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OPTIMIZATION IN MRI BIAS CORRECTION USING RETROSPECTIVE METHOD

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Abstract —- *In this project the retrospective method is used, by exploiting local image region statistics and we presented a set method for segmenting images with intensity inhomogeneity. Our method combines the information from the neighboring pixels belonging to the same class, which equips it with a strong capability to separate the desired object from its background. Using this proposed method, the MRI bias correction has been done.*

Keywords- *Retrospective method, MRI, Bias correction, Segmentation, Inhomogeneity*

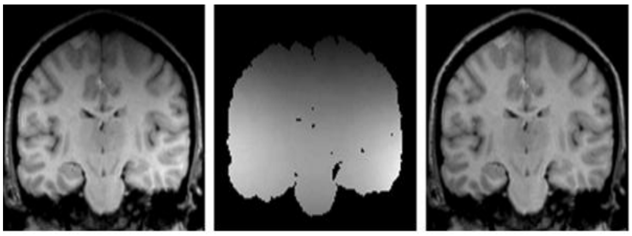
I. INTRODUCTION

Medical image acquisition devices and protocols that have tremendously evolved over the last decades provide a vast amount of data out of which the information essential for diagnosis, therapy planning and execution, and monitoring the progress of disease or results of treatment has to be extracted.

Automated extraction of clinically useful information usually requires a preprocessing step by which various image artifacts, which may degrade the results of subsequent image analysis algorithms, are removed. This project addresses a class of preprocessing methods that deal with spurious smoothly varying image intensities, i.e., with the phenomenon that is usually referred to as intensity inhomogeneity, intensity non uniformity, shading or bias field. This adverse phenomenon is apparent in images obtained by different imaging modalities, such as microscopy, computed tomography, ultrasound, and above all by magnetic resonance imaging (MRI). Intensity inhomogeneity in MRI, which arises from the imperfections of the image acquisition process, manifests itself as a smooth intensity variation across the image (Fig1.1). Because of this phenomenon, the intensity of the same tissue varies with the location of the tissue within the image.

Although intensity inhomogeneity is usually hardly noticeable to a human observer, many medical image analysis methods, such as segmentation and registration, are highly sensitive to the spurious variations of image intensities. This is why a number of methods for intensity inhomogeneity correction of magnetic resonance (MR) images have been proposed in the past.

Original Image Bias filed Bias corrected image



II. LITERATURE SURVEY

Inhomogeneity is usually ascribed to a smooth and spatially varying field multiplying the true signal of the same object in the measured image. This spatially varying smooth field is named as bias field. Bias correction is a procedure to estimate the bias field from the measured image to reduce its side effect [1]. Existing bias correction approaches can be categorized into two categories, namely prospective [6]-[9] and retrospective [1], [2], [10]–[21] approaches. Prospective methods aim at calibrating and improving image acquisition processing by applying specific hardware or devising special imaging sequences. However, these methods cannot correct patient induced inhomogeneity [5], [18]. Comparatively, retrospective methods only rely on the acquired images and sometimes some prior knowledge. Thus, they are relatively more general, and can be used to correct patient induced inhomogeneity from different sources. The retrospective methods can be further categorized into several categories based on filtering [4], surface fitting [19], histogram [20], and segmentation [1], [2], [14]–[17], [22]. Among various retrospective methods, segmentation based ones are most attractive, since they unify segmentation and bias correction under a single framework to benefit from each other, simultaneously yielding better segmentation and bias correction results. In these methods, parameter model based on the maximum-likelihood (ML) or maximum a posterior (MAP) probability criterion is often used, in which the corresponding parameters are often estimated by the expectation maximization (EM) algorithm [14], [15], [21], and [23]. However, an appropriate initialization of the EM algorithm is critical to such algorithms, which requires either a close estimate of the bias field or a coarse segmentation [22]. Manual selections of seed points for each class are often used [21], but it is subjective and irreproducible [5], [22]. Recently, Li et al. [2] proposed a parametric method for simultaneous bias field correction and segmentation by minimizing a least square energy functional.

The bias field is modeled as a linear combination of a set of orthogonal polynomial basis functions [15], [22]. Although this leads to a very smooth bias field, some bias fields cannot be well fitted by polynomials, such as the bias field in 7T MRI [1], [17]. Moreover, each pixel is assigned to one tissue class. However, intensities of the partial volume voxels are composed of multiple class intensities in images, and the proportion of the partial volume voxels in low-resolution datasets can be up to 30% [22]. Thus, the calculated bias field may be partially wrong. Li *et al.* [17] proposed a variational level set (VLS) approach [26], [27] to simultaneous segmentation and bias correction.

However, this method needs to alternatively iterate two partial differential equations, which is very time consuming. Furthermore, the energy functional in the VLS method is not convex in the set of characteristic functions, making it easy to be trapped into local minima [28].

III. BACKGROUND AND PROPOSED METHOD

This project presents a novel variational approach to simultaneous bias correction and segmentation. By exploiting local image redundant information, we define a mapping from original image domain to another domain so that the intensity probability model is more robust to noise. We then define an ML energy functional based on the intensity distributions in each local region in the transformed domain, which combines the bias field, the membership function of each object region, and the constant approximating the true signal from its corresponding object.

Finally, the ML energy functional is extended to the whole image domain, which we call the criterion of maximum likelihood in transformed domain (MLTD). The MLTD criterion achieves a global minimum with respect to each of its variables. Moreover, analysis of the MLTD criterion shows that it is a soft classification model, which assumes that each pixel intensity belongs to more than one class, while the hard classification assigns the intensity of each pixel to only one class. Therefore, the MLTD criterion obtains a better corrected bias field. In addition, the recently proposed CLIC criterion [1] can be viewed as a special case of the MLTD criterion, while the MLTD is more accurate to model inhomogeneous image intensity.

3.1 PROPOSED METHOD

The proposed method presents a novel variational approach for simultaneous estimation of bias field and segmentation of images with intensity inhomogeneity. We model intensity of inhomogeneous objects to be Gaussian distributed with different means and variances, and then introduce a sliding window to map the original image intensity onto another domain, where the intensity distribution of each object is still Gaussian but can be better separated. The means of the Gaussian distributions in the transformed domain can be adaptively estimated by multiplying the bias field with a piecewise constant signal within the sliding window.

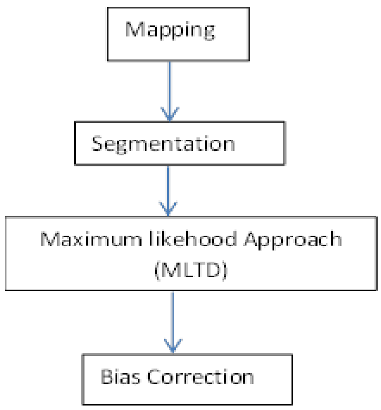


Figure 3.1 Proposed Method

Maximum likelihood energy functional is then defined on each local region, which combines the bias field, the membership function of the object region, and the constant approximating the true signal from its corresponding object. The energy functional is then extended to the whole image domain by the Bayesian learning approach. An efficient iterative algorithm is proposed for energy minimization, via which the image segmentation and bias field correction are simultaneously achieved.

IV. EXPERIMENTAL RESULTS

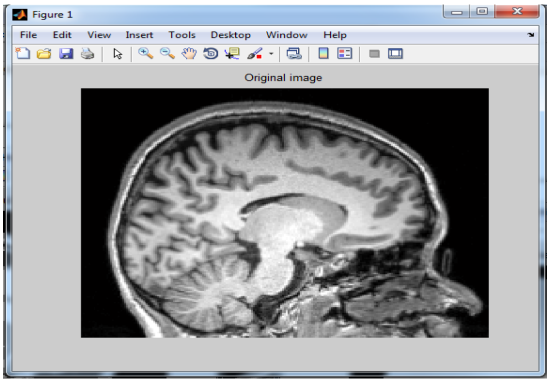


Figure 4.1 Orginal MR Image

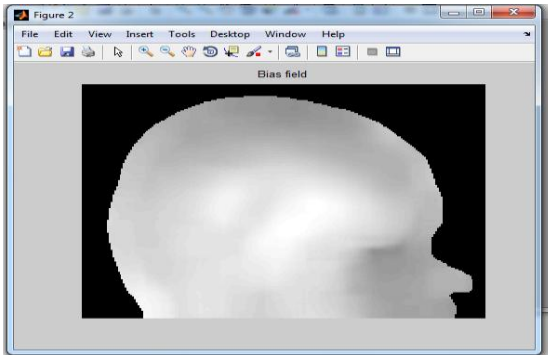


Figure 4.2 Bias Field of the original Image

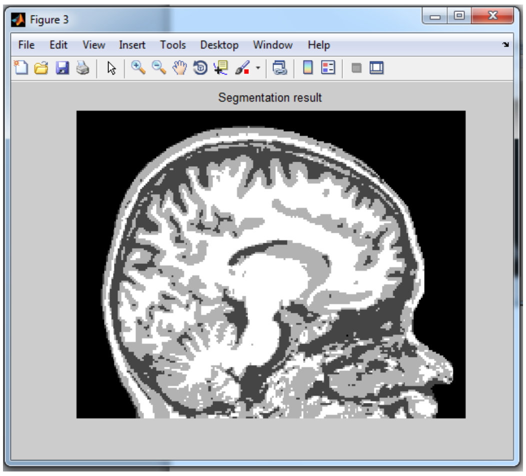


Figure 4.3 Segmentation

The results show the simultaneous estimation of the bias field and segmentation of images with intensity inhomogeneity. Our method combines information of the neighboring pixels belonging to the same class, which makes it robust to noise. Moreover, the proposed method yields a soft segmentation, which can eliminate the partial volume effect to some extent.

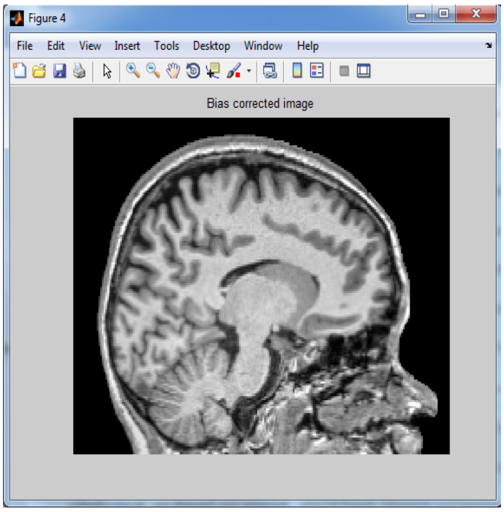


Figure 4.4 Bias Corrected Image

V. CONCLUSION

The estimation of bias field and segmentation of images with intensity inhomogeneity by, model intensity of inhomogeneous objects to be Gaussian distributed with different means and variances, and then introduce a sliding window to map the original image intensity onto another domain, where the intensity distribution of each object is still Gaussian but can be better separated. The means of the Gaussian distributions in the transformed domain can be adaptively estimated by multiplying the bias field with a piecewise constant signal within the sliding window. Maximum likelihood energy functional is then defined on each local region, which combines the bias field, the membership function of the object region, and the constant approximating the true signal from its corresponding object. The energy functional is then extended to the whole image domain by the Bayesian learning approach. An efficient iterative algorithm is proposed for energy minimization, via which the image segmentation and bias field correction are simultaneously achieved.

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