International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-1 Issue-5, June 2012

Improving Medical Image Segmentation Techniques Using Multiphase Level Set Approach Via Bias Correction

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Abstract: In this paper, we present a new variational formulation for geometric active contours that forces the level set function to be close to a signed distance function, and therefore completely eliminates the need of the costly re-initialization procedure. Our variational formulation consists of an internal energy term that penalizes the deviation of the levelset function from a signed distance function, and an external energy term that drives the motion of the zero level set toward the desired image features, such as object boundaries. The resulting evolution of the level set function is the gradient flow that minimizes the overall energy functional.

Index terms: image segmentation, level set formulation, Gradient, bias field and MRI

I. INTRODUCTION

Magnetic resonance imaging (MRI) is a ubiquitous and powerful medical imaging technique, which provides detailed images with high contrast between different soft tissues; MRI thus has significant advantages over other medical imaging modalities for many applications, making it especially useful for neurological, musculoskeletal, cardiovascular, and oncological imaging. However, there are commonly substantial artifacts in real MR image. Automatic image segmentation plays an important role in medical applications. Due to the limitations of the imaging process and the difficulty of transferring manual segmentation protocols into algorithms, automatic segmentation is challenging. Automatic image segmentation plays an important role in medical applications. Due to the limitations of the imaging process and the difficulty of transferring manual segmentation protocols into algorithms, automatic segmentation is challenging. We show that without deeply understanding the Limitations of an existing segmentation method, one easy/straightforward way to make improvements is through a calibration process to directly transfer its results closer to manual segmentations. To this end, we propose to use machine learning techniques to correct segmentation errors.

Manuscript published on 30 June 2012.
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From a theoretical perspective, the segmentation errors produced by a segmentation algorithm can be categorized into two classes: 1) random errors and consistent bias. The random errors are caused by random effects, e.g. imaging noises or random anatomical variations. They can be reduced by averaging techniques such as multi-atlas based segmentation. In this paper, we focus on addressing the other type of errors, consistent bias. Biases are systematic errors mostly caused by mistranslating manual segmentation protocols into the criteria followed by the automatic segmentation method. By definition, bias occurs consistently across different segmentation trials when certain conditions are met a manual segmentation protocol may assign a specific label to a voxel if and only if a certain criterion, e.g. the voxels next to it all have low intensities, is met. However, because of the translation error an automatic method may follow a slightly different criterion, e.g. the average intensity of its neighbors is low. In this example, the automatic segmentation method makes errors whenever a voxel's neighbors have a low average intensity but have at least one bright voxel.

Since bias occurs consistently, it is feasible to detect and correct them. Al-though it may be difficult to figure out the exact cause behind each bias, it is relatively easy to capture the patterns that are strongly correlated to the bias. Hence, one can detect bias via capturing the correlated patterns. For example, the example above demonstrates a simple bias whose correlated appearance pattern, i.e. a voxel's neighbors have a low average intensity but have at least one bright voxel, can be learned using training images. In reality, the bias may appear in more complex and less intuitive patterns. Although it may be difficult for the human to identify such bias, most machine learning techniques are capable of providing satisfactory solutions.

In related work, Morra et al [3] use machine learning to directly learn how to perform segmentation. During training, they use intermediate classification results to improve the classifier's performance. The main difference with our method is that they do not use any other segmentation methods and train the classifier from scratch. By contrast, our contribution lies in proposing the ideas of improving the performance of existing segmentation algorithms relative to a specific manual segmentation protocol via learning-based bias correction. Our approach takes full advantage of other segmentation algorithms to sim-plify learning. To validate our method, we apply it to three segmentation prob-lems/methods and show significant improvements for all of them

II. IMAGE SEGMENTATION

Image segmentation is a low-level image processing task that aims at partitioning an image into Homogeneous regions. How region homogeneity is defined depends on the application.A great number of segmentation methods are available in the literature To Whom It May Concern: segment images according to various criteria such as for example grey level, color, or texture. This task is hard and as we know very important, since the output of an image segmentation algorithm can be fed as input to higher-level processing tasks, such as model-based object recognition systems. Recently, Segmentation of a color image composed of different kinds of texture regions can be a hard problem, namely to compute for an exact texture fields and a decision of the optimum number of segmentation areas in an image when it contains similar and/or non-stationary texture fields. In this work, a method is described for evolving adaptive procedures for these problems. In many real world applications data clustering constitutes a fundamental issue whenever behavioral or feature domains can be mapped into topological domains. We formulate the segmentation problemupon such images as an optimization problem and adopt evolutionary strategy of Genetic Algorithms for the clustering of small regions in color featurespace. The present approach uses k-Means unsupervised clustering methods into Genetic Algorithms, namely for guiding this last Evolutionary Algorithm in his search for finding the optimal or sub-optimal data partition, task that as weak now, requires a non-trivial search because of itsNP-complete nature. To solve this task, the appropriate genetic coding is also discussed, since this is a key aspect in the implementation. Our purpose is to demonstrate the efficiency of Genetic Algorithms to automatic and unsupervised texture segmentation. Some examples in Color Maps are presented and overall results discussed.In the analysis of the objects in images it is essential that we can distinguish between the objects of interest and "the rest." This latter group is also referred to as the background. The techniques thatare used to find the objects of interest are usually referred to as segmentation techniques – segmenting the foreground from background. In this section we will take the two of the most common techniques--threshold and edge finding-- and we will present techniques for improving the quality of the segmentation result.

A. Level Set Approach

In these and many other image processing applications, level sets are of principal importance, while the amplitude of the function(i.e. the image) away from the level set boundary is secondary, if not irrelevant. This paper presents a methodology and associated theoretical analysis for level set estimation. As noted above, the problem arises in several practical image processing contexts and many methods have been devised for level set estimation , yet there is very little theoretical analysis of the basic problem in the literature. One of the key results of the analysis in this paper is that regularization terms required for minimax optimal level set estimation are distinctly different from regularization terms required for minimax optimal image estimation and denoising. Because set estimation is intrinsically simpler than function estimation, explicit level set estimation methods can potentially achieve higher accuracy than "plug-in" approaches based on computing an estimate of the entire function and thresholding the estimate to extract a level set.This is because function estimates aim to minimize the total error, integrated or averaged spatially over the entire function. This does little To Whom It May Concern:control the error at specific locations of interest, such as in the vicinity of the level set. In part, plug-in approaches to can perform poorly because they tend to produce overlysmooth estimates in the vicinity of the boundary of the level set.

Significant volumes of research have been dedicated to the estimation of functions containing singularities, edges, or more generally, lower-dimensional manifolds embedded in a higher-dimensional observation space; for a few examples. In the context of level set estimation, however, the lower-dimensional manifold is an artificial feature which may not correspond to any form of singularity in the function. Related results from the classification literature suggest that unless the underlying function f is guaranteed .To Whom It May Concern: Whom It May Concern lie in a restrictive global smoothness class (a highly unrealistic assumption in many typical applications), conventional function estimation methods are neither appropriate nor optimal in this context . This is because the rates at which plug-in estimates converge to the true level set may be slowed down by the complexity of the function away from the boundary.

The above observations indicate that accurate level set estimation necessitates the development of new error metrics, methodologies, and error bounding techniques. In this paper, we develop such methods and theoretically characterize their performance. In particular, the estimator proposed in this paper exhibits several key properties:

1. nearly achieves the minimax optimal error decay rate,
2. automatically adapts to the regularity of the level set boundary,
3. automatically adapts to the regularity of the underlying function f in the vicinity of the level set boundary,
4. admits a computationally efficient implementation, and
5. possesses enough flexibility to be useful in a variety of applications and contexts.

III. PAPER STRUCTURE

In this paper, we describe a new method designed explicitly for minimax optimal level set estimation.

The basic idea is to design an estimator of the form

$$\widehat{S} = \arg\min_{S \in \mathcal{S}} \widehat{\mathcal{R}}_n(S) + \Phi_n(S),$$

Where S is a class of candidate level set estimates ,bRn is an empirical measure of the level set estimation errorbased onnnoisy observations of the functionf, and n is a regularization term which penalizes improbablelevel sets. We describe choices for bRn, n and S which make b S rapidly computable and minimax optimalfor a large class of level set problems. In particular, a novel error metric, which is ideally suited to the problem at hand, is proposed in Section II. We examine several of its key properties, and describe how it can be modified slightly to solve the closely related problems of (a) simultaneously extracting multiple level

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sets, and (b) density (as opposed to regression) level set estimation. In Section III, we introduce the regularization term n, describe its derivation from fundamental probability concentration inequalities, and develop a dyadic tree-based framework which can be used to minimize the proposed objective function. Tree are utilized for a couple of reasons. First, they both restrict and structure the space of potential estimatorsin a way that allows the global optimum to be both rapidly computable and very close to the best possible(not necessarily tree-based) estimator. Second, they allow us to introduce a spatial adaptivity to the estimator selection criterion which appears to be critical for the formation of provably optimal estimators. The nature of this spatial adaptively and its role in achieving minimax optimal estimators. Which contains derivations of error decay rates under different assumptions on the function f.. energy e can be calculated as follows

$$
\begin{aligned}
\mathcal{E} &= \sum_{i=1}^{2}\int\left(\int K(\mathbf{y}-\mathbf{x})\,|I(\mathbf{x})-c_i|^2 M_i(\phi(\mathbf{x}))\,d\mathbf{y}\right)d\mathbf{x}\\
&= \sum_{i=1}^{2}\int\left(|I(\mathbf{x})-c_i|^2 M_i(\phi(\mathbf{x}))\int K(\mathbf{y}-\mathbf{x})d\mathbf{y}\right)d\mathbf{x}\\
&= \sum_{i=1}^{2}\int |I(\mathbf{x})-c_i|^2 M_i(\phi(\mathbf{x}))\,d\mathbf{x}\\
&= \int |I(\mathbf{x})-c_1|^2 H(\phi(\mathbf{x}))\,d\mathbf{x}\\
&\quad+\int |I(\mathbf{x})-c_2|^2 (1-H(\phi(\mathbf{x})))\,d\mathbf{x}
\end{aligned}
$$

here we have given certain functional formula for the evaluation of energy minimization of MR images these formulas are listed below .

A. Levelset Formulation

$$E \overset{\Delta}{=} \int \sum_{i=1}^{N} \int_{\Omega_i \cap O_x} \left(\log\left(\sqrt{2\pi}\sigma_i\right) + \frac{(I(\mathrm{y})-b(\mathrm{x})c_i)^2}{2\sigma_i^2}\right)\mathrm{dydx}$$

Level set formulation

$$E \overset{\Delta}{=} \int \sum_{i=1}^{N} \int_{\Omega_i} \chi_\rho(\mathrm{x},\mathrm{y})\left(\log\left(\sqrt{2\pi}\sigma_i\right) + \frac{(I(\mathrm{y})-b(\mathrm{x})c_i)^2}{2\sigma_i^2(\mathrm{x})}\right)\mathrm{dydx}$$

$$E(\Phi_N,\mathrm{b},\mathrm{c},\sigma) \overset{\Delta}{=} \int \sum_{i=1}^{N} \int \chi_\rho(\mathrm{x},\mathrm{y})\left(\log\left(\sqrt{2\pi}\sigma_i\right) + \frac{(I(\mathrm{y})-b(\mathrm{x})c_i)^2}{2\sigma_i^2}\right) M_i(\Phi_N(\mathrm{y}))\mathrm{dydx}$$

$$\Phi_N = (\phi_1,\cdots,\phi_n), \text{ where } N = 2^n.$$

Let

$$d_i(\mathrm{y}) = \int \chi_\rho(\mathrm{x},\mathrm{y})\left(\log(\sigma_i) + \frac{(I(\mathrm{y})-b(\mathrm{x})c_i)^2}{2\sigma_i^2}\right)\mathrm{dx}$$

$$E(\Phi_N,\mathrm{b},\mathrm{c},\sigma) \overset{\Delta}{=} \sum_{i=1}^{N} \int d_i(\mathrm{y}) M_i(\Phi_N(\mathrm{y}))\,\mathrm{dy},$$

where $\Phi_N = (\phi_1,\cdots,\phi_n)$, where $N = 2^n$.

When n =2, and set

$$b(\mathrm{x}) = \frac{\sum_{i=1}^{N} \chi_\rho * (IM_i(\Phi_N)) \bullet \frac{c_i}{\sigma_i^2}}{\sum_{i=1}^{N} \chi_\rho * M_i(\Phi_N) \bullet \frac{c_i^2}{\sigma_i^2}},$$

$$c_i = \frac{\int (\chi_\rho * b) IM_i(\Phi_N)\mathrm{dy}}{\int (\chi_\rho * b^2) M_i(\Phi_N)\mathrm{dy}},$$

$$\sigma_i^2 = \frac{\iint \chi_\rho(\mathrm{y},\mathrm{x}) M_i(\Phi_N(\mathrm{y}))(I(\mathrm{y})-b(\mathrm{x})c_i)^2\mathrm{dydx}}{\iint \chi_\rho(\mathrm{y},\mathrm{x}) M_i(\Phi_N(\mathrm{y}))\mathrm{dydx}}$$

When N = 4, then n=2, we can evolve two level set functions to obtain the optimal solution

$$\frac{\partial\phi_1}{\partial t} = -\left[(d_1-d_2-d_3+d_4)H(\phi_2)+d_2-d_4\right]\delta(\phi_1)$$

$$\frac{\partial\phi_2}{\partial t} = -\left[(d_1-d_2-d_3+d_4)H(\phi_1)+d_3-d_4\right]\delta(\phi_2)$$

Segmentation result (SR) showing

$$I_{SR} = \sum_{i=1}^{N} c_i M_i(\Phi_N)$$

B. Bias Correction

In our method, we explicitly perform bias detection and bias correction. This strategy is efficient because for bias correction only the potentially mislabeled voxels need to be relabeled. One variant of our bias correction method is that we skip the bias detection step and directly perform bias correction on the initial segmentation. Instead of only using mislabeled voxels, we use all voxels in ROI for training. We call this method implicit bias correction (IBC). Note that IBC has higher computational complexity for both training and testing. IBC is closely related to [3], where instead of segmentation results produced by other segmen-tation methods the segmentation labels produced by the learning algorithm itself are included in the learning process.

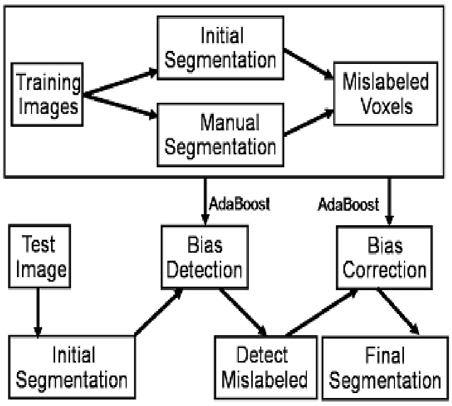

Fig 1 Flow Chart for the bias correction approach

One way to view the segmentation feature produced by other host segmentation methods is that like the low level texture filters any host segmentation method can be considered as a high level, task specific filter. If the host seg-mentation method works reasonably well, i.e. better than random guesses, the produced segmentation provides useful information for the segmentation task. To demonstrate the usefulness of host segmentation methods for learning, we compare with a variant of IBC that each classifier is learned without using seg-mentation results produced by any other segmentation methods.

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We call this variant the direct learning (DL) approach. So given training images and their manual segmentations, we train one classifier for each label to separate voxels belonging to this label from other voxels. The features used for DL, is only image and spatial features. For IBC and DL, the ROI is the whole segmentation pro-duced by the host method plus some dilation. Dilation is necessary only when the background label needs to be corrected

IV. EXPERIMENT RESULT AND VALIDATION

The proposed variational level set formulation has three main advantages over the traditional level set formulations.

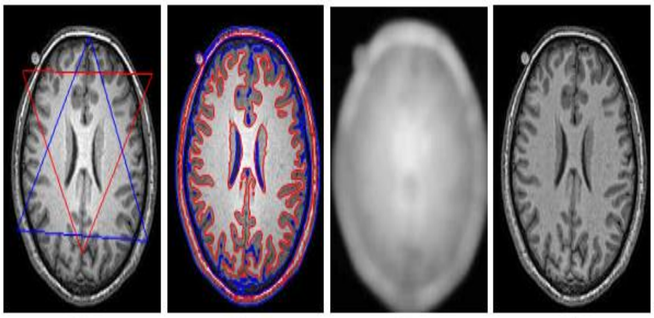
1. Significantly larger time step can be used for numerically solving the evolution partial differential equation, and therefore speeds up the curve evolution.

2. The level set function can be initialized with general functions that are more efficient to construct and easier to use in practice than the widely used signed distance function.

3. The level set evolution in our formulation can be easily implemented by simple finite difference scheme and is computationally more efficient.

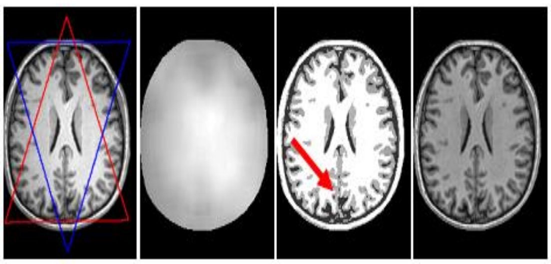
The proposed algorithm has been applied to both simulated and real images with promising result

For the experiments in this paper, we use the parameters $\sigma = 4, \mu = 1,$, and v= 0.001×255^2 for all the images in this paper. Our method are robust to the initialization of th automatic applications, the constants $c_1, \cdots, c_N$ can be initialized as N equally spaced numbers between the minimum and maximum intensities of the original image, and the bias field b is initialized as b=1 . The level set functions can be automatically generated or manually initialized by the users. The number of phases depends on the number of tissue types in the images, which is usually known in practice.

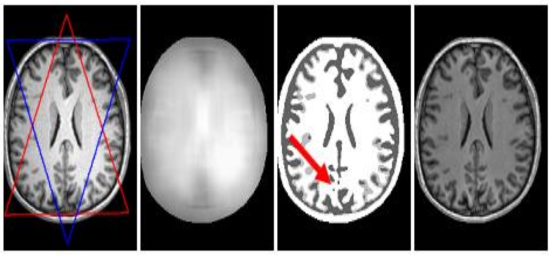


(a) (b) (c) (d)

Fig. 3. Applications of our method to a 3T MR image. (a) Original image and initial contours: zero level contours of initial ϕ_1 (red) and ϕ_2 (blue). (b) Final zero level contours of ϕ_1 (red) and ϕ_2 (blue); (c) Computed bias field; (d) Bias corrected image.

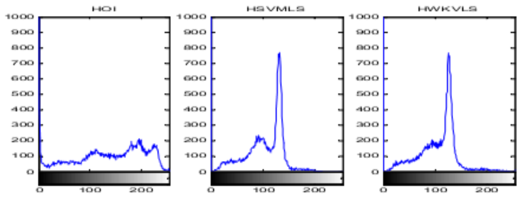


(a)



(b)

(c)



(d)

Fig. 2. (a) and (b): From left to right: the initializations of level set functions, estimated bias fields, tissue classification results, an d bias corrected images by our method (SVMLS) and the WKVLS method, respectively.

(c): An arbitrary initialization of level set functions and the corresponding experimental results.

(d) Histograms of original image (HOI), bias corrected image by our method

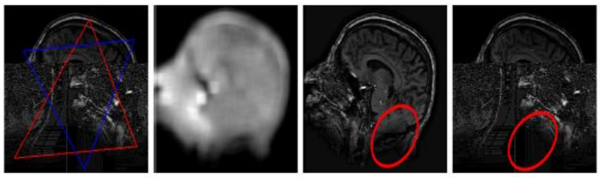


Fig.3. Experiments on 7T MR image. Column 1: Initial contours; Column 2: Estimated bias field. Column 3: Bias correction image. Column 4: Original image

V. CONCLUSION

This paper presents a novel statistical and variation multiphase level set (SVMLS) approach to simultaneous bias correction and tissue segmentation for MRI image. The smoothness of the bias field is intrinsically ensured by the normalized convolution without any extra costs, which makes our method well fitted for images of various modalities, such as 3T and 7T MRI images. Moreover, the proposed SVMLS algorithm is robust to the initializations, therefore allowing for fully automatic applications.

Comparisons with state-of-the-art method on real MRI images show the advantages of the proposed algorithm.

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