Contour Extraction from Ultrasound Images
Viewed as a Tracking Problem

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Abstract – This paper focuses on the problem of contour extraction in medical images and shows that this segmentation task can be viewed as a tracking problem. The influence of the speckle noise and of the high non-linearities is overcome by Monte Carlo methods. An efficient multiple model Monte Carlo algorithm for progressive contour growing (tracking) is developed, accounting for convex, non-circular forms of delineated contour areas. The driving idea of the proposed filter consists in the incorporation of different image intensity inside and outside the contour into the filter likelihood. A PDA procedure using the contour edge magnitude is applied to cope with the measurement origin uncertainty. The filter performance is studied by extracting contours from a number of real and simulated ultrasound medical images and very good accuracy is achieved.

Keywords: Contour extraction, Monte Carlo methods, Particle Filter, Ultrasound images.

1 Introduction

Automated or semi-automated contour extraction is one of the most challenging image processing tasks, pertaining to a great variety of applications. Medical diagnostics relies significantly on images, often with low quality which makes the diagnostics challenging and requires complex processing algorithms for contour extraction [1].

There is a great deal of approaches for medical image segmentation such as active contour models [2], expectation-maximisation [3], principal component analysis [4], level sets [5] and Monte Carlo techniques [6]. Most approaches can be classified in two groups: 1) off-line techniques - quite accurate, but computationally demanding, and 2) on-line fast algorithms, less precise, but suitable for real time applications.

In this paper we develop an approach for fast contour extraction, possessing very good estimation accuracy achievable at reasonable computational costs. Our approach avoids some drawbacks of the optimisation procedures and consists in consecutively growing (tracking) of a contour from a starting point according to a certain criterion of efficiency. We adopt the Bayesian methodology motivated by its power to cope with different kinds of uncertainties, high level of noises and to account for the prior information, as shown in numerous applications surveyed in [1,7]. A number of contour extraction algorithms exploit tracking techniques, e.g., Kalman filtering with an adaptive measurement association gate [8] for prostate border estimation or multiple hypothesis tracking (MHT) for multiple potential contours, which technique is able to avoid contour losses in areas with high level of speckle noise.

Tracking methods are adopted also in [9] for the purposes of heart chambers and breast cyst segmentation. The recursive contour growing is governed by a finite set of switching dynamical models and thus its behavior can be predicted in a probabilistic sense. Candidate edge points, obtained around the predicted contour, represent both a measurement of the true contour position and some false returns. Contour trajectory models are probabilistically chosen within an interacting multiple model (IMM) estimator and a probabilistic data association filter (PDAF) [16]. The accuracy of the IMM-PDAF [9, 10] is shown over convex, non-circular lesion forms of prostate, carotid artery, jugular vein ultrasound images.

In contrast with the MHT and IMM-PDA estimators, which belong to the class of analytical approximations to the optimal Bayesian solution, the sampling (Monte Carlo) approximations offer more accurate representation of multi-modal distributions, inherent to medical images. Particle filters (PFs) as representatives of Monte Carlo methods afford maintaining multiple hypotheses in a very compatible and simple manner. Also, constraints on curvatures and features of the objects in the image can be incorporated into the tracking framework in an easy and natural way.
A robust particle filtering algorithm for contour following is developed in [11]. The potential of this algorithm (called JetStream) is demonstrated in the context of the interactive cut-out in photoediting applications.

This paper develops a new algorithm for contour extraction in ultrasound (US) 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 and the empirical model of intensity distribution inside and outside the segmented object; 3) incorporation of constraints accounting for the contour convexity.

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 US medical images [1]. In our approach, a non-linear Gaussian filter, performing edge preserving diffusion is applied [12, 13].

A high quality segmentation algorithm should provide fully automated contour extraction, without an operator’s intervention. There exist a number of techniques for image partitioning, localizing the areas and points of interests [1, 8]. Some of them combine conventional intensity-based thresholding with fuzzy logic and elaborated decision making rules under uncertainty. However, the quality of automatic segmentation highly depends on the homogeneity of the background and foreground intensity distributions. Also, the feasibility of the algorithms is often limited to a certain class of clinical applications, realised on concrete US machines. We propose a semi-automated approach, motivated by the necessity of real-time applications to a broad range of contour segmentation problems. The positions of three manually selected points are required: a seed point and two other points, bounding the measurement formation area around the contour.

The remaining part of the paper is organised as follows. Section 2 formulates the problem of contour following as a task of tracking and outlines its approximate solution by particle filtering. The proposed multiple model particle filter is presented in Section 3. The stages of the algorithm: preprocessing, filtering and smoothing, are concisely outlined in Section 4. Section 5 validates the performance of the algorithm over real medical US images. Conclusions are given in Section 6.

2 Contour Extraction Viewed as a Tracking Problem

Let \( y \) be the observed image, the intensity of which is used as a measurement in the filter. Consider a state vector \( x \), containing points \( x_k \) in the image plane. Any ordered sequence \( x_0, \ldots, x_n \) defines uniquely the contour to be tracked [11]. Given a prior dynamics \( p(x_{k+1}|x_{0:k}) \), modeling the expected evolution of the contour, the aim is to enlarge the sequence \( x_{0:k} \), using the measurement data \( y \).

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

\[
p_{k+1}(x_{0:k+1}|y) \propto p(y|x_{k+1})p(x_{k+1}|x_k)p_k(x_0|y), \tag{1}
\]

where \( p(y|x_{k+1}) \) corresponds to the data model. Often \( y(x_k) \) is the gradient norm \( |\nabla I(x_k)| \) 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

\[
\mathcal{J}_n(x_{0:n}, y) \equiv -\log p_n(x_{0:n}|y), \tag{2}
\]

can be solved by finding the maximum a posteriori (MAP) estimate (or the expectation) of the posterior state pdf.

The recursion (1) cannot be computed analytically. It can be calculated approximately within the sequential Monte Carlo framework. Then the posterior density function \( p_k(x_0|y) \) is approximated by a finite set \( \{x_{0:k}^{(j)}\}, j = 1, \ldots, N \) of of N sample paths (particles).

The generation of samples from \( p_{k+1}(x_{0:k+1}|y) \) is performed in two steps of prediction and update [17]. At the prediction step, each path \( x_{0:k}^{(j)} \) is grown with one step to obtain \( \tilde{x}_{0:k+1}^{(j)} \) by sampling from the proposal density function \( p(x_{k+1}|x_{0:k}^{(j)}) \). At the update step, each sample path is associated with a weight, proportional to the likelihood of the measurements

\[
w_{k+1}^{(j)} \propto w_k^{(j)} p(y|\tilde{x}_{k+1}^{(j)}). \tag{3}
\]

The resulting set of weighted paths (contours)

\[
\{\tilde{x}_{0:k+1}^{(j)}, w_{k+1}^{(j)}\}, j = 1, \ldots, N
\]

with normalised weights

\[
\tilde{w}_{k+1}^{(j)} = w_{k+1}^{(j)}/\sum_{j=1}^{N} w_{k+1}^{(j)},
\]

provides an approximation to the distribution \( p_{k+1}(x_{0:k+1}|y) \).

When an estimate of the effective sample size \( N_{\text{eff}} = 1/\sum_{j=1}^{N} \left(\tilde{w}_{k}^{(j)}\right)^2 \) falls below a threshold \( N_{\text{thresh}} \), resampling is realised to avoid possible degeneracy of the sequential importance sampling [17]. In the resampling step \( N \) paths \( \{x_{0:k+1}^{(j)}, w_{k+1}^{(j)}\}, j = 1, \ldots, N \) are drawn with replacement from the previous weighted set, where \( w_{k+1}^{(j)} = 1/N \).

Based on the discrete approximation of the posterior state pdf \( p_{k+1}(x_{0:k+1}|y) \), an estimate of the "best" path (contour) at step \( k + 1 \) can be obtained. The path with
a maximum weight (before resampling) provides an approximation to the MAP estimate. The mean
\[
E(x_{0:k+1}|y) \approx \sum_{j=1}^{N} \frac{w_{k+1}^{(j)}}{w_{k+1}^{(0)}} \tilde{x}_{0:k+1}^{(j)}
\]
represents a Monte Carlo approximation of the posterior pdf expectation.

3 PF Algorithm Design

The models of prior dynamics and measurement data should provide growing of a contour, avoiding slowing down and interruption of the process [11]. 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 step: for an arc-length or for an angle and the choice of a step is application dependent. The measurement data are usually characterised by grey level 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 [9, 16]. In the present paper, the gate space is introduced on the image intensity by hard constraints. The details of the filter design are given below.

3.1 Prior Dynamics

We consider the typical case of lesions with a convex form, where all contour points could be seen from a seed point inside the lesion cavity [9]. 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 area can have an arbitrary (non-circular) shape, multiple models describe contour evolution from angle \( \beta_k \) to angle \( \beta_{k+1} = \beta_k + \Delta \beta \), \( k = 0, \ldots, n \). Let \( x^* = (x^*, y^*)' \) be the location of the seed point in the Cartesian coordinate frame, centered at the left and low corner \( x_0^* = (x_0^*, y_0^*)' \) of the image (Fig. 1). Let \( d = (d, \beta)' \) be the location of an arbitrary image point in the relative polar coordinate system, centered at the seed point. Consider the following model of the discrete-angle jump Markov contour dynamics
\[
d_{k+1} = Fd_k + Gu_{k+1}(m_{k+1}) + Bw_{k+1}(m_{k+1}),
\]
where \( d_k = (d_k, \beta_k)' \) is the base (continuous) state vector, representing contour point coordinates along the radius, determined by \( \beta_k \). \( F \) 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: \( w_k \sim N(0, \sigma_w^2(m_k)) \). The modal (discrete) state \( m_k \in \mathbb{S} \equiv \{1, 2, \ldots, s\} \), characterising different contour behaviour modes, is evolving according to a Markov chain with known initial and transition probabilities
\[
\pi_{ij} \triangleq \Pr \{m_{k+1} = j \mid m_k = i\}, \quad (i, j \in \mathbb{S}).
\]
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 \( \mathbb{S} \) 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 \( (\Delta d_k > 0 \text{ for } m = 2) \) and \( (\Delta d_k < 0 \text{ for } m = 3) \) are constants corresponding to distance increase or decrease, respectively. The process noise \( w_k \) models perturbations in the distance increment. The matrices \( F, G \) and \( B \) have a simple form
\[
F = G = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad \text{and} \quad B = \begin{pmatrix} 1 \\ 0 \end{pmatrix}'.
\]
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 on the left-down image corner and the polar coordinates of the internal seed point.

3.2 Constraints

Taking into account the proposed convex form of the contour, the area of measurement formation is bounded by an inner circle and an outer ellipse (as shown on Fig. 1). Two points, \( x_{\min} \) and \( x_{\max} \), selected manually, determine the gating area. The distances \( d_{\min} \) and \( d_{\max} \) of the points in the polar coordinate system correspond respectively to the circle radius \( R_c \) and the major semi-axis of the ellipse \( R_{max} \). The variable \( \gamma = R_{max} - R_c \) is used as a design parameter. It can be viewed as a kind of aspect ratio. The minor semi-axis of the ellipse is calculated according to the relationship: \( R_{min} = R_c + 2/3R_{max} \).

Suppose that a cloud of \( N \) particles \( \{\tilde{x}_{k+1}^{(j)}\}, j = 1, \ldots, N \) is predicted at the angle \( \beta_{k+1} \) according to the state evolution equation (5). At this stage, constraints are imposed on particles falling outside the boundaries,
and these particles are forced to accept the coordinates of the boundaries. Then, the likelihood is computed for each particle, situated inside and on the boundaries.

### 3.3 Likelihood

The likelihood \( p(y|x_{k+1}) \) in the relationship (1) has different forms, depending on the particular application. We suggest a likelihood model that takes into account both the gradient model of the data and the empirical model of intensity distribution. The likelihood function

\[
\ell \propto p(y|x_{k+1}), \quad \ell = \psi_g \ast \psi_e
\]

incorporates two components. The first term \( \psi_g \) contributes to the gradient (contour) information and the second component \( \psi_e \) inserts the features of intensity distribution inside and outside the segmented area.

Relying on the gradient information, several edge points could be detected in the gating area. From the tracking point of view, they represent a measurement of the true contour position as well as some false returns. We have explored two edge detection algorithms. The first one utilises the gradient information along the radii, projected from the seed point towards the contour. The second algorithm involves the intensity gradients along \( x \) and \( y \) axes.

Suppose that \( M \) pixels \( r_i(k+1) = (d_i(k+1), \beta_{k+1})', \) \( i = 1, \ldots, M, \) are situated on the segment, limited by the imposed constraints. The pixels’ coordinates in the Cartesian plane are respectively \( x_i(k+1) = (x_i(k+1), y_i(k+1))' \).

**Edge detection algorithm A.** According to [9], the following filter is applied for edge detection:

\[
F^{A}_{\text{edge}} (d_i, \beta) = \frac{1}{3} \left(1 - I (d_i, \beta) \right)^2 \times \\
I (d_i + 2\delta r, \beta) + I (d_i + \delta r, \beta) + I (d_i, \beta) - \\
I (d_i - \delta r, \beta) - I (d_i - 2\delta r, \beta) - I (d_i - 3\delta r, \beta),
\]

where \( \delta r \) is radial increment (design parameter) from \( d_i \) along the radius, \( I (d_i, \beta) \) is the local gray-level normalised image intensity and \( i = 1, \ldots, M \). Here, \( F^{A}_{\text{edge}} (d_i, \beta) \) is magnitude of the edge at the point \( r_i(k+1) = (d_i(k+1), \beta_{k+1})' \), calculated along the radius.

**Edge detection algorithm B.** A simple gradient operator is adopted by [15]

\[
g_x (x_i, y_i) = I (x_i + 2\delta x, y_i) + 2I (x_i + \delta x, y_i) - \\
2I (x_i - \delta x, y_i) - I (x_i - 2\delta x, y_i),
\]

\[
g_y (x_i, y_i) = I (x_i, y_i + 2\delta y) + 2I (x_i, y_i + \delta y) - \\
2I (x_i, y_i - \delta y) - I (x_i, y_i - 2\delta y),
\]

\[
F^{B}_{\text{edge}} (x_i) = \sqrt{g_x (x_i, y_i)^2 + g_y (x_i, y_i)^2}
\]

where \( \delta x \) and \( \delta y \) are increments from \( x_i \) and \( y_i \) along \( x \) and \( y \) axes. The index \( k+1 \) in the relationships (6) and (7) is dropped for the sake of simplicity. Similarly to \( F^{A}_{\text{edge}} (d_i, \beta) \), \( F^{B}_{\text{edge}} (x_i) \) denotes the magnitude of the same edge point \( (d_i(k+1), \beta_{k+1})' \), but calculated along \( x \) and \( y \) coordinates.

The edges with maximum magnitudes \( F^{B}_{\text{edge}} \), (detected in the gate for each step \( k \)) are presented on Fig. 1 by red points. The set of \( M_e \) edge points with maximum magnitudes takes part in the likelihood \( \psi_g \) computation, according to the probabilistic data association (PDA) procedure [16]. The likelihood of each particle \( L(x^{(j)}_{k+1}) \) accounts for all \( M_e \) edge points-to-particle association hypotheses

\[
L(x^{(j)}_{k+1}) = \sum_{i=1}^{M_e} F_{\text{edge}}^A (d_i, \beta) (i)^2 \exp \left\{ \frac{(d_i(k+1) - \tilde{\beta}^{(j)}_{k+1})^2}{2\sigma^2} \right\}
\]

\[
\psi_g (x^{(j)}_{k+1}) = L(x^{(j)}_{k+1}) \sum_{j=1}^{N} L(x^{(j)}_{k+1}),
\]

where \( x^{(j)}_{k+1} = (\tilde{x}^{(j)}_{k+1}, \tilde{y}^{(j)}_{k+1}, \tilde{\beta}^{(j)}_{k+1})' \), \( j = 1, \ldots, N \) are coordinates of the predicted particles and \( \sigma^2 \) is a design parameter. In the results, presented below, this parameter takes value of \( \sigma^2 = 4 \).

The probability density function of the image intensity is approximated by a Gamma distribution. Denote by \( p_{\text{in}} \equiv p_{\text{in}}(y|x_{k+1}) \) the likelihood of the pixel \( x_{k+1} \), if it is inside the segmented area. Denote by \( p_{\text{out}} \equiv p_{\text{out}}(y|x_{k+1}) \) the likelihood of the same pixel, if it is outside the segmented region. The likelihood multiplier [14]

\[
\psi_e = p_{\text{in}} \ast p_{\text{out}}
\]

extracts useful information, regarding intensity properties inside and outside the segmented object. Normalised intensity histograms for the image parts inside and outside the liver tumor are presented in Fig. 3(b). It can be seen from the figure, that Gamma distribution provides a good approximation to the empirical data. The combined likelihood is used for the update of the particle weights (3)

\[
\ell(x_{k+1}) = \psi_g (x_{k+1}) \ast p_{\text{in}}(x_{k+1}) \ast p_{\text{out}}(x_{k+1}).
\]

The updated weights take part in the calculation of the current contour estimate

\[
(x_{0:k+1} | y) \approx \sum_{j=1}^{N} \frac{\tilde{w}^{(j)}_{k+1}}{\tilde{w}^{(j)}_{k+1}} (\tilde{x}^{(j)}_{0:k+1}).
\]

**Starting point definition.** The initial (starting) position of the contour \( x_0 \) is marked on the radius, determined by the points \( x^* \) and \( x_{\text{max}} \). It is the edge point with a maximum magnitude, evaluated by edge detectors \( A \) or \( B \), as it can be seen from Fig. 2.
4 Algorithm Outline

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

Preprocessing. A preliminary noise filtering is implemented with a non-linear Gaussian filter, performing edge preserving diffusion [12,13]. The images have been processed by a filter chain with three stages and initial parameters $\sigma_x = 1.0$ and $\sigma_z = 0.25$.

Particle Filtering. A multiple model particle filter (MM PF) is realised having the particularity that each particle is a contour. A PDA procedure with contour amplitude feature (edge amplitude) is incorporated into the filter, dealing with the uncertainty of multiple measurements (multiple detected edges) in the gate [9].

Smoothing. The MATLAB Curve Fitting Toolbox is used to smooth the contour curve. The implementation of this post-processing step is optional, in the cases of roughness of the contours. The estimated and smoothed (by the standard moving average built-in procedure) ovary contours are presented in Fig. 5.

5 Contour Extraction Results

According to [1], “there is a general lack of standardisation of performance measures”. This makes difficult the quantitative validation of image segmentation algorithms. Since “there are also no standard databases on which different groups can compare methods”, the quality of our segmentation algorithm is tested over a variety of simulated and real images, obtained by the Internet ultrasound image database: tumor and lesion images (http://www.ultrasound-images.com/).

Design parameters. The selected sampling angle is $\Delta \beta = 1$ [deg], corresponding to $n = 360$ equally spaced radii. A MM PF with three models $s = 3$ is designed for estimating the contour state vector. Each model has different radial incitement: $\Delta d = 0$ for $m = 1$, $\Delta d = \gamma/4$, $(m = 2)$ and $\Delta d = -\gamma/4$ for $m = 3$, where $\gamma = R_{\max} - R_c$ is the aspect ratio. The standard deviation of the process noise $w_k \sim N(0, \sigma^2_k(m_k))$, modeling the perturbations in the distance increment is chosen equal to $\sigma_d = \gamma/16$, the same for all models. The filter is initialised with the coordinates of the starting point $x_0$. The initial mode probability vector of the Markov chain, governing the model switchings is: $P_0 = (0.8, 0.1, 0.1)$. The transition probability matrix $\pi$ has respectively the following diagonal $\pi_{ii} = 0.8$ and off-diagonal $\pi_{ij} = 0.1$ elements, $i, j = 1, 2, 3$. The developed algorithm has been tested with a different number of candidate edge points $M_e$ in the PDA procedure: $M_e = 4$ and $M_e = 10$. The threshold for resampling is $N_{\text{thresh}} = N/10$.

Experiments. Several edge detection algorithms have been explored for the purposes of object segmentation. The algorithm A, presented in [9] has shown very good results over a wide range of US images.

The motivation of using edge detector B is due to the larger edge magnitudes compared with the gradient norm and edge detector A. The results, however, show that in the cases of higher noise levels, the edge detector
A finds out the correct contour edges with a higher confidence. The contours of a liver tumor, outlined by edge detector B are plotted in Fig. 4. The background and foreground characteristics are rather contrasting (as shown in Fig. 3(b)) and this additionally helps the contour tracker through the likelihood $\varphi_e$. The post-processing step is not implemented here.

Figure 5 shows the results for ovary segmentation with edge detector A. The estimation accuracy is very high, especially in the star-shape parts of the object. The lower no-star part of the contour is segmented with less details, due to the imposed convexity constraint. The non-homogeneous background image intensity (Fig. 6(a)) affects negatively the segmentation process. In this case and a number of other similar images the edge detector A certainly outperforms detector B (Fig. 6(b)).

The results from detector B with an increased number of points in PDA procedure $M_c = 10$ and likelihood $\varphi_e$ are better than the results with $M_c = 4$. However, the increase of $M_c$ usually leads to the smoothed contour and some segmentation details could be missed (Fig. 7). The intensity properties inside of a breast cyst (Fig. 8) are very different from Gamma distribution. The results, given in Fig. 8(c) are based on the likelihood $\varphi_g$ only. The better quality of edge detector A is due to its correct detection of contour edges with a maximum amplitude, as it can be seen from Fig. 8(a). The blurrness of the edges with maximum magnitude in detector B (Fig. 8(b)) deteriorates its results.

As a whole, the MM particle filtering algorithm produces convergent contours with a very good estimation accuracy. The incorporation of intensity likelihood $\varphi_e$ improves considerably the segmentation process in the cases of relatively homogenous intensity distributions. The edge detector A is more adaptive to the low quality images with a high levels of speckle noise than edge detector B.
Computational time. The processing time of a contour with $n = 365$ contour points and sample size $N = 500$ is approximately $t_{ex} = 5 \text{[min]}$ on a conventional PC (AMD Athlon(tm) 64 Processor 1.81 GHz) and in MATLAB environment. The contour quality is almost the same for $N = 500$, 800 and $N = 1000$. If the other design parameters are properly selected, the sample of $N = 500$ particles provides sufficient estimation accuracy. All presented results are obtained with a sample size $N = 500$.

Automatic selection of $R_c$. One suggestion for selecting the inner bound of the gate is shown on Fig. 9. The procedure is experimented on breast images with approximately circular lesions and relatively homogeneous background and foreground intensities. The segmentation area is divided into $N_s = 12$ angular sectors of size $2\pi/N_s \text{[rad]}$. The intensities of all pixels in each sector constitute a representative sample of the intensity distribution. A partition of the sample into two parts (inside and outside the contour) could be done by using either the histogram or the position of the edge point with a maximum magnitude. Based on some quantile of the empirical cumulative intensity distribution inside the contour, an intensity threshold could be determined, which locates the inner bound of the gating area. The obtained inner gate bounds for all sectors are displayed on Fig. 9 (a). The segmentation results are shown on Fig. 9 (b).

6 Conclusions

A multiple-model particle filtering algorithm for extracting contours in ultrasound medical images is proposed in this paper. A PDA procedure using the contour edge magnitude is applied to cope with the ambiguity of multiple measurements (multiple detected edges) in the gate. The likelihood function incorporates the gradient information of the image data as well as the features of intensity distribution inside and outside the segmented area. Based on these tracking techniques a robust on-line contour tracking algorithm is proposed. The algorithm can be applied to a broad class of medical images.
In the general case, three 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 to the seed point only. The restriction of the application is related with the convexity of the segmented objects. The algorithm performance is studied by segmenting contours from a number of real US images. A very good estimation accuracy (in the class of on-line procedures) is achieved at the cost of acceptable computational complexity.

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