimum execution time.

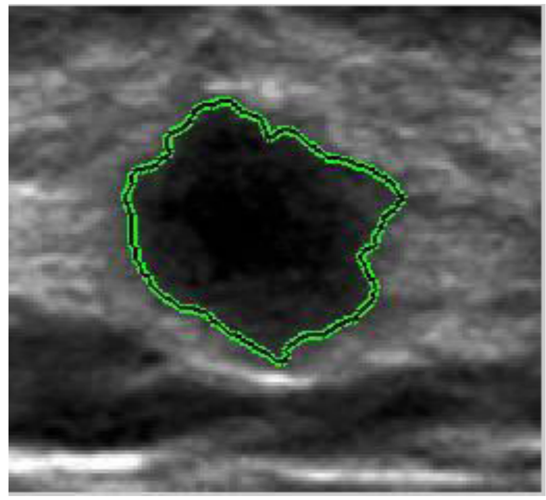


Figure2: segmented output for breast cyst

C. *Smoothing*

The MATLAB curve fitting toolbox is used to smooth the contour curve.

IV. CONTOUR EXTRACTION RESULTS

A. *Segmentation results over simulated images*

The ultrasound simulation package provides an excellent tool for testing newly developed ultrasound sig nal processing and segmentation algorithms.Lesions with different shapes—circular,elliptical and Cassinian oval are designed to obtain echo genicity map of the phantoms. The image, generated by using compounding and coded excitation with signal-to-noise ratio SNR = 1[dB] additive noise. The experiments show, that the number of particles depends mainly on the size of the gating area. The nearly circular form affords maintaining a smaller gate in comparison with the ellipse and cassinian oval. Therefore, the same estimation quality is achieved with a smaller sample size.

B. *Segmentation Results over Real Images*

The segmentation of a breast cyst, ovarianus, **thyroidand Pancreas .The particle filtering algorithm** produces convergent contours with good estimation accuracy. Based on extensive experiments with the **filter, it made conclusions about the influence of the** prior dynamics and measurement formation on the estimation process.

C. Number of initial starting points for contour segmentation

The number of initial starting points can be reduced to three or respectively to two, by using additional information. In a statistical procedure is proposed for automatic localisation of the starting point $\boldsymbol{x}_0$, based on the image gradient intensity. The number of the initial points can be further reduced to two if the foreground is significantly different than the background. A piecewise estimate $\boldsymbol{x}_{\min}$ is automatically determined, based on then empirical intensity distribution inside and outside the lesion.

D. Execution time and signal to noise ratio:

The computational complexity is another important issue that investigated. By using the nonlinear method for preprocessing part, the execution time is 57.9569 and the psnr value is 34.7413. The execution time of the proposed method is 17.4928 and the psnr value is 34.7413.

Parameters	Image Denoising by Nonlinear Gaussian Method	Image Denoising by Robust Estimator
Psnr	34.7413	39.7413
Time	57.9569	17.4928

Table 1: Comparison of 2 image denoising methods

V. CONCLUSION

A multiple model particle filtering algorithm for segmenting contours in ultrasound medical images is proposed in this paper. Some of the advantages of the simulation-based Monte Carlo techniques are shown: multiple hypotheses governed contour dynamics and measurement gating based on constraints. The main novelty of this paper is in the proposed likelihoods that integrate the features of the grey-level distributions inside and outside the segmented areas with intensity gradient information. The algorithm can be applied to different types of images, including from medical applications. The restriction is related with the convexity of the segmented objects. In the general case, four manually selected points are necessary for its proper operation. However, if it is applied to a concrete clinical task, the number of necessary points could be reduced. Very good estimation accuracy is achieved at the cost of acceptable computational complexity and convergence rate.

The proposed denoising algorithm addresses two problems: blurring of images for large window sizes and poor noise removal for smaller window size, which are encountered in other methods. The proposed method uses the window size 7 x 7, which reduces the burring effect compared to the methods that use larger window size for filtering. The performance of noise removal is also better than smaller window filters. The selected window size ensures the higher correlation between pixels; this provides more edge details, leading to better edge preservation. The corrupted pixels up to 7 x 7 window sizes are replaced by robust estimator and above this window size corrupted pixels are replaced by median of the processed neighboring pixels that leads to better result than other existing methods. The proposed filter also shows effective filtering performance across wide range of noise density varying from 10% to 90%.

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