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Statistically Inhomogeneity Correction and Image Segmentation using Active Contours

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Abstract

Objective: To improve results on noisy image. **Method:** We have proposed Gaussian distribution density function based inhomogeneity correction method with active contour. We have implemented proposed method in MATLAB. **Findings:** It is shown through stimulated results that the noise and inhomogeneity both are reduced in segmented images. Experimental work is carried out for gray scale images only and it is proven that noise has been significantly reduced for different gray scale images. **Applications:** Proposed method can be applied for the segmentation and analysis of the various images.

Keywords: Active Contour, Gaussian Distribution, Gray Scale Image, Inhomogeneity, Segmentation

1. Introduction

Intensity inhomogeneity is also known as intensity non-uniformity, bias or shading. If we deal with Magnetic Resonance Images, intensity inhomogeneity emerges from blemishes of image acquiring process. Due of this, intensity of the same tissue differs with location of tissue within the image. So, intensity inhomogeneity correction is required.

Active contours are widespread as they create sub regions having constant boundaries. The level set theory is more suitable in the implementation of active contours.

Active contours are used for boundary tracking. Depending upon the method which we have used, active contours utilize different attributes for segmentation such as edges or statistics.

There are various methods as shown in[1], for cure of intensity inhomogeneity in MRI. The techniques for dispensing intensity inhomogeneity are comprehensively characterized in two classifications to be specific Prospective and Retrospective. The Prospective technique improves image acquisition process which is the part before getting the image. In Retrospective method we relies the information after getting image. The classification of **Prospective** methods can be done into following three categories:

- Phantom
- Multicoil
- Special sequences

The classification of **Retrospective** methods can be done into following categories:

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- Filtering which can be further divided into Homomorphic and Homomorphic unsharp masking
- Surface fitting which can be further separated into Intensity and gradient
- Segmentation which can be further separated into ML, MAP and so forth.
- Histogram based.

The **Prospective** methods can be briefly described as follows:

In phantom based[2,3] intensity inhomogeneity estimation is done by obtaining an image of a uniform spectra having known attributes. In multi coil type[4,5] we deal with surface coils and volume coils. Surface coils have better SNR than volume coils but it generates more inhomogeneity than volume coil.

Special sequences related to specific requirements like Hardware.

The **Retrospective** methods can be briefly described as below:

The assumptions made in Filtering methods[6] is that intensity inhomogeneity is a low frequency artefact and it can be isolated from high frequency signal by filtering[7,8].

In Surface fitting methods, the image features having information inhomogeneity are fitted with parametric surface. The resultant surface have multiplicative inhomogeneity field which is utilized to evacuate the off base features of the input image[9,10].

The probability distribution of image intensity is estimated using ML/MAP criteria based parametric models[11].

Fuzzy C changes objective function to adapt to the intensity inhomogeneity using mean segmentation[12].

The nonparametric methods usually make use of nonparametric max-shift or mean-shift clustering. The methods based on histograms works directly on image intensity histogram, which can be further divided into following methods

The high frequency maximization method is iterative method. It requires multiplicative field to build the high recurrence content of tissue intensity distribution[13].

In data minimization, the intensity inhomogeneity is subtracted in view of obliged minimization of picture data anticipated by picture (image) entropy. Histogram matching divides the image in small sub sizes where intensity inhomogeneity remains almost same[14].

The Evaluation approaches are classified into two namely The Qualitative and Quantitative, they are described below:

- **Qualitative evaluation depends** on subjective visual investigation of rectified results. They are further characterized into spatial and statistical evaluation[15].
- **Quantitative evaluation depends** on certain target measures that are viewed as relevant for a compact application. It can be further classified into segmentation, intensity variation and inhomogeneity field[16].

Active contours have widespread applications like segmentation and image tracking. The two important methods of active contours are snake and level sets. Snake shifts already defined snake points using method of energy minimization, while level set approaches move contours completely as a particular level of function[17,18].

The two main approaches in image segmentation are Edge based and Region based segmentation. Edge based segmentation partitions image based on discontinuities while region based segmentation partition the image based on the uniformity.

Kass proposed first model of active contour and named it snakes due to the contour appearance. The snake problem can be solved by locating contour that leads to total energy minimization.

Osher and Sethian proposed level set theory for active contour. They spoke to shape by means of two dimensional consistent functions.

Region based information and integration of edges are some of the methods proposed to develop the performance of segmentation.

The segmentation in Active Contour Model (ACM) produces closed object contours essential for shape recognition and analysis.

ACM can be categorized as edge based model and region based models.

1.1 Edge Based Model

Here active contours are forced towards the desired boundaries using image gradient. These models are inclined to commotion and frail limits which have little gradient values. Frail limits can bring about edge spillage.

1.2 Region Based Model

Here active contours get attracted to object boundaries by using image statistical information. In spatial intensity inhomogeneity techniques last ideal arrangements are procured by performing segmentation and bias field estimation at the same time in each cycle.

As appeared in[19] new ACM is proposed to part pictures with intensity inhomogeneity and gauge the bias field. This model uses a nearby force grouping rule work which has utilization of the neighbourhood effect amongst measured and assessed picture.

A level set process is used for energy minimization. A level set process makes use of regularization to make sure that the contours have fine level. It also eliminates the re-instatement of level set function for development of active contours.

2. Proposed Method

For statistically inhomogeneity correction in our proposed model may assume that it follows Gaussian distribution function.

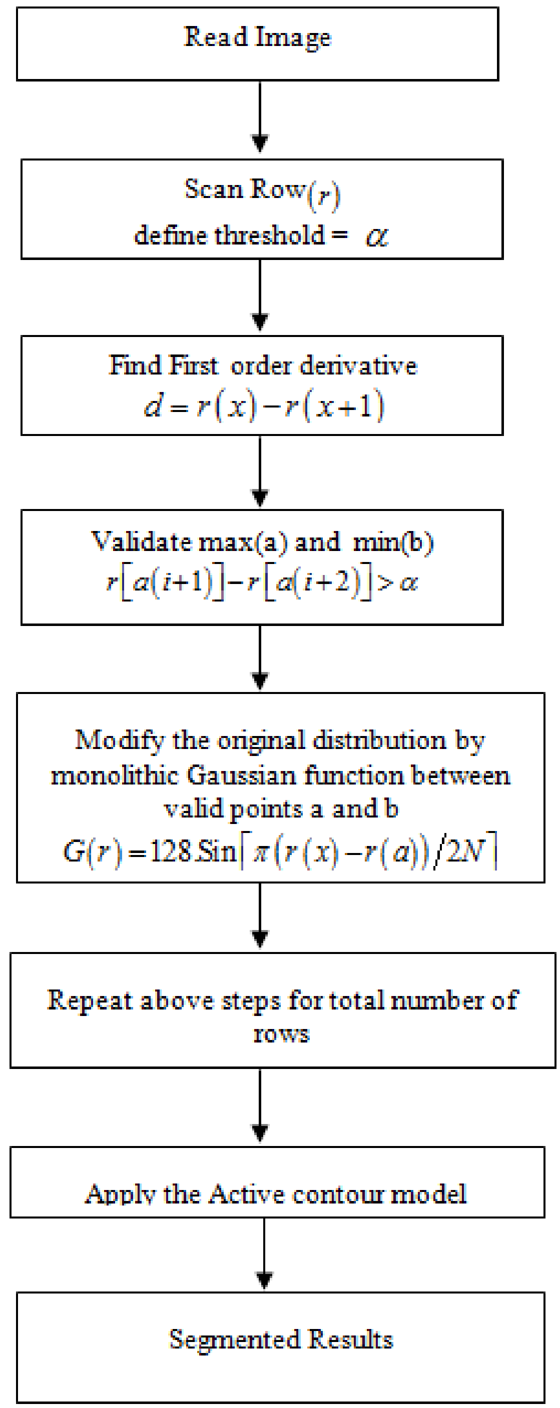
Histogram equalization method is generally used to improve the image in which the contrast of image is adjusted by changing the distribution of image pixels. However, this method does not work for the noisy images. Therefore in this paper, Gaussian distribution density function based inhomogeneity correction method is proposed.

Let image intensity values are given by $K_i, i = 1, 2, \ldots, n$. The probability of intensity values are defined by $P(K_i)$. The image can be decomposed into number of regions. Ideally each region in the image follows the Gaussian distribution density function. However, due to noise addition and inhomogeneity, it fails to follow Gaussian distribution. Therefore, in the proposed method, the each row of an image is decomposed and analysed for the particular region. Once the region within row is identified, the intensity values of that region are modified by convolving it with Gaussian functions. Thus by repeating this method over an each row, the noise effect and inhomogeneity problem can be solved.

The overall algorithm is as follows.

- Read the image and find the maximum and minimum point within row where Gaussian distribution can be well fitted.
- For the initial first order derivative of row is calculated. From the first order derivative peak and minimum point is identified.
- Now to validate that there are two points are truly fitted with defined Gaussian function. A threshold has been assigned by the user here in proposed model. Threshold α = 10.
- Once substantial 'a' and 'b' are acquired, the intensity value inside this scope of 'a' and 'b' are upgraded utilizing taking after condition.

$$G(r) = 128.\mathrm{Sin}\left[\pi\left(r(x) - r(a)\right)/2N\right]$$



3. Results

To validate the proposed algorithm, the algorithm is applied on standard image datasets obtained from Berkeley. The original images[20] of Bird, Shape, Butterfly, Snake and Setsquare are shown in Figure 1(a) to 1(e) respectively. The obtained segmentation results are presented in Figure 1(f) to 1(j) respectively. As suggested in the proposed approach, the each row with in region is modified to follow the Gaussian distribution. And hence modified intensity distribution enhances the edges within image. It is the basic requirement in the active contour model where the energies rely on the strength of edges / region. Thus modification in the intensity distribution helps to reduce the noise, to enhance the edges under inhomogeneous region. It leads to proper segmentation using active contour model.

Figure 1(a). Original image of bird[20].

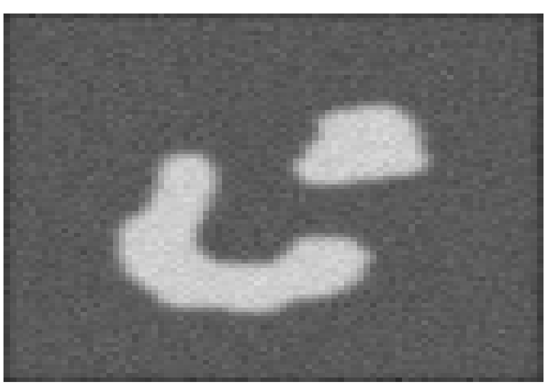


Figure 1(b). Original image of shape[20].

Figure 1(c): Original image of butterfly[20].

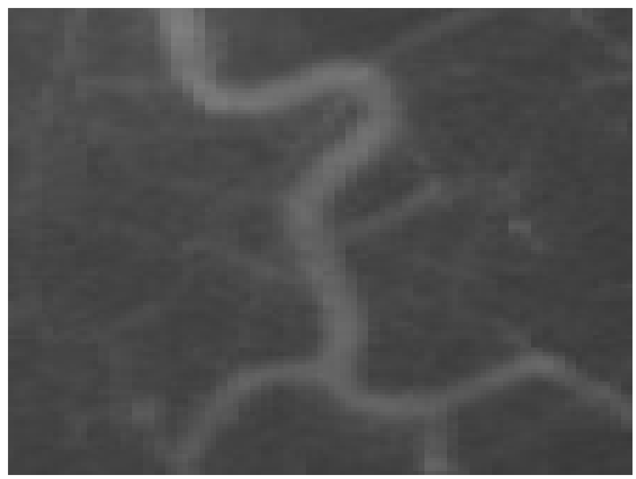


Figure 1(d). Original image of snake20.

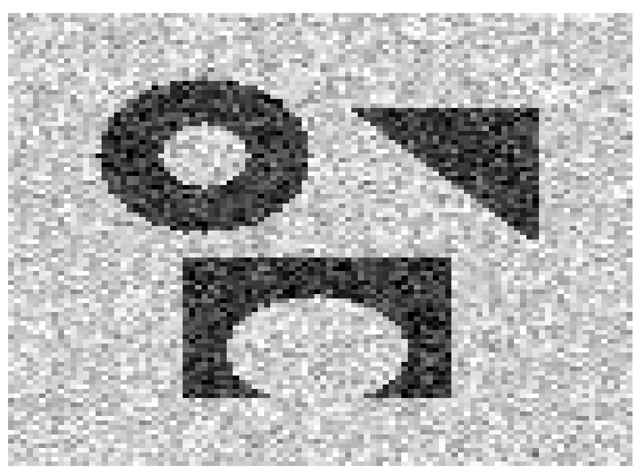


Figure 1(e). Original image of setsquare[20].

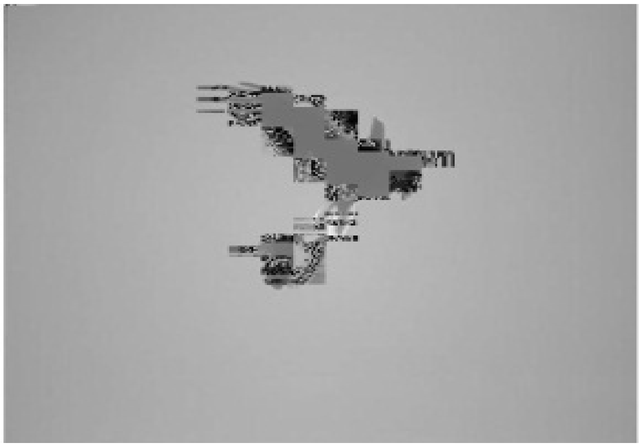


Figure 1(f). Segmented image of bird.

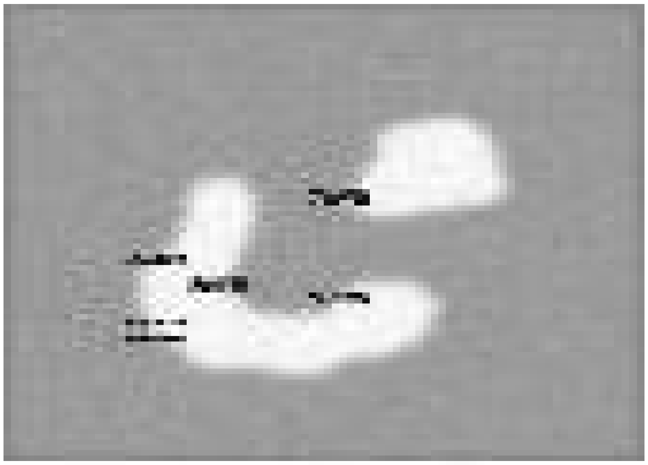


Figure 1(g). Segmented image of shape.

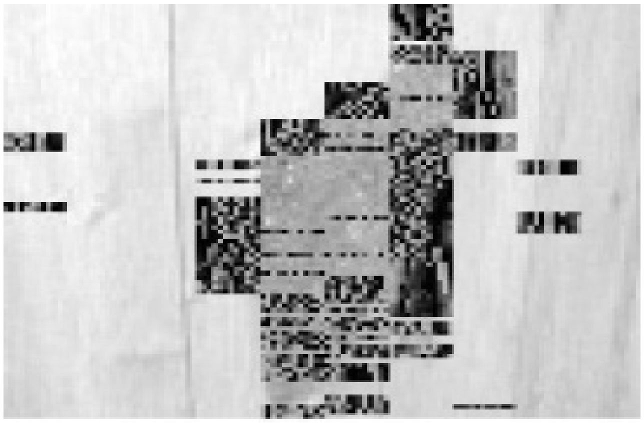


Figure 1(h). Segmented image of butterfly.

Figure 1(i). Segmented image of snake.

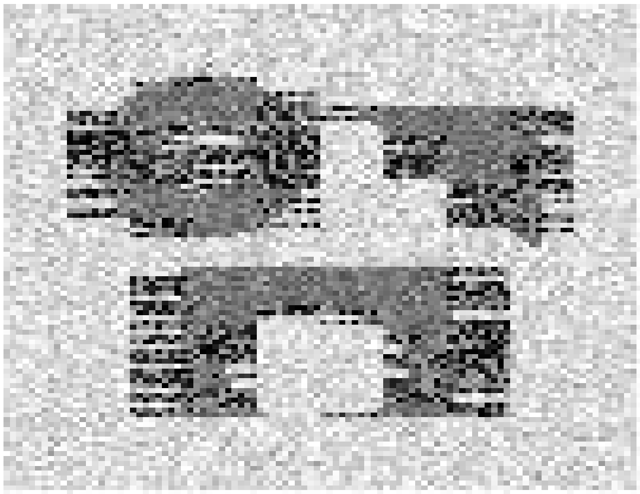


Figure 1(j). Segmented image of setsquare.

Figure 1. Noise - inhomogeneity reduction and segmentation results using proposed approach (Image courtesy: Berkeley data base[20]).

4. Conclusion

This paper presents the image segmentation model where distribution of intensity is modified and resultant image is served as initial segmentation in the active contour model for the final segmentation. The Gaussian distribution function based modification within defined region helps to reduce the noise and inhomogeneity within image. And hence, active contour model succeeded to segment images having intensity inhomogeneity. At present, the proposed approach is applicable to gray scale images. So in future, method can be extended for color images.

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6. References

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