A RBF-BASED MULTIPHASE LEVEL SET METHOD FOR SEGMENTATION IN ECHOCARDIOGRAPHY USING THE STATISTICS OF THE RADIOFREQUENCY SIGNAL

O. Bernard , B. Touil, A. Gelas, R. Prost, D. Friboulet

CREATIS UMR 5220, U630 INSERM, INSA, Blaise Pascal, 69621 Villeurbanne, France
bernard@creatis.insa-lyon.fr

ABSTRACT

This work presents an algorithm for the segmentation of myocardial regions in echocardiography imaging based on the statistics of the radiofrequency image. We formulate the problem of segmentation in a Maximum Likelihood framework using the Generalized Gaussian as an a priori distribution. We minimize the resulting functional using a Radial Basis Functions-based multiphase level set model. Numerical results obtained on both simulation and in vivo data demonstrate the capacity of our approach to segment myocardial regions in echocardiography imaging.

Index Terms— Segmentation, Multiphase level set, Radial Basis Functions, echocardiography, statistics, radiofrequency signal

1. INTRODUCTION

In the medical imaging, clinical parameters quantification is a challenging goal because it represents an important clinical need due to the diagnostic and therapeutic implications in the management of patients. One crucial step for extracting these parameters in a fast and accurate way is image segmentation. As noted in a recent review [1], in the field of echocardiography most of the work has been devoted to the segmentation of the endocardium, *i.e.* the interface that separate blood pool and tissue border. On the opposite, there is a very limited amount of work related to the segmentation of the whole myocardium [2]. This task is indeed more difficult, due to the specificity of ultrasound image formation, *i.e.* low signal to noise ratio which yielding low contrast between myocardium and the surrounding structures

We propose in this paper an original method dedicated to the segmentation of the myocardium in echocardiographic imaging. We derive a level set model driven by the statistics of the radiofrequency signal, modeled through a Generalized Gaussian distribution. The evolution of the level set is formulated through a collocation method using Radial Basis Functions (RBF) that we recently described in [3]. We extend this approach to handle multiphase level set and we show that this multiphase formulation permits to segment the cardiac structures present inside the ultrasound image. Numerical results are demonstrated on both simulation and in vivo data.

The paper is organized as follows. In Section 2 we present the statistical model used to characterize the statistics of the radiofrequency image for both blood and myocardial regions. Using a Maximum Likelihood approach, we derive in Section 3 corresponding functional and give in Section 4 the RBF-based formulation of the level set evolution. In this framework, we describe in Section 5 a multiphase level set formulation of the segmentation functional. We show in section 6 numerical results obtained on both simulation and in vivo data and conclude this work in Section 7.

2. ULTRASOUND IMAGE INFORMATION USING STATISTICS

Based on the modeling of image formation, we recently showed that the statistics of the radiofrequency signal from both fully developed (blood pool) and partially developed speckle (tissue area) can be reliably described through a Generalized Gaussian distribution [4, 5].

This model is based on the assumption that the scatterers present inside the system resolution cell are uniformly distributed and that their amplitude follow a K distribution. This distribution has the main advantage to have a simple expression with robust, maximum-likelihood-based parameters estimation. The ability of this distribution to characterize the statistics of both fully and partially developed speckle from the radiofrequency image has been quantitatively validated on clinical data set [4].

3. A VARIATIONAL FRAMEWORK FOR ULTRASOUND IMAGE SEGMENTATION

The framework we use for segmentation is based on the approach initially described by Zhu & Yuille [6]. Let $\Omega \subset \mathbb{R}^2$ denote the image plane and let $f : \Omega \times \mathbb{R} \rightarrow \mathbb{R}$ be a given ultrasound radiofrequency image. Under the assumption that the image is composed of a set of regions following a Generalized Gaussian distribution with different parameters values,

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the Maximum-Likelihood function corresponding to this image can be written as:

$$ML\left(f(\mathbf{x})\right) = \prod_{i=1}^{n}\left(\prod_{\mathbf{x}\in R_i} p\left(f(\mathbf{x})/\zeta_i\right)\right) \quad (1)$$

where n corresponds to the number of regions present in the image and $p(.)$ corresponds to the Generalized Gaussian distribution with parameters vector $\zeta_i = \{a_i, b_i\}$. Maximizing criterion (1) is equivalent to minimizing its negative logarithm, which is given (up to a constant) by the following energy functional:

$$E\left(C, \{\zeta_i\}\right) = \sum_{i=1}^{n}\left(\int_{R_i} -log\left[p\left(f(\mathbf{x}/\zeta_i)\right)\right] d\mathbf{x}\right) \quad (2)$$

where C is a closed subset in Ω, made up of the regions boundaries. For brevity sake, we will note $p\left(f(\mathbf{x}/\zeta_i)\right)$ as p_i in the remainder of the paper.

4. LEVEL SET MODEL BASED ON COLLOCATION METHOD USING RBF

We minimize the functional (2) using a level set representation of the boundary C. The boundary C is thus represented as the zero level set of a Lipschitz continuous function ϕ of higher dimension, satisfying:

$$\begin{cases} \phi(\mathbf{x},\tau) > 0 \text{ , for } \mathbf{x} \in \Omega_{in}(\tau) \text{ ,} & (3)\\ \phi(\mathbf{x},\tau) < 0 \text{ , for } \mathbf{x} \in \Omega_{out}(\tau) \text{ ,} & (4)\\ \phi(\mathbf{x},\tau) = 0 \text{ , for } \mathbf{x} \in \partial\Omega_{in}(\tau) = C(\tau) & (5)\end{cases}$$

where Ω_{in} is a region in Ω bounded by C and Ω_{out} is defined as $\Omega_{out} = \Omega \backslash \Omega_{in}$.

The problem of segmenting one object is typically handled by the evolution of one level set according to the following general equation [7, 8]:

$$\frac{\partial\phi(\mathbf{x},\tau)}{\partial\tau} = V(\mathbf{x},\tau)\cdot\delta_\epsilon\left(\phi(\mathbf{x})\right) \quad (6)$$

where $\delta_\epsilon(.)$ is a regularized version of the Dirac function [8] and V is a velocity function derived from a variational scheme.

We have recently shown in [3] that (6) can be implemented using a RBF collocation method. In contrast to the conventional finite difference narrow band implementations, the RBF collocation scheme allows an overall control of the level set (*i.e.* over the whole computational domain of the level set) with a reasonable computational cost and allows to avoid the usual reinitialization step of the level set. In this formalism, the implicit function ϕ is modeled using a RBF decomposition according to the following inner product:

$$\phi(\mathbf{x}) = \Psi(\mathbf{x})\cdot\alpha \quad (7)$$

with

$$\begin{cases} \Psi(\mathbf{x}) = [\varphi(\|\mathbf{x}-\mathbf{x}_1\|), \cdots, \varphi(\|\mathbf{x}-\mathbf{x}_P\|)] & (8)\\ \alpha = [\mu_1, \cdots, \mu_P]^T & (9)\end{cases}$$

where φ is a RBF, $\{\mathbf{x}_j\}$ corresponds to the RBF centers and $\{\mu_j\}$ corresponds to RBF coefficients. Our implementation is build upon Wendland's C^2 compactly supported RBFs, which allows reducing the computational complexity of the algorithm [3].

In order to solve for the coefficient α, equation (6) is first expressed through the RBF decomposition and then sampled at P distinct collocation points that are chosen in our implementation to be the RBF centers. We thus obtain the following general equation:

$$H\cdot\frac{d\alpha(\tau)}{d\tau} = B\left(\alpha(\tau),\tau\right) \quad (10)$$

where H is an interpolation square matrix of size P and $B(\alpha)$ is a column vector related to the velocity function:

$$\begin{cases} H_{ij} = \varphi(\|\mathbf{x}_i - \mathbf{x}_j\|) & (11)\\ B(\alpha(\tau),\tau) = V(\mathbf{x}_i,\tau)\cdot\delta_\epsilon\left(\Psi(\mathbf{x}_i)\cdot\alpha(\tau)\right) & (12)\end{cases}$$

From (10), the level set evolution computed on the whole image plane is now cast into a simple Ordinary Differential Equation (ODE). By using the conventional forward Euler method, the resolution of this ODE amounts to solve the following linear system:

$$\alpha^{n+1} = \alpha^n - \tau\cdot H^{-1}\cdot B^n\left(\alpha^n\right) \quad (13)$$

where τ is the step size.

5. A RBF-BASED MULTIPHASE LEVEL SET METHOD

The above approach based on the evolution of one level set permits to segment only two structures in an ultrasound image. This limitation can be overcome by using multiple level set functions. We follow for this purpose the approach described by Chan & Vese in [9], who introduced a compact representation of up to n phases which needs only $m = log_2(n)$ level set functions. This approach has the main advantage to generate a partition of the image plane and therefore does not suffer from overlap or vacuum formation.

Let $\boldsymbol{\phi} = (\phi_1, \cdots, \phi_m)$ be a vector level set function, with $\phi_i : \Omega \to \mathbb{R}$. Let $H\left(\boldsymbol{\phi}(\mathbf{x})\right) = \left(H\left(\phi_1(\mathbf{x})\right), \cdots, H\left(\phi_m(\mathbf{x})\right)\right)$ be the associated vector Heaviside function. This function maps each point $\mathbf{x} \in \Omega$ to a binary vector and therefore permits to encode a set of $n = 2^m$ phases R_i defined by:

$$R = \{\mathbf{x} \in \Omega \mid H\left(\boldsymbol{\phi}(\mathbf{x})\right) = \text{ constant }\} \quad (14)$$

We thus propose to replace the functional (2) by the following multiphase functional:

$$E\left(\{\zeta_i\}, \boldsymbol{\phi}\right) = \sum_{i=1}^{n}\left(\int_\Omega - log(p_i)\ \chi_i\left(\boldsymbol{\phi}\right) d\mathbf{x}\right) \quad (15)$$

where χ_i denotes the indicator function for the region R_i.

Because in ultrasound imaging there is a limited number of structures to be segmented, it seems reasonable to assume that n should be small. We thus explicitly give in this part the functional for the case of $n = 4$ phases. The corresponding expression is:

$$\begin{aligned} E\left(\{\zeta_i\}, \boldsymbol{\phi}\right) = & \int_\Omega - log(p_{11})\ H\left(\phi_1\right)\ H\left(\phi_2\right) d\mathbf{x} \\ & + \int_\Omega - log(p_{10})\ H\left(\phi_1\right)\ \left(1 - H\left(\phi_2\right)\right) d\mathbf{x} \\ & + \int_\Omega - log(p_{01})\ \left(1 - H\left(\phi_1\right)\right)\ H\left(\phi_2\right) d\mathbf{x} \\ & + \int_\Omega - log(p_{00})\ \left(1 - H\left(\phi_1\right)\right)\ \left(1 - H\left(\phi_2\right)\right) d\mathbf{x} \quad (16) \end{aligned}$$

where p_{ij} corresponds to the Generalized Gaussian distribution with parameters ζ_{ij} given by

$$\begin{cases} \zeta_{11} = \text{ML estimate of } \zeta \text{ in } \{\phi_1 \geq 0,\ \phi_2 \geq 0\} & (17) \\ \zeta_{10} = \text{ML estimate of } \zeta \text{ in } \{\phi_1 \geq 0,\ \phi_2 < 0\} & (18) \\ \zeta_{01} = \text{ML estimate of } \zeta \text{ in } \{\phi_1 < 0,\ \phi_2 \geq 0\} & (19) \\ \zeta_{00} = \text{ML estimate of } \zeta \text{ in } \{\phi_1 < 0,\ \phi_2 < 0\} & (20) \end{cases}$$

ML corresponds to the Maximum-Likelihood estimator of the Generalized Gaussian parameters described in [10].

Using Euler-Lagrange equations, the minimization of (16) with respect to $\boldsymbol{\phi}$ (for fixed parameters values $\{\zeta_{ij}\}$) yields to the following evolution equations:

$$\begin{aligned} \frac{\partial \phi_1}{\partial \tau} = \delta_\epsilon\left(\phi_1\right) \Bigg[& log\left(\frac{p_{11}}{p_{01}}\right) H\left(\phi_2\right) \\ & + log\left(\frac{p_{10}}{p_{00}}\right)\left(1 - H\left(\phi_2\right)\right)\Bigg] \end{aligned} \quad (21)$$

$$\begin{aligned} \frac{\partial \phi_2}{\partial \tau} = \delta_\epsilon\left(\phi_2\right) \Bigg[& log\left(\frac{p_{11}}{p_{10}}\right) H\left(\phi_1\right) \\ & + log\left(\frac{p_{01}}{p_{00}}\right)\left(1 - H\left(\phi_1\right)\right)\Bigg] \end{aligned} \quad (22)$$

In this paper, we propose to exploit the RBF-level set formalism to implement these equations. We obtain the following equations:

$$\begin{cases} \alpha_1^{n+1} = \alpha_1^n - \tau \cdot H^{-1} \cdot C^n\left(\alpha_1^n, \alpha_2^n\right) & (23) \\ \alpha_2^{n+1} = \alpha_2^n - \tau \cdot H^{-1} \cdot D^n\left(\alpha_1^n, \alpha_2^n\right) & (24) \end{cases}$$

where C^n and D^n are two column vectors defined as:

$$\begin{aligned} C^n\left(\alpha_1^n, \alpha_2^n\right) = & \Bigg[log\left(\frac{p_{11}}{p_{01}}\right) H\left(\Psi(\mathbf{x}_i) \cdot \alpha_2^n\right) + \\ & log\left(\frac{p_{10}}{p_{00}}\right)\left(1 - H\left(\Psi(\mathbf{x}_i) \cdot \alpha_2^n\right)\right)\Bigg] \cdot \delta_\epsilon\left(\Psi(\mathbf{x}_i) \cdot \alpha_1^n\right) \end{aligned} \quad (25)$$

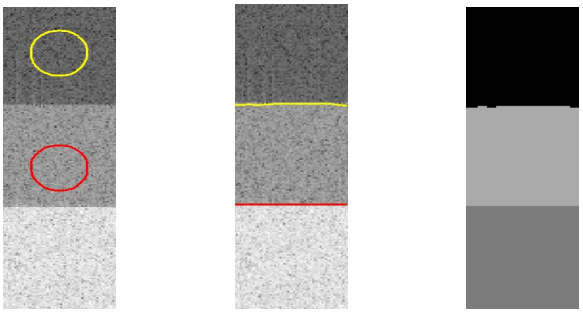
and

$$\begin{aligned} D^n\left(\alpha_1^n, \alpha_2^n\right) = & \Bigg[log\left(\frac{p_{11}}{p_{10}}\right) H\left(\Psi(\mathbf{x}_i) \cdot \alpha_1^n\right) + \\ & log\left(\frac{p_{01}}{p_{00}}\right)\left(1 - H\left(\Psi(\mathbf{x}_i) \cdot \alpha_1^n\right)\right)\Bigg] \cdot \delta_\epsilon\left(\Psi(\mathbf{x}_i) \cdot \alpha_2^n\right) \end{aligned} \quad (26)$$

6. EXPERIMENTS

6.1. Simulated data

The proposed method has been tested on a simulated image given in figure 1. This image consists of three regions generated using a Generalized Gaussian distribution with different parameters. These parameters have been chosen from real data (in parasternal long axis orientation) and correspond to the three main tissues usually present in the cardiac image, *i.e.* pericardium (brighter region), myocardium and blood (the darker region). The results presented on figure 1(b) and (c) show how the multiphase level set allows to properly segment these different regions based on their statistics.



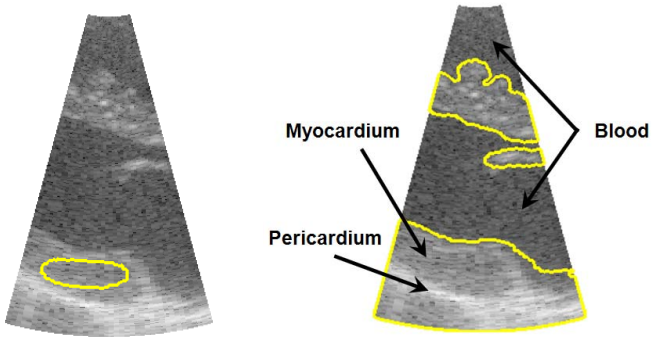
(a) (b) (c)

Fig. 1. Segmentation of a simulated image using two level set functions. (a) initialization. (b) segmentation result. (c) obtained regions

6.2. In vivo data

The ability of the proposed method to segment myocardium region from RF image was tested on ultrasound cardiac images acquired in vivo. Data were acquired using Toshiba Powervision 6000 equipped with an RF interface for research purposes and a 3.75 MHz-probe. The RF sample frequency was fixed to 25 MHz.

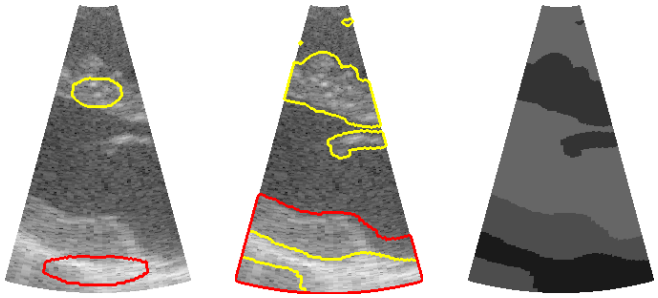
Figure 2 shows the result obtained for a parasternal long axis view using a single level set function. Figure 2(a) shows the initialization of the level set inside myocardial and figure 2(b) shows the result obtained at convergence. From this example, it can be observed that the model yields proper segmentation of all the blood/tissue interfaces in the image. However, because there are more than 2 statistical regions present



(a) Initialization (b) Segmentation results

Fig. 2. Segmentation of a parasternal long axis view using a single level set function

in the lower part of the image, the method can not separate the myocardium from the pericardium.



(a) (b) (c)

Fig. 3. Segmentation of a parasternal long axis view using two level set functions. (a) initialization. (b) segmentation result. (c) obtained regions

Figure 3 shows the result obtained for the same parasternal image using the formalism described in Section 5 with two level sets. Figure 3(a) shows the initialization of the two level sets figure and 3(b) and (c) show the result obtained at convergence. In this case, the method allows proper segmentation of the two different tissue regions, *i.e.* the myocardium and the pericardium.

7. CONCLUSIONS

We have presented in this paper a RBF-based multiphase level set model for the segmentation of myocardial region in echocardiographic images using the statistics of the radiofrequency signal. The problem of segmentation is formulated in a Maximum Likelihood framework using the Generalized Gaussian distribution as an a priori model of the statistics. We minimize this functional using a RBF-based multiphase level set model. This formulation allows segmenting echocardiographic images into several homogeneous regions from a statistical point of view. Simulation results show that our model is well suited to segment several regions distributed according to a Generalized Gaussian distribution. Results obtained from in vivo echocardiographic data acquired in parasternal long axis view show that the proposed method yields proper segmentation of the myocardial tissue.

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