

# AN UNSUPERVISED MULTISCALE APPROACH FOR THE DYNAMIC CONTOUR-BASED BOUNDARY DETECTION ISSUE IN ULTRASOUND IMAGERY

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## ABSTRACT

We<sup>1</sup> present a new multiscale approach for deformable contour optimization. The method relies on a multigrid minimization method and a coarse-to-fine relaxation algorithm. This approach consists in minimizing a cascade of optimization problems of reduced complexity. Contrary to classical multi-resolution algorithms, no reduction of image is applied. The family of defined energy functions are derived from the original (full resolution) objective function, ensuring that the same function is handled at each scale and that the energy decreases at each step of the minimization process. The efficiency and the speed of this approach is demonstrated in the difficult context of the boundary detection of anatomical structures in ultrasound imagery.

## 1. INTRODUCTION

Segmentation remains a necessary step in medical imaging to obtain qualitative measurements such as the location of objects of interest as well as for quantitative measurements such as area, volume or the analysis of dynamic behavior of anatomical structures over time. Among these images, ultrasound images play a crucial role, because they can be produced at video-rate and therefore allow a dynamic analysis of moving structures. Moreover, the acquisition of these images is non-invasive, cheap, and does not require radiations compared to other medical imaging techniques. On the other hand, the automatic segmentation of anatomical structures in ultrasound imagery is a real challenge due to speckle noise and artifacts which are inherent in these images. These artifacts create open contour and/or ill defined boundaries, making ineffective algorithms such as Markov Random Field-based segmentation technique [1].

Among the existing segmentation techniques, the active contour models, or so-called *snakes* [2], are an effective way to overcome these artifacts and to rightly model the fact that the object to be detected is assumed to be connected. Besides, their ability to efficiently combine both the available *a priori* knowledge about the structure of interest and local correspondances with the image features, makes them very attractive for the segmentation tasks in ultrasound imagery. Nevertheless, this modeling finally requires to solve an intricate energy function minimization problem. The configuration space of this optimization problem is generally *very large* and the resulting energy function may exhibit many local *minima*, especially when the image contains strong noise, which

is frequently the case in ultrasound imagery. In order to cope with this optimization problem, gradient-based methods have originally been proposed [2]. The main drawback of these techniques is to require a proper initialization of the initial contour not *too far* from the expected boundary, otherwise they will converge towards bad local *minima*. Dynamic Programming [3] solves the optimality problem, although at the expense of a very high computational load. In order to shorten execution times, researchers have recently suggested to combine gradient or DP-based methods with a multi-resolution framework. Nevertheless, the optimal solution is no more guaranteed. Besides, the construction of the “multi-resolution pyramid” results in losing some important information that our energy function is sensitive to.

In order to overcome this problem, we propose herein to extend to our optimization problem, the multiscale strategy combined with the multi-resolution framework introduced in [4] for the estimation of the optical flow in an image sequence. The key idea of this strategy consists in minimizing the global energy function through an appropriate hierarchy of subspaces of the whole configuration space. These subspaces contain constrained configurations describing the expected solution at different scales. In our application, these solutions are modeled as being the optimal positions of a sequence of dynamic contour models, of decreasing thickness, whose energy function is derived from the original energy function. This constrained optimization is implemented using a coarse-to-fine procedure on a pyramidal structure. This method has shown to be very robust for optimizing a highly non-linear objective function and has turned out to provide quickly a good estimate very close to the global *minima* [4].

This paper is organized as follows: Section 2 presents the dynamic contour model used in our application and the resulting energy function to be optimized. The multiscale minimization strategy adapted to our problem is described in Section 3. In Section 4, we report some experimental results on real ultrasound images. Finally, Section 5 contains concluding remarks.

## 2. THE ACTIVE CONTOUR MODEL

Formally, an active contour  $V$  is simply defined by an ordered set of  $n$  nodes,  $V = [v_1, v_2, \dots, v_n]$ , giving coordinates of points on the contour in a circular manner. A cubic B-spline curve involving these  $n$  control points (or a simple straight line between each node) allows to completely define this model. Given an image  $y$ , its energy function is generally given by:

$$E_{\text{snake}}(V) = \sum_{i=1}^n (E_{\text{int}}(v_i) + \beta E_{\text{ext}}(v_i, y)) \quad (1)$$

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where  $\beta$  is a weighting parameter.  $E_{\text{int}}$  and  $E_{\text{ext}}$  are the internal and external energy terms respectively, also called the constraint forces, of the contour element  $v_i$ . These two energy terms play different roles in the energy minimization process. The internal energy allows to express the available *a priori* knowledge about the contour shape to be detected whereas the external energy allows to pull the snake towards the desired image features [2] (such as edges, regions, textures, etc.).

In order to model our *a priori* knowledge on the smoothness of the anatomical shape boundary to be detected, a commonly used solution consists in measuring the curvature at each node of the contour [5] and then in using this measure as the internal energy term:

$$E_{\text{int}}(v_i) = \arccos\left(\frac{\overrightarrow{v_{i-1}v_i} \cdot \overrightarrow{v_iv_{i+1}}}{\|\overrightarrow{v_{i-1}v_i}\| \cdot \|\overrightarrow{v_iv_{i+1}}\|}\right) \quad (2)$$

that is the angle between the two vectors  $\overrightarrow{v_{i-1}v_i}$  and  $\overrightarrow{v_iv_{i+1}}$ . In the minimization process, this *a priori* energy term penalizes high curvature on the contour.

In a commonly used active contour model-based segmentation approach, spatial gradient measures derived from the input image, are generally exploited in the external energy term [6]. In our application, due to the speckle noise and artifacts which are inherent to ultrasound images, our external energy term cannot rely efficiently on this type of measure. An alternative model consist in exploiting the statistical distribution of the grey levels inside and outside the boundary of the object to be detected [7]. Let  $y = \{y_s \in S\}$ , the set of pixels of the image located on a lattice  $S$  of  $M$  sites  $s$ . Assuming one Probability Density Function (PDF),  $P_{\text{in}}$ , for the pixels inside the object and another PDF,  $P_{\text{out}}$ , for the pixels outside the object, we can then define the following external energy term by:

$$E_{\text{ext}}(v_i, y) = -\frac{1}{N_{\text{in}}} \sum_{s \in v_i^{\text{in}}} \ln P_{\text{in}}(y_s) - \frac{1}{N_{\text{out}}} \sum_{s \in v_i^{\text{out}}} \ln P_{\text{out}}(y_s) \quad (3)$$

where  $y_s$  designates the grey level of the pixel at site  $s$ . The summation of the first and second term of  $E_{\text{ext}}$  is over all the  $N_{\text{in}}$  and  $N_{\text{out}}$  selected points belonging to the straight segment perpendicular to the contour at node  $v_i$ , passing through this point, and respectively located inside and outside the contour (see Fig. 1). This likelihood term is minimal when the snake delineates two homogeneous regions, at node  $v_i$ , distributed according to the grey level statistical distribution corresponding to each region. Using these two energy terms, the optimal contour,  $V_{\text{opt}}$ , can then be obtained by finding the one that minimizes the energy  $E_{\text{snake}}(V)$ .

Unfortunately, minimizing such a global energy function is often an intricate problem: the space of possible contours  $\Omega$  is generally *very large* and the energy function may exhibit many local *minima*, especially when the image contains strong noise, which is our case in ultrasound imagery (see Section 4). In [2] and in many other works, gradient-based methods are used for the energy minimization of this energy function type. These methods are simple but have the disadvantage to require a proper initialization of the dynamic contour not *too far* from the expected boundary, otherwise they will converge toward bad local *minima*. In order to overcome this problem, stochastic methods based on Simulated Annealing (SA) [6] have then been proposed. These ones have the capability of avoiding local *minima* and consequently no human interaction is required to initialize the contour model. However, one of the major drawbacks of these procedures is their very

high computational load. Various deterministic algorithms based on Dynamic Programming (DP) or variational methods [3] have then been constructed for finding the optimal (minimum energy) contour in a neighborhood of the initial contour. If this neighborhood, also called the search window, is too small and an improper initialization of the initial contour is given, a local sub-optimal solution is then found. Nevertheless, if this search window is large enough, the optimal contour is then guaranteed, although at the expense of a significant increase of the computational complexity.

In order to shorten execution times for practical applications, researchers have recently suggested to combine DP algorithm with a multi-resolution framework [8]. The main idea in using a multi-resolution method is to allow to reduce the number of candidates in the search window, so that the research process gets faster. Deformable contour optimization algorithm is applied to the coarser resolution level and the obtained solution is used as the initial snake position for the next lower level. The process continues until the contour is optimized at the original image level. This procedure noticeably shorten the computational time. Nevertheless, the optimal solution is no more guaranteed. In addition, the construction of different resolution levels, usually obtained by low-pass filtering the data, results in losing some important information that our external energy term is sensitive to. In our case, this low pass-filter would change the nature and the parameter of the different PDFs exploited in the external energy term (Eq. (3)). It is even more true if the PDFs are not Gaussian, which is our case (see Section 4). At coarser levels, the optimization algorithm will converge towards a biased solution. The same problem remains valid for external energies using edges or textures. In these cases, the information used by the external energy can be altered or simply destroyed.

In order to overcome this problem, we propose to extend the discrete multi-scale relaxation strategy combined with the multi-resolution framework introduced by Heitz *et al* in [4] for the minimization of our global energy function and also for all type of energy function associated to a dynamic contour. We consider this in the next Section.

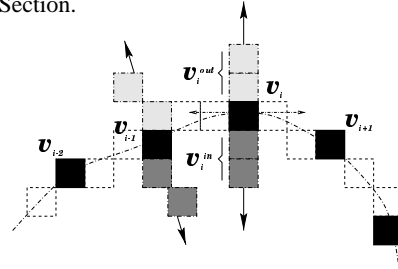


Figure 1: Portion of a contour model showing five connected nodes and the set of points  $v_i^{\text{in}}$  and  $v_i^{\text{out}}$  used in the external energy term.  $N_{\text{in}} = N_{\text{out}} = 2$  in this example.

### 3. MULTISCALE MINIMIZATION STRATEGY

Instead of minimizing our global energy function directly on the full configuration space  $\Omega$ , i.e., the space of possible contours, the optimization is led through a sequence of constrained configuration subspaces of increasing sizes:

$$\dim(\Omega^L) < \dim(\Omega^{L-1}) < \dots < \dim(\Omega^0)$$

with  $\Omega^0 \equiv \Omega$  and where  $\Omega^l$ ,  $l = 0, \dots, L$ , designates the constrained configuration space at level  $l$ . At this resolution level, we define  $V^l$  as a rough estimate of the contour model, defined by a

ordered set of  $n_l$  nodes,  $V^l = [v_{b_1^l}, v_{b_2^l}, \dots, v_{b_{n_l}^l}]$  (with  $V^0 \equiv V$  and  $v_{b_i^0} \equiv v_i$ ), giving coordinates of points of this crude contour.

Each point (or node) of this contour is indexed on a grid  $S^l$  which results from the reduction of  $S \equiv S^0$  by  $2^l$  in each direction and is associated to the block of pixels  $b_s^l \subset S$  of size  $2^l \times 2^l$ , “descendant” of node  $v_{b_s^l}$  (see Fig. 2).

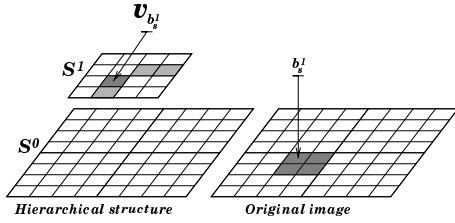


Figure 2: Hierarchical structure ( $L = 1$  in this example) involved in the multiscale minimization strategy and block of pixels  $b_s^l$  associated to the node  $v_{b_s^l}$ .

The constrained optimization in  $\Omega^l$  of our original boundary detection problem is then equivalent to the minimization of the new energy function:

$$E_{\text{snake}}(V^l) = \sum_{i=1}^{n_l} \left( E_{\text{int}}(v_{b_i^l}) + \beta_l E_{\text{ext}}(v_{b_i^l}, y) \right)$$

Using a multigrid approach [4], we can easily defined  $E_{\text{ext}}(v_{b_i^l}, y)$ :

$$E_{\text{ext}}(v_{b_i^l}, y) = -\frac{1}{N_{\text{in}}} \sum_{s \in v_{b_i^l}^{\text{in}}} \sum_{p \in b_s^l} \ln P_{\text{in}}(y_p) - \frac{1}{N_{\text{out}}} \sum_{s \in v_{b_i^l}^{\text{out}}} \sum_{p \in b_s^l} \ln P_{\text{out}}(y_p)$$

The definition of  $E_{\text{int}}(v_{b_i^l})$  remains similar to the one given in Eq. (2). However, one has to keep in mind that the angle between the two vectors has to be estimated on the reduced grid  $S^l$ . In addition, due to the size of each node at level  $l$ , we have  $\beta = 4^l \beta_l$ . From this family of energy functions, we are now able to define our minimization scheme as a cascade (from  $l = L$  to  $l = 0$ ) of optimization problems of reduced complexity:

$$V_{\text{opt}}^l = \arg \min E_{\text{snake}}(V^l), \quad l = L, \dots, 0.$$

These optimization problems are solved using a standard “coarse-to-fine” multigrid strategy. Starting from a coarse scale  $L$ , the optimization problem is first solved in  $\Omega^L$ . This defines a first (crude) solution to the original problem and the obtained solution, a rough contour, is then used as the initial snake position for the next lower level. This process continues until the contour is optimized at the original image level (see Fig. 3). Contrary to standard multi-resolution approaches, no reduction of image data is applied. The family of defined energy functions uses the original image, ensuring that the same energy function (or more precisely, different smoothed versions of this energy function) is handled at each scale, and that the energy decreases at each step of the minimization process. This method has shown to exhibit fast convergence property and robustness against local *minima* for highly non-linear combinational problem [4].

Each of the associated energy minimization problems can be efficiently solved with a standard deterministic optimization algorithm, such as a classical gradient-based method or a DP algorithm requiring a small search window. In our application, we use simply the following iterative technique: for each node  $v_{b_i^l}$  of the contour, we compute  $E_{\text{snake}}(V^l)$  for the current position of the node and for the two consecutive points belonging to the perpendicular of the contour at the current node, respectively located inside and outside the contour. At a given iteration, and for each node, we accept the position of the contour that minimizes  $E_{\text{snake}}(V^l)$  and this process is iterated until there is no change in the shape of the contour between two iterations.

In our case, once the optimization problem at level  $l$  is solved, the initial snake position for the next lower level (level  $l-1$ ) is then obtained by keeping the descendant (among four) of each node ensuring the minimal external energy (see Fig. 3).

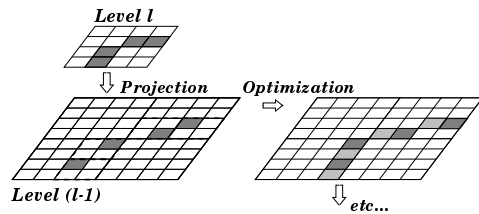


Figure 3: “Coarse-to-fine” minimization strategy.

Finally, in order to initialize the model at the coarsest level  $l = L$ , we exploit the result of a two-class segmentation result achieved in a Maximum Likelihood (ML) sense on the coarsest grid  $S^L$ . To this end, let  $x^L = \{x_s^L, s \in S^L\}$ , the set of labels associated to each block of pixels  $b_s^L$ . Each  $x_s^L$  can take two labels  $\{e_{\text{in}}, e_{\text{out}}\}$ , associated to the two homogeneous regions and distributed according to the conditional distribution  $P_{\text{in}}$  and  $P_{\text{out}}$ . This ML blocky segmentation is given by:

$$\forall s \in S^L, \hat{x}_s^L = e_{\text{in}} \quad \text{if} \quad \sum_{p \in b_s^L} \ln P_{\text{in}}(y_p) > \sum_{p \in b_s^L} \ln P_{\text{out}}(y_p) \\ \text{else} \quad \hat{x}_s^L = e_{\text{out}}$$

This blocky segmentation is then high-pass filtered in order to extract the initial crude contour that will be used for the initialization of the optimization procedure at the coarsest level (see Section 4 and upper left of the Fig. 4a).

## 4. EXPERIMENTAL RESULTS

In order to take into account the speckle noise phenomenon [9] in the reverberation areas, we model the conditional PDFs  $P_{\text{in}}$  and  $P_{\text{out}}$  of each homogeneous region of the input ultrasound image by a shifted Rayleigh law [7]. The first region arises from the low acoustic wave reverberation in the different cavity of anatomical structures, generally filled with blood. The second region is due to the acoustic signal reverberation on the different organs (cardiac muscles for an echographic image, or wall of arteries for an echobrachial image). In our application, the parameter of these distribution laws are given by a preliminary statistical estimation method called Iterative Conditional Estimation (ICE) [7].

We have validated our multiscale detection method on real echographic and echobrachial images, in order to detect the endocardial contour or the inner wall of an artery respectively. For

the experiments, we have chosen  $\beta = 1$  for the weighting factor penalizing the internal energy with respect to the external energy and  $L = 4$  for the number of resolution levels. The size of these acoustic pictures is  $256 \times 256$  pixels (256 grey levels).

Fig. 4a (at upper left) shows the ML blocky segmentation at the coarsest resolution level  $l = L$  that is used to extract the initial crude endocardial contour. Figs. 4[b-f] show the resulting estimated snakes at different resolution levels. Figs. 5 and 6 present the segmentation results obtained on other echographic images and on three echobrachial images respectively. We can notice (Fig. 4a) that the ML blocky segmentation maps exhibits improper *blood* or *muscle* areas at lower levels (higher resolution levels) of the pyramidal structure due to artifacts created by the ultrasound imagery process. The boundary of the endocardial contour cannot be efficiently extracted on these lower levels. Nevertheless, a closed (but crude) contour can be efficiently extracted at the highest level of the pyramidal structure. We can notice (Figs. 4[a-f]) that the proposed multiscale strategy allows efficiently to obtain a good initial guess at each level that is refined at the finer scales. A reliable detection of the endocardial contour or of the inner wall of an artery is obtained. The proposed boundary segmentation procedure is very fast and takes about 3–4 seconds (average CPU time) on a standard Sun/Sparc 2 workstation that makes this procedure compatible with a practical application.

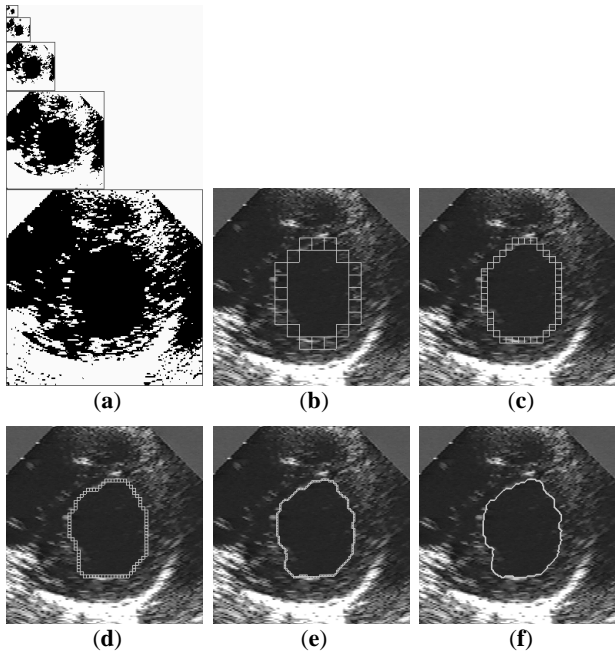


Figure 4: (a) ML blocky segmentation at different resolution levels and estimated snakes at different resolution levels (b-f).

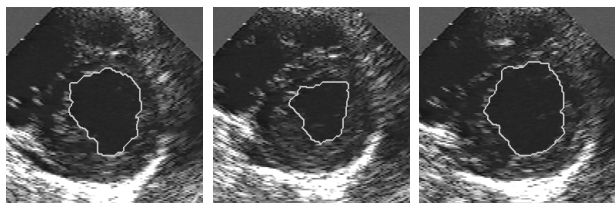


Figure 5: Detection of the endocardial contour at different time frames during the cardiac cycle.

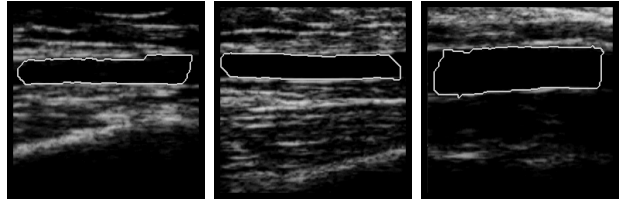


Figure 6: Detection of the inner wall of an artery on echobrachial images.

## 5. CONCLUSION

In this paper, we have developed a robust algorithm to detect the boundaries of anatomical structures in ultrasound images. We have stated this detection problem in the active contour model framework and we have presented a multiscale framework for the minimization of the global energy function resulting of this modeling. The minimization is efficiently performed through a multi-grid algorithm which consists in imposing successively weaker and weaker constraints on the searched estimate. In our application, this procedure results in estimating successively the optimal position of contour models of decreasing thickness. This framework can be easily generalized to edge or texture-based energy-minimizing contour model as well as for three-dimensional boundary detection. This scheme is fast, exhibits good convergence properties, and is well suited to automatic extraction of anatomical structure boundaries in ultrasound imagery.

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