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Identification of Nerves in Ultrasound Scans Using a Modified Mumford-Shah Functional and Prior Information

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***Abstract*—Ultrasound scans have many important clinical applications in medical imaging. One of clinical applications is to find nerves. One of the skills necessary to conduct ultrasound guided nerve blocks is the ability to recognize the nerves, vessels, muscles and bones in sagittal and axial cross sections. In fit healthy patients, these structures are reasonably easy to recognize but in obese patients, extra adipose tissue attenuates the ultrasound beam. The goal of this paper is to acquire an efficient image segmentation algorithm which identifies nerves in ultrasound scans. A new region based variational model is proposed using a modified piecewise constant Mumford-Shah functional and prior information. The region of interests are extracted by using Γ-approximation to a piecewise constant Mumford-Shah functional. However, this method only is not able to accommodate all types of imaging difficulties including noise, artifacts, and loss of information. Therefore, the prior knowledge is necessary to obtain an efficient image segmentation result. The prior information is incorporated with the distance function. The distance function consists of the global rigid transformation and local non-rigid deformation. The proposed model is applied to healthy human neck ultrasound images. The preliminary numerical results show the effectiveness of the suggested algorithm and is compared to an existing piecewise constant Mumford-Shah model and expert results.**

***Index Terms*—A piecewise constant Mumford-Shah functional, distance function, gamma-approximation, prior information, ultrasound nerve images.**

I. Introduction

DIAGNOSTIC medical imaging has been developed rapidly in the last three decades. One widely used method in medical imaging is ultrasound, since it does not use ionizing radiation which imposes potential hazards. Ultrasound-based imaging techniques are used to recognize muscles, tendons, and other internal organs with many clinical applications. One application is the conduction nerve blocks. Therefore, it is important to develop an efficient algorithm which recognizes the nerves, vessels, muscles, and bones. In this paper, the problem to solve identifying nerve regions in ultrasound scans is considered. Hence the region based image segmentation algorithm is developed.

The most celebrating region based image segmentation model is introduced by Mumford and Shah [20]. An image is decomposed into a set of regions within the bounded open set Ω and these regions are separated by smooth edges Γ in this model. Due to the difficulties in numerical computation of the Mumford-Shah model, several numerical approximation methods have been developed. Chan and Vese proposed a piecewise constant Mumford-Shah model in [5], [6] by using a level set formulation [21]. Developments of variational level set implementation techniques are followed by [13], [14], [18]. Another approach has been developed by Ambrosio and Tortorelli [1]. The measurement of an edge Γ length term in the Mumford-Shah model by a quadratic integral of an edge signature function [1]. The segmentation is represented by characteristics functions using phase fields in [13], [18]. The details of phase field theory can be found in [2], [3], [13], [19], [23], [24], [25]. However, these algorithms have a limit to obtain an efficient segmentation result on images with noise, artifacts, or loss of information. The prior shape information has been incorporated into the segmentation process to overcome these problems [2], [4], [7], [8], [9], [10], [11], [12], [15], [16], [17], [22].

The proposed model is motivated by [2], [11], [23], [24]. Using Γ-approximation to a piecewise constant Mumford-Shah functional is similar to [2], [23], [24]. But prior information is incorporated in our model. The combination of piecewise constant Mumford-Shah functional and prior shape information in segmentation processing is similar to [11], but our model uses Γ-approximation to piecewise constant Mumford-Shah functional and non-rigid deformation for incorporating prior information. This paper is organized as follows: In section II, a new region based variational model is proposed. The suggested model uses Γ-approximation to a piecewise Mumford-Shah functional and prior shape information. Experimental results of the presented model which were applied to healthy human neck ultrasound images are shown in section III. The numerical results compared to an existing piecewise constant Mumford-Shah model and expert results are also shown in this section. Finally, the conclusion follows and future work is stated in section IV.

II. Description of the Proposed Model

A. The Proposed Model

In this section, a new region based variational image segmentation model is introduced. The segmentation is attained using a modified Mumford-Shah functional and the prior information. The model is aimed to find ϕ, u, μ, R, and T by minimizing the energy functional:

$$E(\phi, u, \mu, R, T) =$$
$$\lambda_1 \int_\Omega H_\varepsilon^2(\phi)(I(\bar{x}) - c_1)^2 + (1 - H_\varepsilon(\phi))^2 (I(\bar{x}) - c_2)^2 d\bar{x}$$

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$$+\int_{\Omega}\varepsilon_1|\nabla H_{\varepsilon}(\phi)|^2+\frac{\lambda_2 H_{\varepsilon}(\phi)^2(1-H_{\varepsilon}(\phi))^2}{\varepsilon_1}d\bar{x}$$
$$+\frac{\lambda_3}{2}\int_{\Omega}\delta_{\varepsilon}(\phi)d^2(\mu R\bar{x}+T+u)|\nabla(\frac{\phi}{\varepsilon})|d\bar{x}$$
$$+\lambda_4\int_{\Omega}|\nabla u|^2 d\bar{x}+\lambda_5\int_{\Omega}u^2 d\bar{x}, \quad (1)$$

where I is a given image, Ω is domain, $\lambda_i > 0, \quad i = 1, 2, 3, 4, 5$ are parameters balancing the influences from the five terms in the model, d is the distance function from the given prior shape, and ε and ε_1 are positive parameters. For the numerical computation, $H_{\varepsilon}(\phi) = [\frac{1}{2}(1+\frac{2}{\pi}\arctan(\frac{\phi}{\varepsilon}))]^2$ and $\delta_{\varepsilon}(\phi) = H'_{\varepsilon}(\phi)$ are used. The first term forces $H^2_{\varepsilon}(\phi)$, towards 0 if $I(\bar{x})$ is different from c_1 and towards 1 if $I(\bar{x})$ is close to c_1, for every $\bar{x} \in \Omega$. In a similar way, $(1-H_{\varepsilon}(\phi))^2$, towards 0 if $I(\bar{x})$ is different from c_2 and towards 1 if $I(\bar{x})$ is close to c_2, for every $\bar{x} \in \Omega$. The second term is for measuring an edge length term using Γ-approximation. In the theory of Γ-convergence, the measuring an edge Γ length term in the Mumford-Shah functional can be approximated by a quadratic integral of an edge signature function which was proposed by Ambrosio and Tortorelli [1]. This model is combined with double-well potential function which is quadratic around its minima and is growing faster than linearly at infinity in [13], [23], [24]. Here $\varepsilon_1 \ll 1$ controls the transition bandwidth. As $\varepsilon_1 \to 0$, the first term is to penalize unnecessary interfaces and the second term forces the stable solution to take one of the two phase field values 1 or 0. For the details of phase field models and double-well potential functions, please refer [13], [23], [24], [25]. Prior information incorporated with the distance function is in the third term. The distance function is consisted of the global transformation and non-rigid deformation. The fourth term is smoothing the non-rigid term u is in the term. Minimizing the magnitude of the non-rigid deformation term u is in the last term.

B. Euler-Lagrange Equations of the Proposed Model

The evolution equations associated with the Euler-Lagrange equations in Equation (1) are

$$\frac{\partial\phi}{\partial t} = -2\lambda_1\delta_{\varepsilon}(\phi)\{H_{\varepsilon}(I-c_1)^2-(1-H_{\varepsilon})(I-c_2)^2\}$$
$$+2\varepsilon_1\{div(\nabla\phi(\delta_{\varepsilon}(\phi))^2)-|\nabla\phi|^2\delta_{\varepsilon}(\phi)\delta'_{\varepsilon}(\phi)\}$$
$$-\frac{2\lambda_2 H_{\varepsilon}(\phi)(1-H_{\varepsilon}(\phi))(1-2H_{\varepsilon}(\phi))\delta'_{\varepsilon}(\phi)}{\varepsilon_1}$$
$$+\delta_{\varepsilon}(\phi)div\{\frac{\lambda_3}{2}d^2(\mu R\bar{x}+T+u)\frac{\nabla(\frac{\phi}{\varepsilon})}{|\nabla(\frac{\phi}{\varepsilon})|}\}, \quad in \quad \Omega$$
$$\frac{\partial\phi}{\partial n} = 0, \quad on \quad \partial\Omega$$
$$\frac{\partial u}{\partial t} = \delta_{\varepsilon}(\phi)\lambda_3 d(\mu R\bar{x}+T+u)\nabla d(\mu R\bar{x}+T+u)|\nabla(\frac{\phi}{\varepsilon})|$$
$$+\lambda_4|\triangle u|-\lambda_5 u, \quad in \quad \Omega$$
$$\frac{\partial u}{\partial n} = 0, \quad on \ \partial\Omega$$
$$\frac{\partial\mu}{\partial t} = -\lambda_3\int_{\Omega}\delta_{\varepsilon}(\phi)d(\mu R\bar{x}+T+u)$$
$$\nabla d(\mu R\bar{x}+T+u)R\bar{x}|\nabla(\frac{\phi}{\varepsilon})|d\bar{x}$$
$$\frac{\partial\theta}{\partial t} = -\lambda_3\int_{\Omega}R\delta_{\varepsilon}(\phi)\mu d(\mu R\bar{x}+T+u)$$
$$\nabla d(\mu R\bar{x}+T+u)\frac{\partial R}{\partial\theta}\bar{x}|\nabla(\frac{\phi}{\varepsilon})|d\bar{x}$$
$$\frac{\partial T}{\partial t} = -\lambda_3\int_{\Omega}\delta_{\varepsilon}(\phi)d(\mu R\bar{x}+T+u)$$
$$\nabla d(\mu R\bar{x}+T+u)|\nabla(\frac{\phi}{\varepsilon})|d\bar{x},$$

where R is a rotation matrix with respect to θ.

III. Numerical Results

In this section, numerical methods to solve the Equation (1) are explained and the experimental results of applications to the human neck ultrasound images are shown. The Equation (1) was solved by finding a steady state solution of the evolution equations. The evolution equations are associated with the Euler-Lagrange equation. A finite difference scheme and the gradient descent method is applied to discretize the evolving equations. During the numerical experiments, $\lambda_1 = 0.05$, $\lambda_i = 1$ with $i = 2, 3, 4, 5$, $\varepsilon = 1$, $\varepsilon_1 = 0.01$, $H_{\varepsilon}(\phi) = [\frac{1}{2}(1+\frac{2}{\pi}\arctan(\frac{\phi}{\varepsilon}))]^2$, and $\delta_{\varepsilon}(\phi) = H'_{\varepsilon}(\phi)$ are used.

To demonstrate an image with noise, artifacts, and loss of information, the neck ultrasound scans with zoomed images are shown in Figure 1 and Figure 2. It is easily noticed in zoomed images that ultrasound scans are full of noise, artifacts, and loss of information. Therefore, it is difficult to find the location of nerves without prior knowledge. The prior information is incorporated with the distance function which consists of the global transformation and local non-rigid deformation. The prior shape is also used as an initial contour during experiments.

In Figure 3 and Figure 4, the proposed model segmentation result is compared to Chan-Vese model [5] and the suggested model without prior information [2] which is $\lambda_i = 0$ for $i = 3, 4, 5$ in Equation (1). The first one is the given image with an initial contour and the second one is the segmented result by Chan-Vese model as a dark solid line and comparison to an expert result as a white solid line in Figure 3. In Figure 4, the first one is the segmented result without prior information as a dark solid line and comparison to an expert result as a white solid line and the second one is the segmented result of the proposed model as a dark solid line and comparison to an expert result as a white solid line.

In Figure 5, experimental results are shown with and without non-rigid deformation term in prior information. The first one is the segmented result without non-rigid deformation term in prior information, $u = 0$, as a dark solid line and comparison to an expert result as a white solid line and the second one is the segmented result of the proposed model as a dark solid line and comparison to an expert result as a white solid line.

From Figure 6 and Figure 7, numerical results are shown with segmented binary images. Segmented binary images are created by a heaviside function, $H(\phi)$, where $H(\phi) = 1, \quad if \quad \phi \geq 0$ and $H(\phi) = 0, \quad if \quad \phi < 0$,. The first one is the segmented image result by heaviside function and the second one is the segmented contour result as a white solid line.

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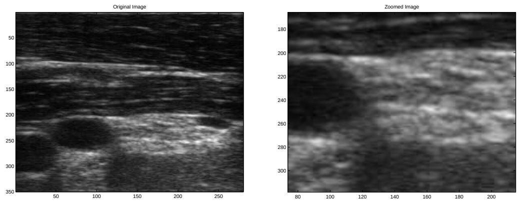

Fig. 1. First: An Example of Ultrasound Image and Second: A Zoomed Image.

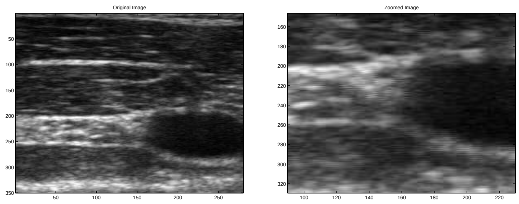

Fig. 2. First: Another Example of Ultrasound Image and Second: A Zoomed Image.

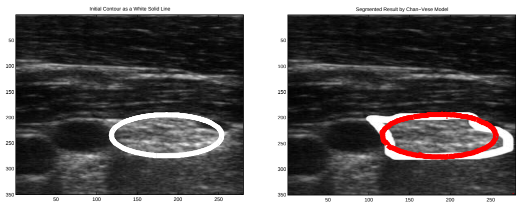

Fig. 3. First: The Given Image with An Initial Contour and Second: The Segmented Result by Chan-Vese Model as A Dark Solid Line and Comparison to An Expert Result as A White Solid Line.

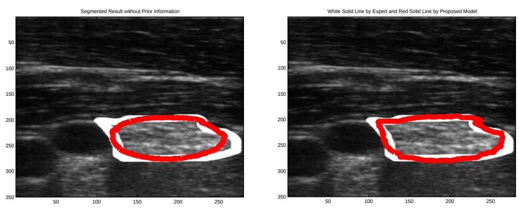

Fig. 4. First: The Segmented Result Without Prior Information as A Dark Solid Line and Comparison to An Expert Result as a White Solid Line and Second: The Segmented Result of The Proposed Model as A Dark Solid Line and Comparison to An Expert Result as A White Solid Line.

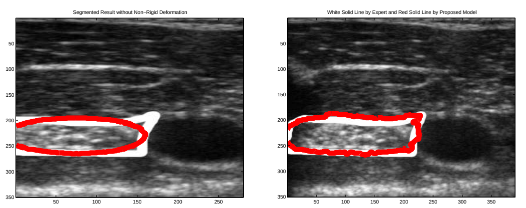

Fig. 5. First: The Segmented Result Without Non-rigid Deformation Term in Prior Information as A Dark Solid Line and Comparison to An Expert Result as A White Solid Line and Second: The Segmented Result of The Proposed Model as A Dark Solid Line and Comparison to An Expert Result as A White Solid Line.

IV. Conclusion

A new region based image segmentation model is proposed. Image segmentation is obtained using Γ-approximation to a piecewise constant Mumford-Shah functional and prior information. The prior information is incorporated by the distance function which consists of global rigid transformation and non-rigid deformation. The model is applied to healthy human neck ultrasound images and compared to an existing piecewise constant Mumford-Shah model and expert results. The preliminary numerical results showed the effectiveness of the presented model against noise, artifact, and loss of information. Even though experiments were done on 2D ultrasound images, the proposed model can be applied to any types of images and dimension. However, the numerical result depends on an initial choice of contour. Developing the algorithm which is independent of the choice of initial contour and automatic parameter estimation will be continued in the future work. In addition, more numerical experiments will be done with the development of validation methods and an extension to 3D is going to be considered.

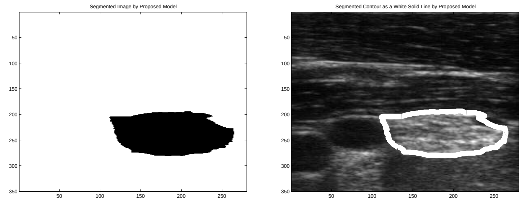

Fig. 6. First: The segmented Image Result by A Heaviside Function and Second: The Segmented Contour Result as A White Solid Line

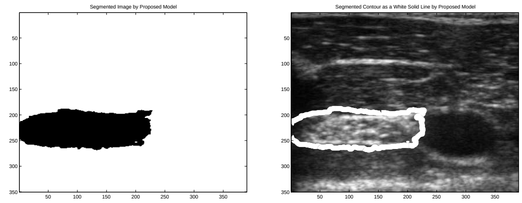

Fig. 7. First: The Segmented Image Result by A Heaviside Function and Second: The Segmented Contour Result as A White Solid Line

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