International Journal of Engineering & Technology, 7 (3.20) (2018) 683-689

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Segmentation of Medical Images with Intensity Inhomogeneity using Multiphase Level Set Functions

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Abstract

In this paper, concurrent segmentation and bias removal is proposed on magnetic resonance images with intensity inhomogeneity. Intensity inhomogeneity is basically a smoothest variation, which makes a homogeneous region of intensity an inhomogeneous. Inhomogeneity leads to poor performance of image processing algorithms in particular, in medical image processing algorithms. In this paper a level set function based solution is proposed with a variety of control over the inhomogeneity. The intensity of an individual region is modelled using Gaussian distribution with mean and variance that spatially vary. The distribution overlap between different regions is suppressed significantly using a new intensity domain. An ML function is defined for every point on the newly defined domain and a level set is formulated. The proposed method is found to be initialization robust hence can be used readily for applications and also has an extra facility in terms of iterations to exploit thinner sharper boundaries.

Keywords: *bias correction; image segmentation; intensity inhomogeneity; level set function.*

1. Introduction

The deficiencies in imaging devices and scanning procedures often results in intensity inhomogeneity in images. It can be usually modelled as soft/smooth field, which varies spatially. This is smooth field gets multiplied with the original signal of same matter in the image. The field varying spatially is termed as bias field. The aim of the works in this line is to predict this bias field and with this predicted bias field restoring the original image by that removing the effects of intensity inhomogeneity. This broadly called Bias correction [1][2]. The intensity inhomogeneity in MRI arise from the non-uniform magnetic fields formed by RF coils as well as from deviations in object openness [3]. Intensity inhomogeneity has to be dealt with more intricate models than piecewise constant models. Vese and Chan [4] and Tsai individually proposed two like region-based models for general images. Both the models which are basically aimed to minimize the Mumford–Shah functional, treats segmentation of an image as a task of calculating the best approximation by a piecewise smooth function.

These models were then widely called to be piecewise smooth models, and exhibited assured competence to handle intensity inhomogeneity. However, the piecewise smooth models are computational extensive and undergo other difficulties. Michailovih proposed an active contour model by utilizing the Bhattacharyya difference between the intensity distributions inside and outside a contour [5]. This model does not depend on the intensity homogeneity, hence overcome the limitation of piecewise constant models. The segmentation based bias correction models are of most attractive of different kinds of bias correction schemes. Parametric models based on maximum – likelihood or maximum–a–posterior probability is widely used to unify bias correction and segmentation [1], whose parameters can be calculated using an expectation maximization algorithm [2][6].

But, this kind of algorithms have severely affected by the variable initializations [7][2]. Hence these schemes cannot be used in applications where automatic segmentation is needed. A number of other techniques on bias correction and segmentation are proposed in the literature [8-13]. Li et al. proposed a level set method to perform concurrent segmentation as well as bias correction, which has many benefits [1]. These incudes robustness to initialization and decent approximation to bias fields of general contours [1]. This level set method is originally inspired from weighted K-means clustering [14], hence it is termed as weighted K-means level set (WKLS) method. But, this method is shown to be one case of the proposed method in this paper. The proposed method is statistical and multiphase level set (SMLS) method.

In the proposed method, first, a maximum likelihood objective function was defined for each point in a transformed domain, where the distribution overlaps between different matters can be reduced to some range [15]. Next, by integrating the maximum likelihood function over the complete image region, an energy functional is defined [16]. Then, this energy functional is merged into a multiphase level set formulation. The level set formulation is exploited to obtain both bias correction and matter segmentation. The remarkable benefit of this method is that the smoothness of the resulting bias field is attained by normalized convolution without extra cost .

2. Modelling of Intensity Inhomogenity

The Images with intensity inhomogeneity is represented using the following notation.

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$$I = bJ + n \tag{1}$$

where I is the read image, b is the spatially varying bias field, J is original image which is to be estimated, n is zero-mean finite variance Gaussian noise. Hence the image intensity can directly be estimated to be a Gaussian distribution with mean bJ and variance σ^2, by assuming that the variance of n is σ^2. But the statistical characteristics of the intensity of the image cannot be completely described by the Gaussian model alone. To have a better introspection each domain should be indorsed to a Gaussian model. The intensity conforming to the domain μ_i is modelled as

$$p(I(y) \mid \beta_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(- \frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2} \right), y \in \mu_i \tag{2}$$

where β_i takes on different values from {b, c_i, σ_i}, σ_i is a constant with respect to the standard deviation of image intensity ad $b(x)c_i$ is spatially varying local mean. A circular neighborhood center is considered for each point x in the image domain μ. The circular neighborhood is represented by

$$O_x = \{ y \mid \| y - x \| \le \rho \} \tag{3}$$

Here ρ is the radius of neighborhood region O_x. Now a different domain is defined with the following mapping from the original image domain to the new domain.

$$M : I(x \mid \beta_i) \to \bar{I}(x \mid \beta_i) \tag{4}$$

Now the original image domain may be represented by D(M) and new domain by R(M). The mapping is formally defined as follows.

$$\bar{I}(x \mid \beta_i) = \frac{1}{m_i(x)} \sum_{y \in \mu_i \cap O_x} I(y \mid \beta_i) \tag{5}$$

where $m_i(x) = \|\mu_i \cap O_x\|$.

As the intensity of pixel 'y' can be independently distributed [15], the newly defined domain can be treated as normal distributed with a non-zero mean of bc_i and variance $\frac{\sigma_i^2}{m_i(x)}$.

The overlap that exists between adjacent regions can always be suppressed. As the inhomogeneity changes so smoothly throughout the image, an approximation can be made as follows

$$I(y \mid \beta_i) = I(x \mid \beta_i), \forall y \in \mu_i \cap O_x \tag{6}$$

Also, because of the peculiar property of Gaussian density functions, i.e. the product of two Gaussian density functions is also a Gaussian, the following can be arrived.

$$\prod_{y \in \mu_i \cap O_x} p(I(y \mid \beta_i)) = p(I(x \mid \beta_i))^{m_i(x)} \propto N\left(bc_i, \frac{\sigma_i^2}{m_i(x)} \right) \tag{7}$$

Now use the notation $D = \{ \bar{I}(x \mid \beta_i), i = 1,..., N \}$.

Then the likelihood function is defined as

$$p(D \mid \beta) = \prod_{i=1}^{N} p(\bar{I}(x \mid \beta_i)) \propto \prod_{i=1}^{N} \prod_{y \in \mu_i \cap O_x} p(I(y \mid \beta_i)) \tag{8}$$

Where $\beta = \{ \beta_i, i=1,...,N\}$. The energy functional is defined as follows

$$E(\beta) = -\int_\mu \log\ p(D \mid \beta)\, dx = L - \sum_{i=1}^{N} \int_\mu \int_{\mu_i \cap O_x} \log(p(I(y \mid \beta_i)))\, dy\, dx \tag{9}$$

Here L is a constant. Let $K_\rho(x,y)$ be function that characterizes the region O_x

$$K_\rho(x,y) = \begin{cases} 1, & \| y - x \| \le \rho \\ 0, & else \end{cases} \tag{10}$$

Now $E(\beta)$ can be written as

$$E(\beta) = \sum_{i=0}^{N} \int_\mu \int_{\mu_i} K_\rho(x,y) \left(\log(\sqrt{2\pi}\sigma_i) + \frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2} \right) dy\, dx \tag{11}$$

C. Li R. Huang et al.[1] presented a level set method with weighted K-means (WKLS). The energy functional of this method is given below.

$$E_\beta = \sum_{i=1}^{N} \int_\mu \int_{\mu_i} G_\rho(x,y) (I(y) - b(x)c_i)^2\, dy\, dx \tag{12}$$

where $\beta = \{ b, c_i, i = 1,...N \}$ and $G_\rho(x,y)$ is curtailed Gaussian kernel. This method is very close to the one presented earlier except few considerations. They are K_ρ to be Gaussian and σ_i to be $1/\sqrt{2\pi}$ and $E(\beta)$ and E_β are similar. But the model presented in this paper considers the variations of variance among different tissues. This result in a better accuracy than WKLS.

3. Formulation of Level Set

To represent each of the regions $\{ \mu_i, i = 1,..., N \}$ with N as a power of 2, multiple level set functions $\{ \phi_i, i = 1,..., n \}$. These multiple level set functions are originally inspired from the work in [4]. Let $M_i(\Phi_N(.))$ be the function that characterizes the complete region μ_i. $\Phi_N(.)$ is basically a function of set $\{ \phi_i, i = 1,..., n \}$. The energy functional which is already given can now be written as follows.

$$E_{\Phi_N, \beta}^{SMLS} = \sum_{i=1}^{N} \int_\mu d_i(y) M_i(\Phi_N(y)) dy \tag{13}$$

here $d_i(y)$ is defined as follows

$$d_i(y) = \int_\mu K_\rho(x,y) \left(\log(\sqrt{2\pi}\sigma_i) + \frac{(I(y) - b(x)c_i)^2}{2\sigma_i^2} \right) dx \tag{14}$$

M_i is defined as follows for i = 1,2,3 and 4, which is four – phase case, by using which any other phase can be extended.

$$\begin{cases} M_1 = H(\phi_1)H(\phi_2), M_2 = H(\phi_1)(1 - H(\phi_2)) \\ M_3 = (1 - H(\phi_1))H(\phi_2), M_4 = (1 - H(\phi_1))(1 - H(\phi_2)) \end{cases} \tag{15}$$

Here $H(\Phi)$ is Heaviside function and is given by

$$H_\varepsilon(\phi) = \frac{1}{2} \left[1 + \frac{2}{\pi} \tan^{-1}\left(\frac{\phi}{\varepsilon} \right) \right]. \tag{16}$$

The minimization of $E_{\Phi_4, \beta}^{SMLS}$ with respect to each variable is obtained by setting the remaining variables. The variables c, b and σ takes the following expressions for minimizing $E_{\Phi_4, \beta}^{SMLS}$ in each case.

$$c_i = \frac{\int (K_\rho * b) I M_i(\Phi_4) dy)}{\int (K_\rho * b^2) M_i(\Phi_4) dy)} \tag{17}$$

$$b = \frac{\sum_{i=1}^{4} K_\rho * (I M_i(\Phi_4)) \frac{c_i}{\sigma_i^2}}{\sum_{i=1}^{4} K_\rho * (M_i(\Phi_4)) \frac{c_i}{\sigma_i^2}} \tag{18}$$

$$\sigma_i = \sqrt{\frac{\int\int K\rho(y,x)\left(I(y)-b(x)c_i\right)^2 M_i\left(\Phi_4(y)\right)dy\,dx}{\int\int K\rho(y,x)M_i\left(\Phi_4(y)\right)dy\,dx}} \tag{19}$$

The smoothness of the bias is guaranteed by the normalized convolution [14]. The energy functional can also be minimized with respect to the level set functions.

The respective gradient descent is given below.

$$\frac{\partial\phi_1}{\partial t} = -\left[(d_1 - d_2 - d_3 + d_4)H(\phi_2) + d_2 - d_4\right]\delta(\phi_1) \tag{20}$$

$$\frac{\partial\phi_2}{\partial t} = -\left[(d_1 - d_2 - d_3 + d_4)H(\phi_1) + d_3 - d_4\right]\delta(\phi_2) \tag{21}$$

Here $\delta(\phi)$ is the delta function and the regularized form of this function is

$$\delta_\varepsilon(\phi) = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + \phi^2} \tag{22}$$

4. Simulation Results

The proposed method is applied to segment the images as well as to correct the bias which removes the intensity inhomogeneity. The peculiar property or feature of the proposed scheme is that it generates the segmented version of the input as an intermediate step in bias correction. The inhomogeneity results in misleading diagnosis in medical field. Brain MR Images are the main threats of intensity inhomogeneity. Few millimeter difference in identification of any tissue abnormality will influence the diagnosis [17] and may result in even more severe medical issues. As the proposed method considers the variations in variance tissue by tissue, it produces better bias correction and yields closer neighborhood boundaries. In this section the simulation results of proposed method on images with intensity inhomogeneity are presented. The input images are shown in Fig. 1. A typical set of images with intensity inhomogeneity was considered. Medical images were considered as intensity inhomogeneity is common and also important to eradicate it from medical images. The presence of inhomogeneity in these images expands and spreads the spikes in histogram from the left end to right end, showing the overlap of significant regions from neighbors. The histograms of input images are shown in Fig. 3.

The initial level set functions which are originally triangular in shape are shown in column 1 of Fig. 2. After an exhaustive study of the recurring process, it is identified that the optimum number of iterations needed to get the most accurate results is always depends on the features that an input image has. Hence two different number of iterations are considered. In the first case 15 iterations and in the second case 30 iterations. Fig. 2 and 3 are with respect to 15 iterations case. In Fig. 2, the column two shows the bias that was estimated by the proposed method. Column 3 shows the segmentation results based on the proposed method. Column 4 shown the bias corrected image with very light intensity inhomogeneity.

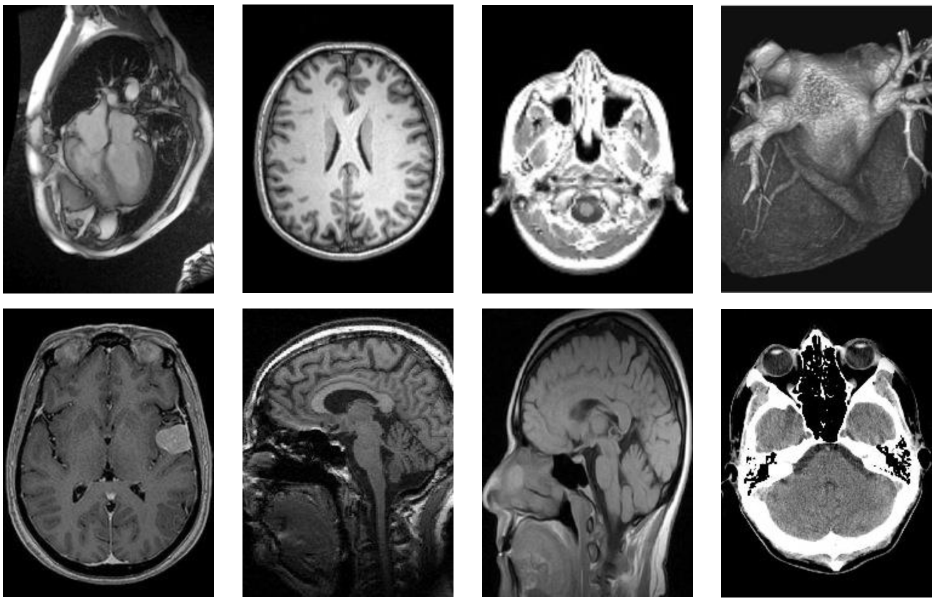
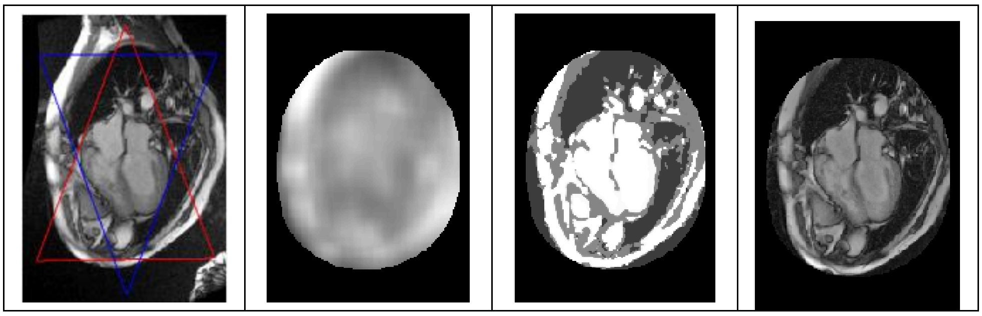
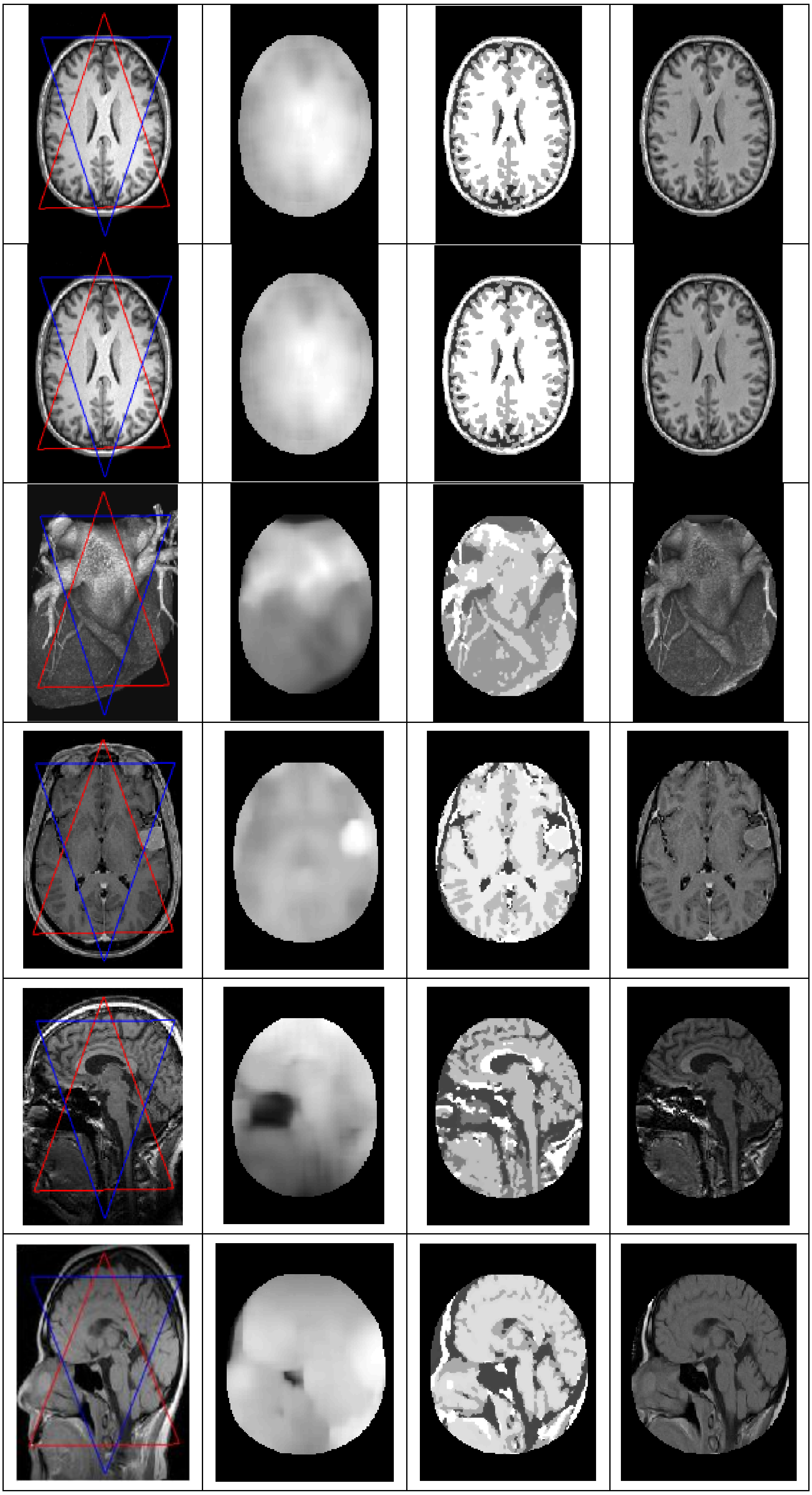


Fig. 1: Input Images

Fig. 3 shows the histograms of image with intensity inhomogeneity and the bias corrected image. As the bias is removed from the input image, the sharpness of the image increased to a significant level. That can easily be observed from the histograms of respective images.





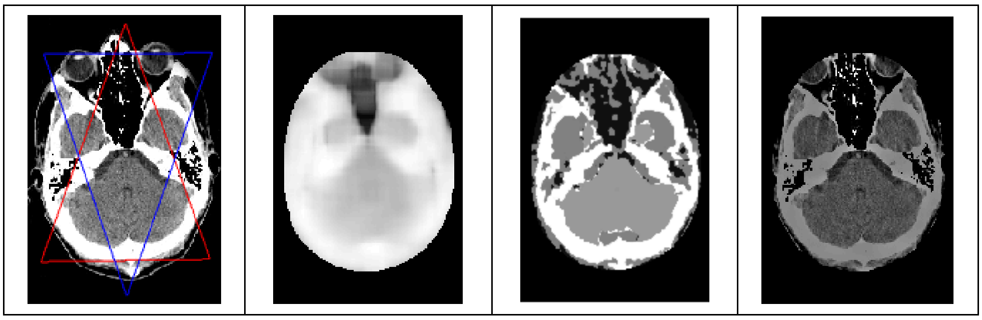


Fig. 2: Column 1: Initial level set functions, column 2: Estimated bias field, column 3: Segmentation results and column 4: Bias corrected image. Rows 8 shows the respective results of eight different input images given in Fig. 1

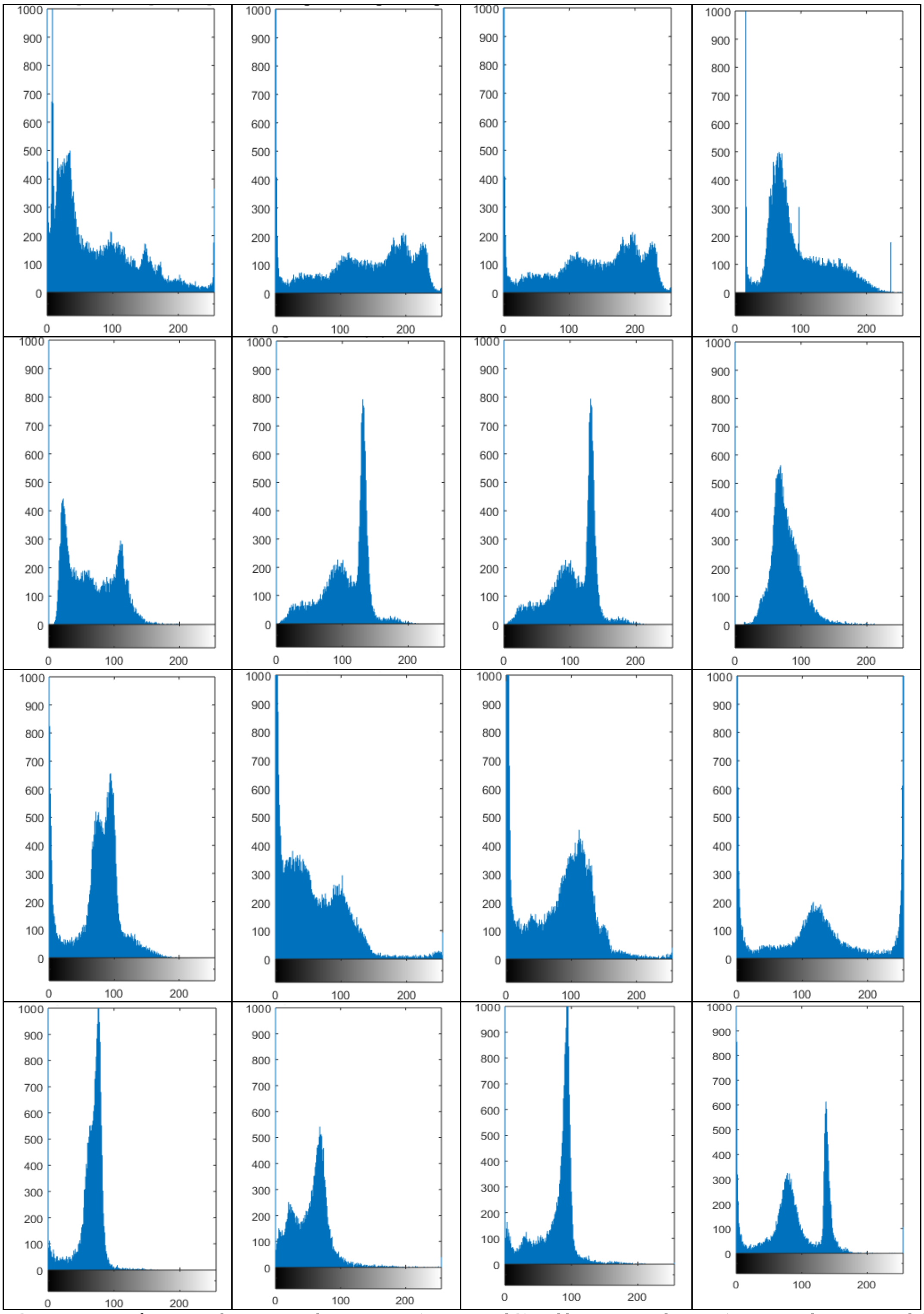


Fig. 3: Histograms of image with intensity inhomogeneity (Rows 1 and 3) and bias corrected image (Rows 2 and 4 respectively)

Simulation results with 30 iterations are presented in Fig. 4 and 5. Fig. 4 show the initial level set functions, estimated bias, segmented results and bias corrected image. Fig. 4 shows the histograms of images with intensity inhomogeneity and bias corrected images.

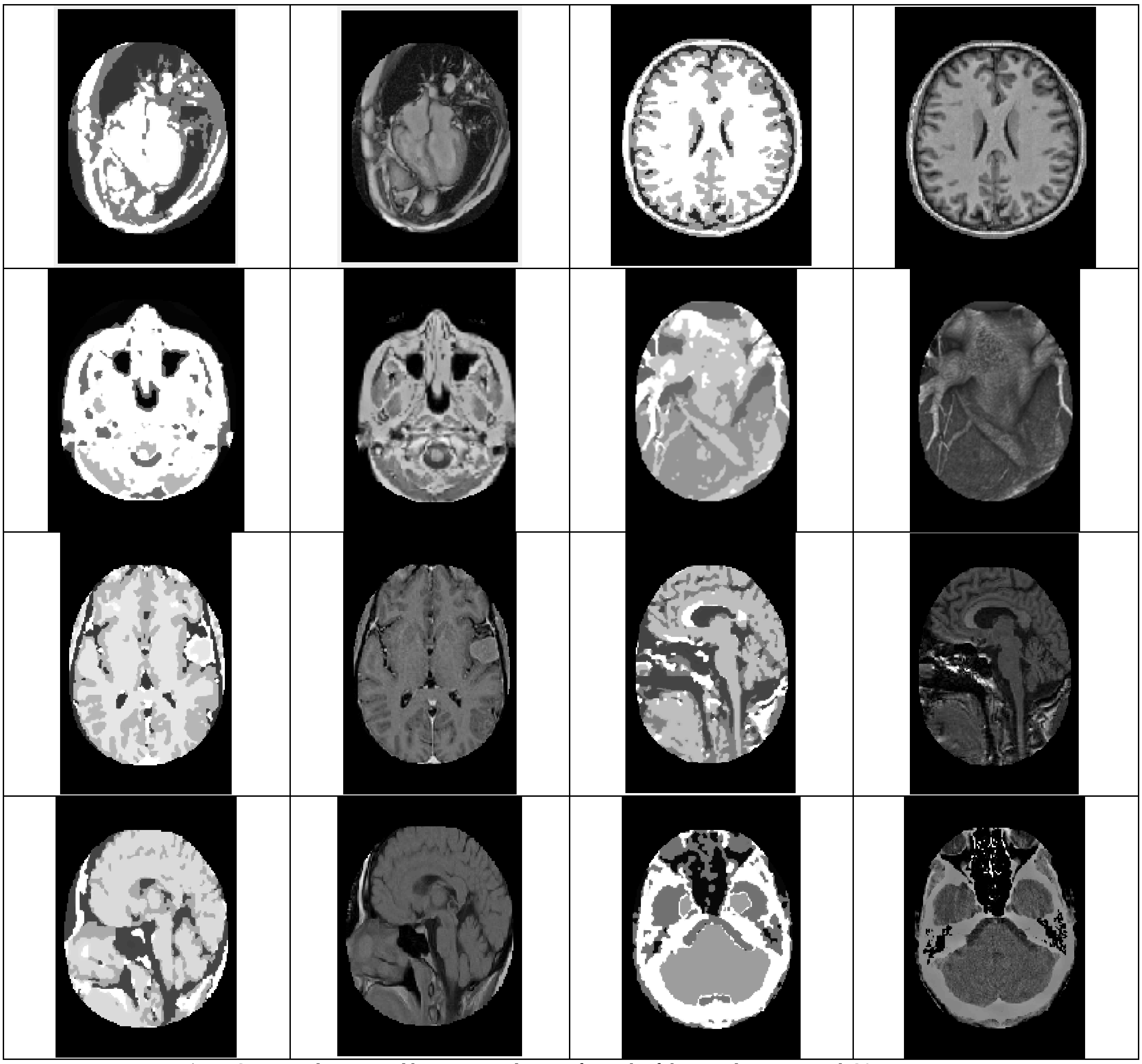
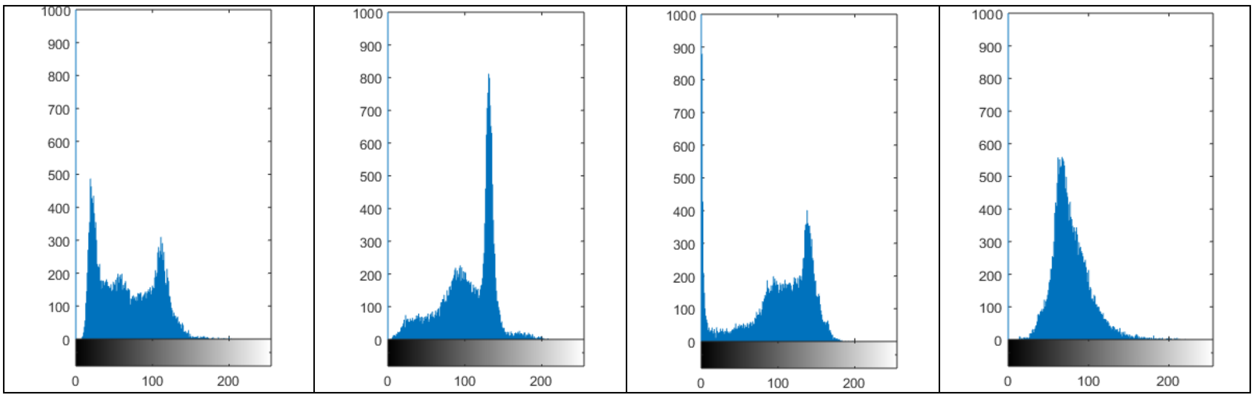


Fig. 4: Segmented image and bias corrected image for each of the sample images with 30 iterations



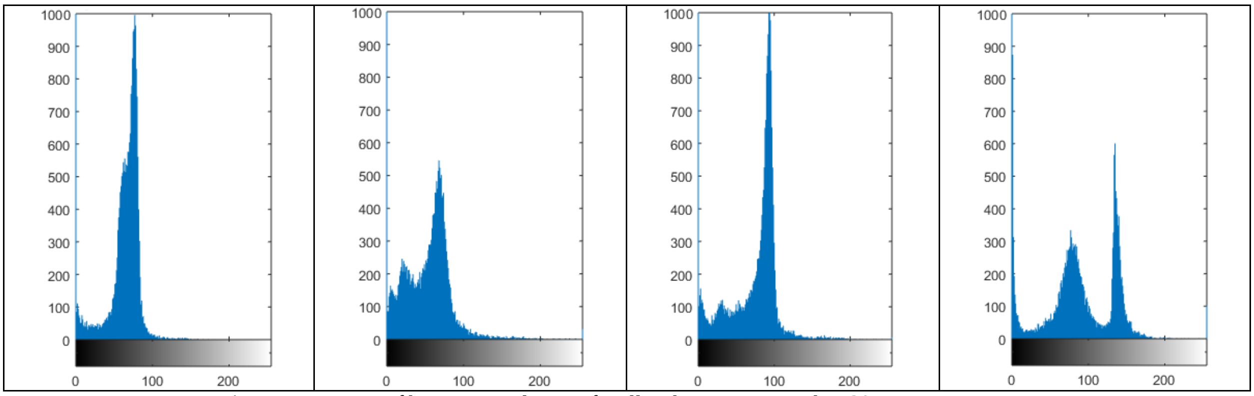


Fig. 5: Histograms of bias corrected image for all eight-test images when 30 iterations are run

The results from Fig. 4 and 5 indicates that when 30 iterations are run, even a minute detail of the image is clearly enhanced and was represented in segmented as well as bias corrected versions of the input image. The histograms when compared with that of Fig. 2, shows an improvement in terms of the sharpness it has.

5. Conclusions

In this paper, a statistical level set function based simultaneous bias correction and segmentation of MRI images are conceived. Simultaneous segmentation and bias correction are performed. Multiphase level set functions provides the initialization insensitive bias correction. The iterations provides an extra control over the quantity of details to be sharpen and highlighted. Hence this method can be immediately used in automatic mode applications, where the techniques which are initialization sensitive methods may not perform well. The simulation results on the medical images shows that the segmented and bias corrected images can then be easily processed for further applications. The histograms show a clear difference and improvement when more number of iterations are used.

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