Simultaneous Image Segmentation and Bias Correction Using Neural Network and MLTD

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Abstract: In MRI images, Intensity inhomogeneity occurs due to the imperfection of imaging devices and the subject induced susceptibility effects. Bias field is magnetic based inhomogeneity. Essentially this is smooth, low frequency gradient signal, which covers valuable data. Bias field is particularly severe in high field MRI and ultra high field MRI, which challenges quantitative image analysis algorithms, such as segmentation and registration. Therefore, intensity inhomogeneity correction is usually a prerequisite before applying quantitative algorithms. We propose a novel bias correction method for magnetic resonance (MR) imaging for simultaneous tissue segmentation and bias correction. This develops a new bias correction approach using Artificial Neural Networks (ANN). The proposed model relies on a supervised learning approach (back propagation) to construct a functional relationship between the input and output. The ANN trained network can noticeably reduce the estimation error and improve structure of the bias-corrected variables. Here, Gaussian distribution is used to calculate means and variances for intensity of inhomogeneous object. A window is used to transform the original image intensity into another domain. In the transformed domain means can be adaptively estimated. An energy functional is defined on each region, which combines bias field, membership function and the constant approximate the true voxels from its corresponding objects. Energy minimization, via which image segmentation and bias correction are simultaneously achieved by using this efficient iterative algorithm. The superiority of the proposed method compared to other state of the art representative methods.

***Index Term*-- Image segmentation, Bias field, Neural Network, Energy minimization, Histogram.**

I. INTRODUCTION

The inhomogeneity in MRI is mainly caused by non uniform magnetic field produced by radio frequency coils as well as from object susceptibility. Intensity inhomogeneity is usually ascribed to a smooth and spatially varying field multiplying the true signal of the same object in the measured image[1]. 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[2].Existing bias correction approaches can be categorized into two categories, namely prospective and retrospective here, we mainly focus on the retrospective methods .This methods can be further categorized into several categories based on filtering [3], surface fitting [4], histogram [5], and segmentation. 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. Maximum Likelihood 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. The MLTD criterion achieves a global minimum with respect to each of its variables[1].Markov random fields (MRF) model[6] can yield improved segmentation results that are less sensitive to noise [7].A parametric method for simultaneous bias field correction and segmentation by minimizing a least square energy functional. 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. 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% [8]. Thus, the calculated bias field may be partially wrong. A variational level set (VLS) approach [9] 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 [10].Existing methods take large computation time in order to process the images. Usually MRI images has large amount of data in order to process that data it take more time. To overcome these problems we combine both the neural network and the maximum likelihood transformed domain(MLTD)[1] through this we will get the better results. In the following section II shows the related work, section III shows the proposed scheme in detail. In Section IV, Experiments are demonstrated. Finally, the conclusions are in Section V.

II. RELATED WORK

In [2], a coherent local intensity clustering (CLIC) model is proposed for simultaneous segmentation and bias correction. For each single point $x \in \Omega$, we define a local region $O_x = \{y : |y - x| \le \rho\}$ with radius ρ. The true voxel $J(x)$ in each region Ω_i is approximated equal to be a constant c_i. Since the bias function b varies slowly, it can also be approximated as a constant in a local region $O_x \cap \Omega_i$ Therefore, we have

$$b(y)J(y) \approx b(x)c_i, y \in O_x \cap \Omega_i \qquad (1)$$

Hence in (1),we have $b(x)c_i$ is the cluster center for the intensities in the neighborhood $O_x \cap \Omega_i$. A clustering criterion functional is proposed in which a weight function $w(y - x)$ is introduced to measure the similarity of each pixel intensity $I(y)$ to its cluster center $b(x)c_i$:the weight at position y far from its cluster center x is smaller than the nearby ones, meaning its intensity has less similarity than those near the center. The clustering criterion function is defined as

$$E_X^{local}(u,c,b(x)) = \sum_{i=1}^{N} \int_{O_X} u_i^q(y) w(x-y) \,|\, I(y) - b(x)c_i \,|^2 \, dy \qquad (2)$$

where in (2) q is appositive integer, N is the assumed number of regions, u_i is the indicator function for region Ω_i u={ u_i ,i=1, . . .,N},and C={ c_i ,i=1, . . .,N}.w(.) in (3) is a weight function defined as below where weight function is failed then it is zero.

$$w(x) = \frac{1}{a} e^{\frac{-|x|^2}{2a^2}}, |\, x \,| \leq \rho \qquad (3)$$

where a is a normalization constant. Then, (4) is extended to the whole domain that defines the following CLIC energy functional.

$$E_{u,c,b}^{CLIC}(u,c,b) = \int_{\Omega} \sum_{i=1}^{N} \int_{O_x} u_i^q(y) w(x-y) \,|\, I(y) - b(x)c_i \,|^2 \, dydx. \qquad (4)$$

Then the objective is to minimize $E_{u,c,b}^{CLIC}$ with respect to the membership function set u (for any set X, a membership function on X to the real unit interval [0,1]),true signal set c and bias field b subject to the constraints $u_i \geq 0$ and $\sum_{i=1}^{N} u_i = 1$.

III. SIMULATANEOUS IMAGE SEGMENTATION AND BIAS CORRECTION USING NEURAL NETWORK AND MLTD

This section describes proposed method in detail. Initially, we are training the images through a supervised learning approach (back propagation) in neural network, for that image apply the Maximum likelihood transformed domain. Back propagation method consists of three layers—input layer ,hidden layer and output layer. In between layer the weights are present which are randomly initiated .Each neuron contain image intensity values of the original image. These intensity values are multiplied with weights and added to hidden layer. The process continue to hidden layer and output layer. In the output layer the occurred image intensity value is compared with the estimated intensity value .The difference between these values are known as error which back propagated and changes the weight functions.

3.1. Neural Network

In our method intensities of the whole image caused by the intensity inhomogeneity, in a relatively small local region are separable, despite of the inseparability of the intensities. The proposed model relies on a supervised learning approach (back propagation) to construct a functional relationship between the input and output. This relationship learns the error structure by training the inputs with observations (intensity) to understand prediction biases. The predictive capacity of the ANN confirms that the network can perform well with new and unseen datasets without any need for re-training. The ANN trained network can markedly reduce the estimation error and improve structure of the bias-corrected variables.

The main steps are as follows:

1.Initialize the weights to small random values.

2.Select a training vector pair (input and the corresponding output) from the training set and present the input vector to the inputs of the network.

3.Calculate the actual outputs this is the forward phase.

4.According to the difference between actual and desired outputs (error). Adjust the weights Wo and Wh to reduce the difference this is the backward phase.

5.Repeat from step 2 for all training vectors.

6.Repeat from step 2 until the error is acceptably small.

3.2. Maximum likelihood in transformed domain

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.

$$E_{u,c,b,\sigma}^{MLTD} = \frac{1}{N} \sum_{i=1}^{N} \int_{\Omega} \int_{\Omega} \chi_{\rho}(y,x) u_i(y) (\log(\sqrt{2\pi}\sigma_i) + (I(y) - b(x)c_i)^2 / 2\sigma_i^2) dydx \qquad (5)$$

Where $c = \{c_1, \ldots\ldots, c_N\}$ c=true signal

$$u = \{u_1, \ldots\ldots, u_N\} \quad \text{u=membership function}$$

$$\sigma = \{\sigma_1, \ldots\ldots, \sigma_N\}$$

From (5) the whole minimization procedure consists of the following three steps, which are implemented iteratively.

1) Keep u fixed, optimize and update the variable sets c, b, and σ .
2) Keep c, b, and σ fixed, optimize and update u.
3) Check whether the convergence has been reached. If not, return to 1).

An efficient iterative algorithm is proposed for energy minimization, via which the image segmentation and bias field correction are simultaneously achieved. In section –III we compare with neural network with Maximum likelihood in transformed domain and only Maximum likelihood in transformed domain.

IV. EXPERIMENTS AND DISCUSSIONS

In this section, to evaluate the effectiveness of the proposed neural network using MLTD are conducted. In the following experiments, real and synthetic images are used.Fig.1 shows the bias corrected synthetic image results of proposed scheme.Fig.2 shows bias corrected synthetic image results of MLTD only.Fig.3 shows the histogram plots of proposed scheme where the two peaks in the (b)plot are GM and WM. Fig.4 shows the bias corrected real image results of proposed scheme.Fig.5 shows bias corrected real image results of MLTD only.Fig.6 shows the histogram plots of proposed scheme where the two peaks in the (b)plot are GM and WM.Fig.7 shows the efficiency comparisons among different methods.

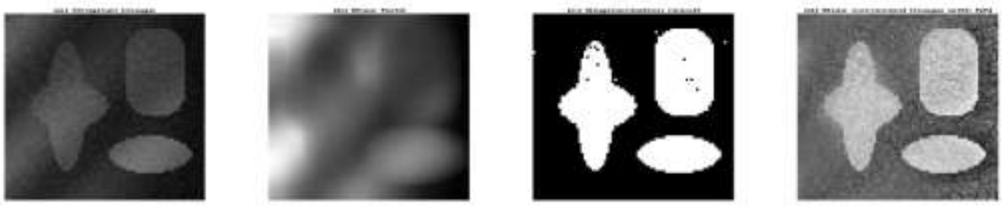

Fig.1: Application to a synthetic image with noise.(a)original image(b)bias field (c)segmentation result (d)bias corrected result of neural network using MLTD.

The Fig.1 shows the variation between original image and output image. From the original image we estimated the bias field showed in the (b).Here, the processing is done simultaneously Fig.1(d) shows the simultaneous image segmentation and bias correction using NN and MLTD.

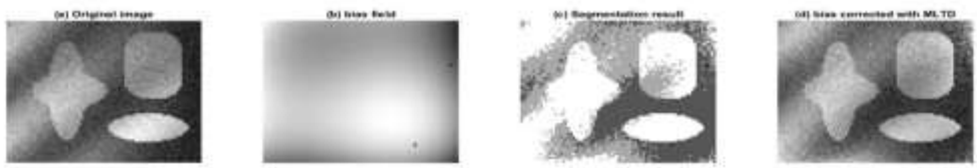

Fig.2: Application to a synthetic image with noise (a)original image(b)bias field (c)segmentation result (d)bias corrected result of MLTD.

The Fig.2 is the synthetic image it shows the variation between original image and output image. From the original image we estimated the bias field showed in the (b).Here, the processing is done simultaneously Fig.2(d) shows the simultaneous image segmentation and bias correction using MLTD.

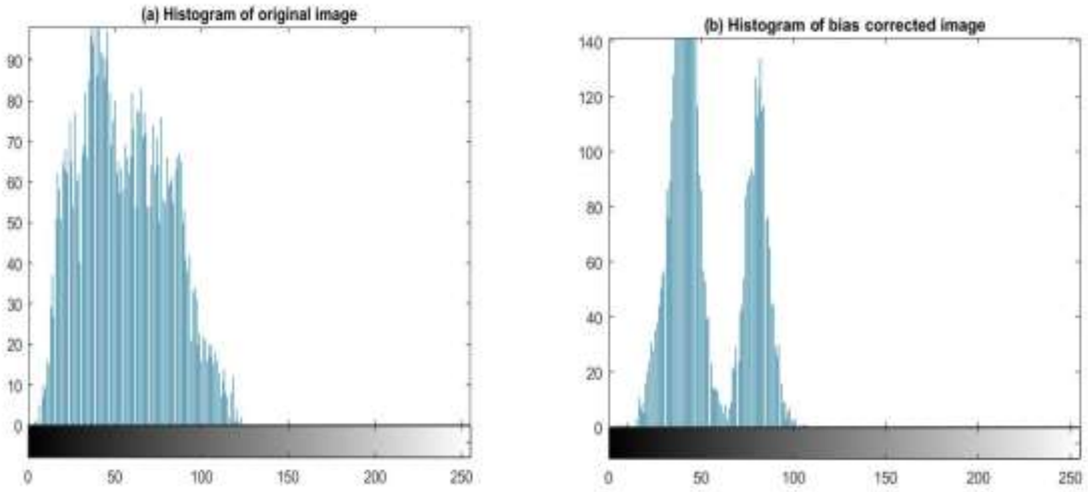

Fig.3: Histograms of original image and bias corrected images of neural network using MLTD.

The Fig.3 is the synthetic image histogram plots it shows the variation between histogram of original image and histogram of bias corrected image.Fig.3 shows the histogram plots of proposed scheme where the two peaks in the (b)plot are Gray Matter(GM) and White Matter(WM).

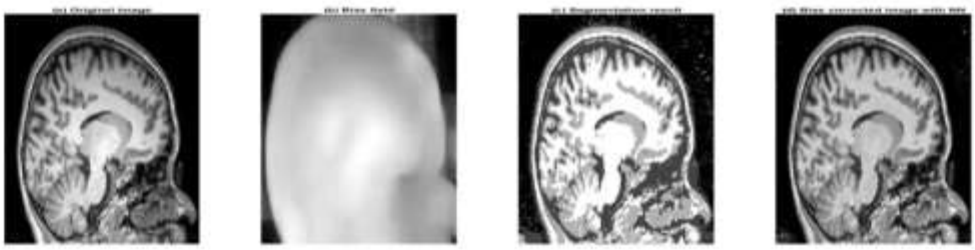

Fig.4: Application to a real image with noise.(a)original image(b)bias field (c)segmentation result (d) bias corrected result of neural network using MLTD.

The Fig.4 is the synthetic image it shows the variation between original image and output image. From the original image we estimated the bias field showed in the (b).Here, the processing is done simultaneously Fig.4(d) shows the simultaneous image segmentation and bias correction using NN and MLTD.

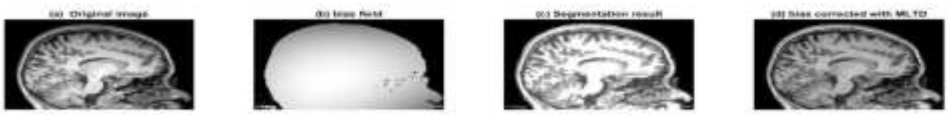

Fig.5: Application to a real image with noise.(a)original image(b)bias field (c)segmentation result (d)bias corrected result of MLTD.

The Fig.5 is the synthetic image it shows the variation between original image and output image. From the original image we estimated the bias field showed in the (b).Here, the processing is done simultaneously Fig.5(d) shows the simultaneous image segmentation and bias correction using MLTD.

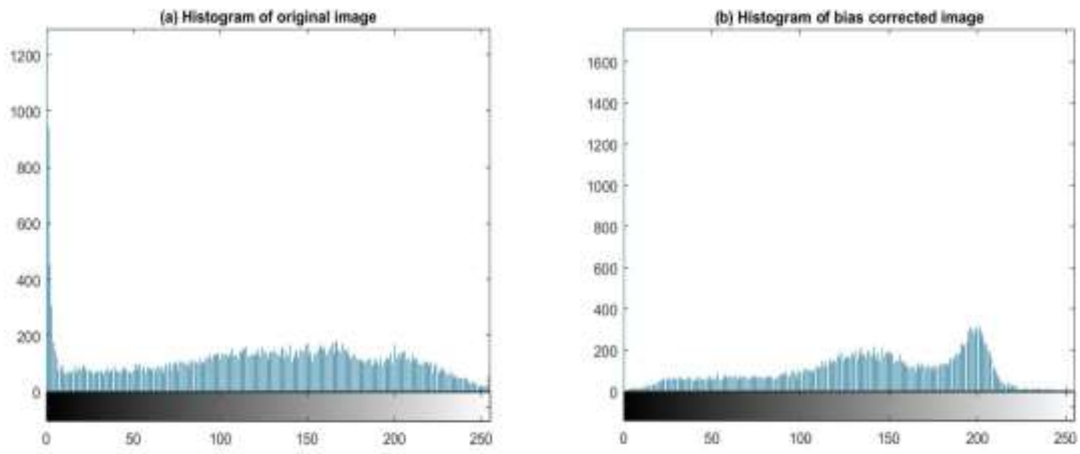

Fig.6: Histograms of original image and bias corrected images of neural network using MLTD.

The Fig.6 is the synthetic image histogram plots it shows the variation between histogram of original image and histogram of bias corrected image.Fig.6 shows the histogram plots of proposed scheme where the two peaks in the (b)plot are Gray Matter(GM) and White Matter(WM).

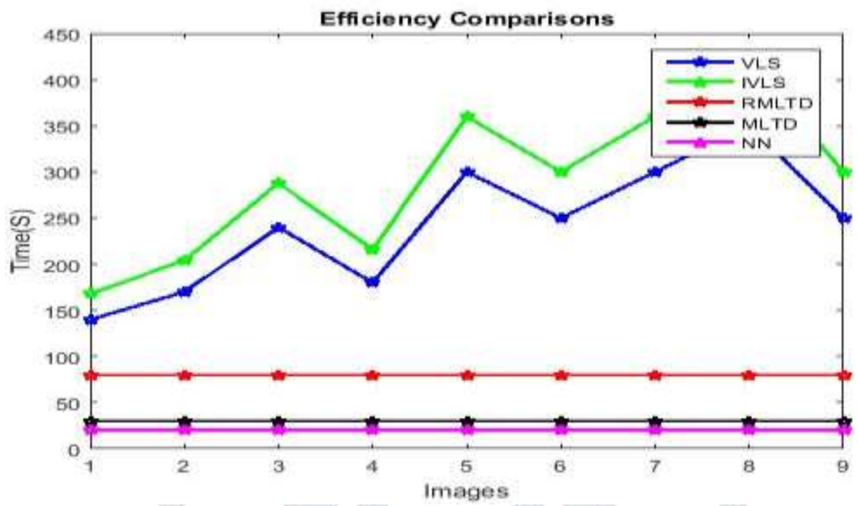

Fig.7: Efficiency comparisons among five methods: VLS, IVLS, RMLTD, MLTD, NN.

Fig.7 shows the comparisons with other methods on synthetic and real images which shows the effectiveness and advantages of the proposed method. Computation time is less for the proposed method compared to other existing methods which shows the effectiveness of the proposed method.

V. CONCLUSION

In this paper, we have proposed a novel bias correction method for magnetic resonance (MR) imaging for simultaneous tissue segmentation and bias correction using Artificial Neural Networks (ANN). In our method, intensities of the whole image caused by the intensity inhomogeneity, in a relatively small local region are separable, despite of the inseparability of the intensities. The proposed model relies on a supervised learning approach (back propagation) to construct a functional relationship between the input and output. This relationship learns the error structure by training the inputs with observations (intensity) to understand prediction biases. The predictive capacity of the ANN confirms that the network can perform well with new and unseen datasets without any need for re-training. The ANN trained network can markedly reduce the estimation error and improve structure of the bias-corrected variables Our proposed scheme combines information of the neighbouring voxels belongs to the same class, which makes robust to noise. Hence proposed method can eliminate partial volume effect to some extent. Comparisons with other methods on synthetic and real images which shows the effectiveness and advantages of the proposed method.

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