IDENTIFICATION OF NERVES IN ULTRASOUND SCANS USING MODIFIED MUMFORD-SHAH MODEL AND PRIOR INFORMATION

Jungha An *

Paul Bigeleison †

Steven Damelin‡

University of Minnesota
Inst. for Math. and its Applications
Minneapolis, MN, 55455, U.S.A.

University of Pittsburgh
UPMC Presbyterian Hospital
Pittsburgh, PA, 15213, U.S.A.

Georgia Southern University
Dept. of Mathematical Sciences
Statesboro, GA, 30460, U.S.A.

ABSTRACT

The goal of this paper is to acquire the efficient image segmentation algorithm which identify nerves in ultrasound scans. The new region based variational PDE algorithm is proposed using a modified Mumford-Shah model and prior information. The region of the interests are extracted by using a soft stochastic numerical approximation of a piecewise constant Mumford-Shah model and prior information. 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 neck ultrasound images of healthy patients. The numerical results show the effectiveness of the suggested model with noise, artifact, and speckles.

***Index Terms*—** Brachial Plexus, Image Segmentation, Metric, Mumford Shah, Numerical PDE

1. INTRODUCTION

Ultrasound has been shown to be an aid to peripheral nerve block. Amongst its advantages are higher success rates, shorter onset times, a decreased incidence of vascular puncture and a faster learning curve to master the techniques of regional anesthesia1,2,3,4. 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.

The Mumford-Shah model is reviewed briefly in this section. Mumford and Shah introduced the most celebrating region based image segmentation model in 1989 Using this model for a segmentation, an image is decomposed into a set of regions within the bounded open set Ω. These regions are separated by smooth edges Γ. The model is formulated as a variational problem to minimize the following functional :

$$\min_{u,\Gamma} MS(u,\Gamma) = \lambda_1 \int_\Omega (u-I)^2 d\bar{x} + \lambda_2 H(\Gamma) + \int_{\Omega\setminus\Gamma} |\nabla u|^2 d\bar{x},$$

where H stands for $(n-1)$ dimensional Hausdorff measure, $\lambda_i > 0$ $(i = 1, 2)$ are parameters which balances three terms in the model. The first term reconstructs an original noisy image I to u closely. Γ is to be a closed subset of Ω given by the union of a finite number of curves. It represents the set of ”edges” (i.e. boundaries of homogeneous regions) in the given image I. The second term minimizes the measurement of the edge Γ length. The piecewise smoothing of a reconstructed image u within each region is the last term.

2. DESCRIPTION OF THE PROPOSED MODEL

2.1. The Proposed Model

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

$$\begin{aligned} E(\phi,u,\mu,R,T) = \\ \lambda_1 \int_\Omega \{\frac{1}{2}(1+\frac{2}{\pi}\arctan(\frac{\phi}{\epsilon}))\}^2 (I(\bar{x})-c_1)^2 + \\ \{\frac{1}{2}(1-\frac{2}{\pi}\arctan(\frac{\phi}{\epsilon}))\}^2 (I(\bar{x})-c_2)^2 d\bar{x} + \\ \int_\Omega \{\frac{\epsilon_1 |\nabla(\frac{\phi}{\epsilon})|^2}{\pi^2(1+(\frac{\phi}{\epsilon})^2)^2} + \frac{\lambda_2(\pi^2-4\arctan^2(\frac{\phi}{\epsilon}))^2}{\epsilon_1 16\pi^4}\} d\bar{x} + \\ \frac{\lambda_3}{2}\int_\Omega \delta_\epsilon(\phi) d^2(\mu R\bar{x}+T+u)\} |\nabla(\frac{\phi}{\epsilon})| d\bar{x} + \\ \lambda_4 \int_\Omega |\nabla u|^2 d\bar{x} + \lambda_5 \int_\Omega u^2 d\bar{x}, \end{aligned} \tag{2.1}$$

*Acknowledges gracious support from the Institute for Mathematics and its Applications at the University of Minnesota and this work began while the first author was at the Institute for Mathematics and its Applications, University of Minnesota during the 2005-2006 Imaging Thematic year.

†Acknowledges gracious support from a chairman's grant from the department of anesthesiology at the University of Pittsburgh.

‡Acknowledges gracious support from EP/C000285, NSF-DMS-0439734 and NSF-DMS-0555839 and this work began while the third author was at the Institute for Mathematics and its Applications, University of Minnesota during the 2005-2006 Imaging Thematic year.

where I is a given novel 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.

The first term forces $\{\frac{1}{2}(1 + \frac{2}{\pi}\arctan(\frac{\theta}{\epsilon}))\}^2$, 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, $\{\frac{1}{2}(1 - \frac{2}{\pi}\arctan(\frac{\theta}{\epsilon}))\}^2$, 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 an edge detection term. In the theory of Γ-convergence, the measuring an edge Γ length term in the Mumford-Shah model can be approximated by a quadratic integral of an edge signature function $p(x)$ such that

$$\int_\Gamma dS = \int_\Omega (\epsilon|\nabla p|^2 + \frac{(p-1)^2}{4\epsilon})d\bar{x}, \epsilon \ll 1$$

by Ambrosio and Tortorelli in 1990 This model is combined with double-well potential function $W(p) = p^2(1-p)^2$ which is quadratic around its minima and is growing faster than linearly at infinity, where $p \in H^1(\Omega)$. In the following model is suggested :

$$\int_\Omega (9\epsilon|\nabla p_i|^2 + \frac{(p_i(1-p_i))^2}{\epsilon})d\bar{x},$$

where for each $p_i \in H^1(\Omega), i = 1, 2$. Here $\epsilon \ll 1$ controls the transition bandwidth. As $\epsilon \to 0$, 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 In our model, the idea is followed from The geometric active contour which detects higher gradient is in the last term as a level set form.

3. NUMERICAL RESULTS

Here are some preliminary numerical results of infraclavicular regions of healthy human neck ultrasound images. The numerical results compared between original given images and the smoothed given images. $I1$ = 20060730EveInf1.tif and $I2$ = 20060730EveInf2.tif

4. CONCLUSIONS AND FUTURE WORK

5. REFERENCES

[1] L. Ambrosio and V. Tortorelli, " Approximation of functionals depending on jumps by elliptic functionals via Γ-convergence," Comm. on Pure and Applied Math. vol.43, pp. 999-1036, 1990.

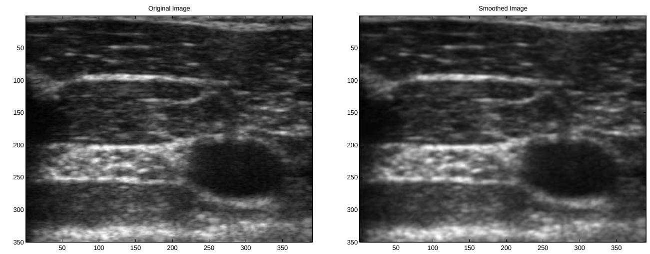

Fig. 1. Left : A Novel Image $I1$ and Right : Smoothed Image

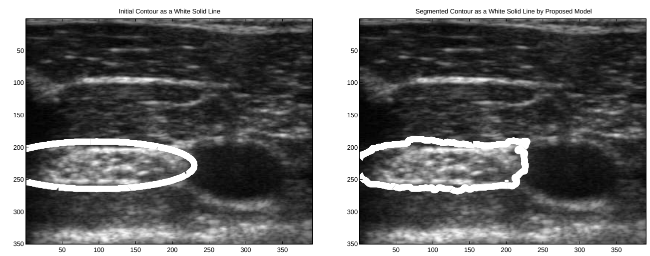

Fig. 2. Left : A Novel Image $I1$ with Initial Contour and Right : Segmented Contour as a White Solid Line

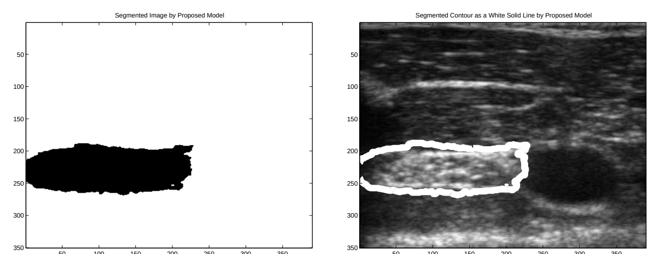

Fig. 3. Left : Segmented Image and Right : Segmented Contour as a White Solid Line

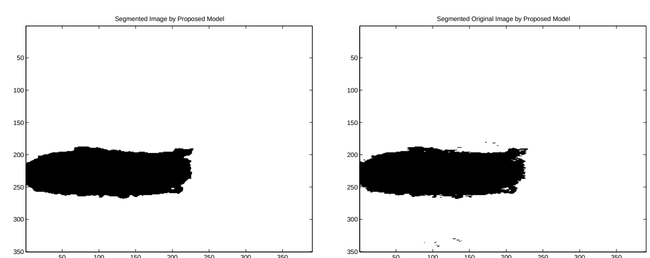

Fig. 4. Left : Segmented Image of Smoothed Image and Right : Segmented Image of Original Noisy Image

Fig. 5. Expert Result as a White Solid Line and Proposed Model Result as a Red Solid Line

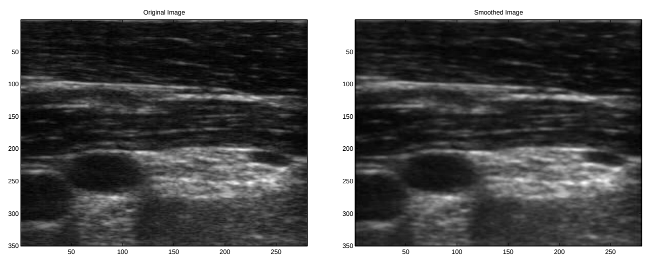

Fig. 6. Left : A Novel Image $I2$ and Right : Smoothed Image

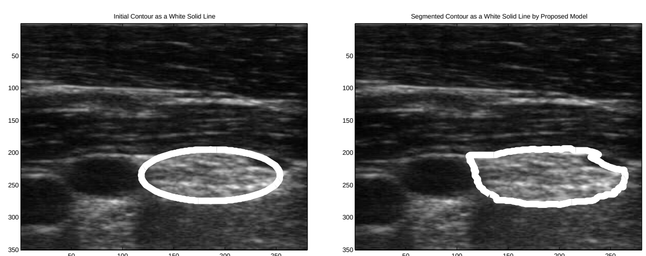

Fig. 7. Left : A Novel Image $I2$ with Initial Contour and Right : Segmented Contour as a White Solid Line

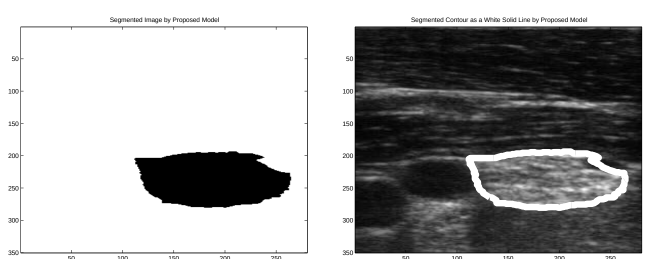

Fig. 8. Left : Segmented Image and Right : Segmented Contour as a White Solid Line

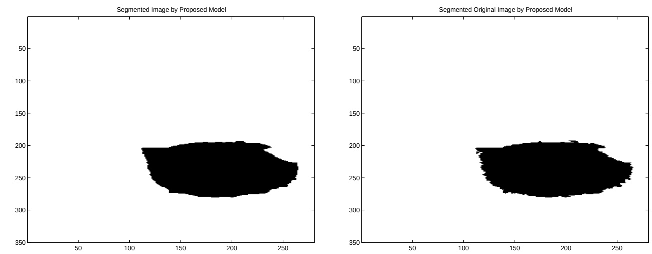

Fig. 9. Left : Segmented Image of Smoothed Image and Right : Segmented Image of Original Noisy Image

Fig. 10. Expert Result as a White Solid Line and Proposed Model Result as a Red Solid Line