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TISSUE SEGMENTATION AND BIAS CORRECTION IN MRI USING LEVEL SET APPROACH.

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ABSTRACT:
This paper presents a novel level set approach to simultaneous tissue segmentation and bias correction of Magnetic Resonance Imaging (MRI) images. We model the distribution of intensity belonging to each tissue as a Gaussian distribution with spatially varying mean and variance. We define a maximum objective function for each point in a transformed domain, where the distribution overlap between different tissues can be suppressed to some extent, and then an energy functional is defined by integrating the maximum likelihood function over the entire image domain. The segmentation and bias correction are simultaneously achieved via a level set evolution process. A salient advantage of our method is that the smoothness of the computed bias field is ensured by the normalized convolution without extra cost. The method is robust to initialization, there allow automatic applications. Experiments on images of various model demonstrated the superior performance of the proposed approach over state-of-the-art methods. ***Keywords***: Bias correction, LSA, MR Segmentation.

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. 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.

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.

The method is motivated by the weighted K-means clustering, and we name it as weighted K-means variational level set (WKVLS) method. However, as we will see from the following discussions, the

WKVLS method can be viewed as a special case of our proposed SVMLS (statistical and variational multiphase level set) method, while the latter is more accurate.

The intensity inhomogeneity often exists in magnetic resonance imaging (MRI) images due to the imperfection of imaging devices. The intensity inhomogeneity can be generally modeled as a smooth and spatially varying field, multiplied by the constant true signal of the same tissue in the measured image. This spatially varying field is named as the bias field. Bias correction is a procedure to estimate the bias field and restore the true signals, thereby eliminating the side effect of the intensity inhomogeneity. Among various bias correction methods, those based on segmentation are most attractive.

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. 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 its NP-complete nature.

1.1. 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.

The 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 overly smooth 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.

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.
5. Possesses enough flexibility to be useful in a variety of applications and contexts.

1.1.1 Level Set Formulation

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

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

Let,

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

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

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

III. PAPER STRUCTURE

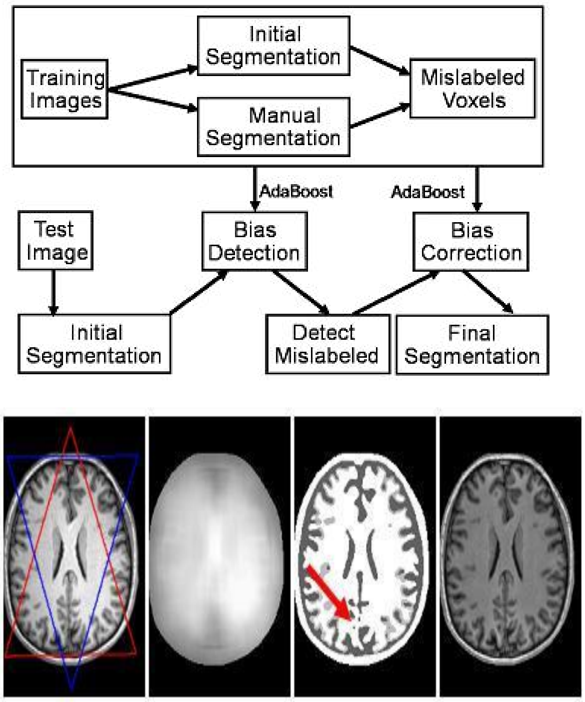
In this paper, we describe a new method designed explicitly for minimax optimal level set estimation. The basic idea is to design an estimator of the form

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

Where, S is a class of candidate level set estimates , bRn is an empirical measure of the level set estimation error based on noisy observations of the function f, and n is a regularization term which penalizes improbable level sets. We describe choices for bRn, n and S which make bS rapidly computable and minimax optimal for 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 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 estimators in 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.

1.2. 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 relabeld. Instead of only using mislabeled voxels, we use all voxels in ROI for training. 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.



(b)

Fig.1 Flow Chart for the Bias Correction Approach.

IV. EXPECTED RESULT AND VALIDATION

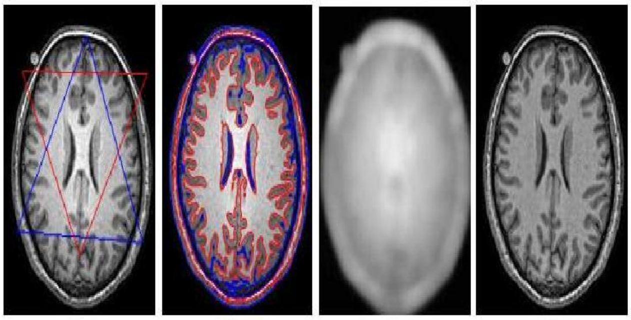
The proposed variational level set formulation has three main advantages over the traditional level set formulations.

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.

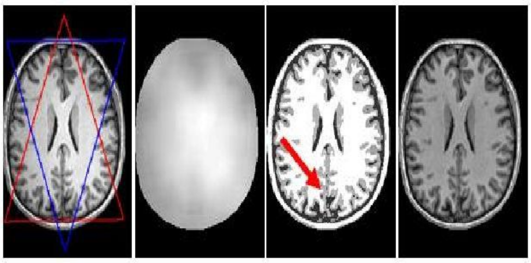
3. The level set evolution in our formulation can be easily implemented by simple finite difference scheme and is computationally more efficient.

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

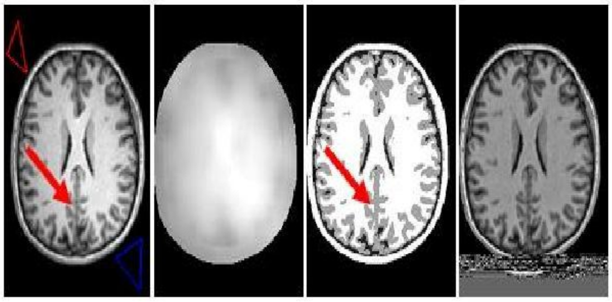


(a)

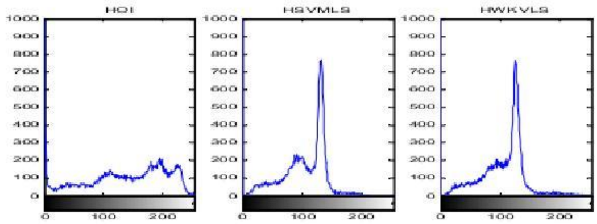
Fig. 2. (a) and (b): From left to right: the initializations of level set functions, estimated bias fields, tissue classification results, an d bias corrected images by our method (SVMLS) and the WKVLS method, respectively.

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

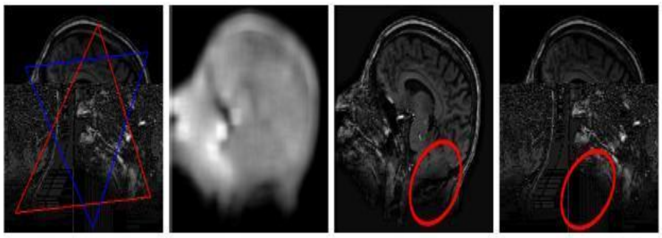
(d) Histograms of original image (HOI), bias corrected image by our method.Fig.3. Experiments on 7T MR image. Column 1: Initial contours; Column 2: Estimated bias field. Column 3: Bias correction image. Column 4: Original image



(c)



(d)



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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