A local Rayleigh model with spatial scale selection for ultrasound image segmentation

Djamal Boukerroui
http://www.hds.utc.fr/~dboukerr

Université de Technologie de Compiègne
Heudiasyc UMR CNRS 7253
BP 20529 - 60205 Compiègne Cedex, France.

Ultrasound data are very noisy, with poor contrast, and often presents missing boundaries of the object of interest due to problems of specular reflection, shadows, signal dropout and attenuation. As a consequence, conventional intensity gradient-based methods have had limited success on typical clinical images [5]. Note also that segmentation methods based on global statistical models, regardless of the used framework, fail on this type of data, mainly because of the attenuation problem. Adaptive solutions robust to attenuation exist in the literature [1, 2, 5]. Local image statistics were used for the estimation of the segmentation model's parameters. Recently, there has been a reinvestigation of the use of local statistics by the image segmentation community, but in a variational framework [3, 4, 6]. These recent studies show a better behavior of these local models on images with strong intensity inhomogeneities. This contribution falls under this context.

First, we propose the adaptation of the model proposed by Sarti et al. [7]. The latter assumes a global Rayleigh model envelope image statistics. Let $I : \Omega \rightarrow \mathbb{R}^+$ denote a given observed image and $\mathcal{C}$ be a closed contour represented as the zero level set of a signed distance function ϕ. The interior Ω_i and the exterior Ω_e of $\mathcal{C}$ are defined by a smooth approximation of the Heaviside function respectively by: $H_i(\phi) = H(\phi)$ and $H_o(\phi) = 1 - H(\phi)$. We seek the partition of Ω that maximizes the likelihood function of the observed data. Given the independence assumption, this leads to the minimization of the following energy function [7]

$$E(\phi) = -\sum_{r\in\{i,o\}} \int_\Omega H_r(\phi) \log p(I(\mathbf{x}))d\mathbf{x} + \lambda \int_\Omega \delta(\phi)|\nabla\phi|d\mathbf{x}, \qquad (1)$$

where the first two terms are the data terms and the last one is a length regularisation with a weight penalty λ. We will further assume that the random intensity $I(\mathbf{x})$ follows a Rayleigh pdf with a parameter σ^2:

$$p(I(\mathbf{x})) = \frac{I(\mathbf{x})}{\sigma^2} \exp\left(-\frac{I(\mathbf{x})^2}{2\sigma^2}\right) \quad \text{and} \quad \widehat{\sigma^2}_{\mathrm{ML}} = \frac{\int_{\Omega_r} I(\mathbf{x})^2 d\mathbf{x}}{2\int_{\Omega_r} d\mathbf{x}} \quad ,$$

where $\widehat{\sigma^2}_{\mathrm{ML}}$ is a Maximum Likelihood estimates under the assumption that all the observed pixels in the domain Ω_r are identically distributed. In Sarti et al. [7], only two global domains were used, Ω_i for the inside and Ω_e for the outside pixels. Therefore the hypothesis of identically distributed observations is generally false for ultrasound images because of the presence of strong intensity inhomogeneities. However, the assumption remains true if the estimate is made locally in a region centered around each pixel of the domain Ω. Thus the energy corresponding to the inside term of (1) is given by:

$$E_i(\phi) = \int_\Omega H(\phi)\left[\frac{I(\mathbf{x})^2}{2\sigma_i^2(\mathbf{x})} + \log(\sigma_i^2(\mathbf{x}))\right] d\mathbf{x} \qquad (2)$$

$$\text{and} \quad \sigma_i^2(\mathbf{x}) = \frac{\int_\Omega H(\phi)K(\mathbf{x}-\xi)I(\xi)^2 d\xi}{2\int_\Omega H(\phi)K(\mathbf{x}-\xi)d\xi} \quad , \qquad (3)$$

where $K(\cdot)$ is any given kernel defining the spatial locality around the position $\mathbf{x}$. Here, a Gaussian kernel with a standard deviation σ_K is used.

Local region-based segmentation models are surely a better alternative to global ones in the presence of intensity inhomogeneities. Such models however may be more sensitive to initialisation if the chosen local spatial scale is not appropriate. A decrease of robustness to noise is also observed when small scales are used. To our knowledge, two pixel dependent scale selection methods have been introduced recently [6, 8]. The second contribution of this paper is the proposition of a novel Intersection of Confidence Intervals (ICI) rule for the spatial scale selection. Our approach is based on the idea of choosing the largest scale that gives the best estimate of the segmentation model parameters. Specifically, in the presence of intensity inhomogeneities, the hypothesis of identically distributed data in the local window will become less and less valid as the scale of the kernel K grows and will lead to an increasingly biased estimations. This means that there exists a bias-variance balance that gives the ideal scale. We can make use of the ICI algorithm to search for the largest local window (minimising variance) that gives us the best estimate of σ^2 (minimising bias).

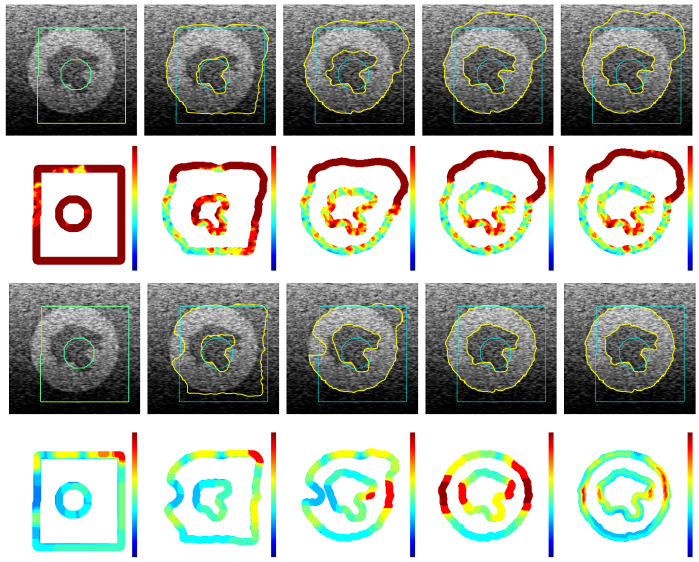

Figure 1: 1st & 3rd lines: Example of contour evolution of the local Rayleigh segmentation model for iterations 1, 10, 25, 75 and 120 respectively when using the scales estimated with [6] (2nd line) and with the proposed ICI rule (4th line). The colormap Blue-Red corresponds to scales from 5 to 80. Image size 256×256.

In order to demonstrate the usefulness of the proposed approach and quantify its performances, we chose to test it on realistic US simulations. To this end, we have used the simulation program Field-II, to synthesize phantom data with known ground truth. Two phantoms with two scatters amplitudes and three levels of tissue attenuations were simulated. We also used several dB ranges for the envelope logarithmic compression to simulate different image contrasts. A quantitative evaluation is then conducted on 240 images and statistics of the Dice similarity measure and the Mean Absolute Distance are shown. The results show the robustness and the superiority of the proposed segmentation approach in comparison to [3, 7]. The efficiency and the genericity of the proposed scale selection strategy is also demonstrated.

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