IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 9, Issue 2, Ver. V (Mar - Apr. 2014), PP 68-71
www.iosrjournals.org

Gaussian Based Image Segmentation In The Presence Of Intensity Inhomogeneity

W.Shylu [1], A.JacksonRibero[2]
[1] *Electronics And Communication Engineering,Loyola Institute Of Technology And Science,India*
[2] *Electronics And Communication Engineering,Loyola Institute Of Technology And Science,India*

Abstract*: In this project a variational level set approach for bias correction and segmentation in the analysis of magnetic resonance (MR) images with intensity inhomogeneities is proposed. Local intensity variations in relatively smaller regions are separable, despite of the inseparability of the whole image. Local intensity variations are described by the Gaussian distributions with different mean and variance. In this work the objective functions are integrated over the entire domain with local Gaussian distribution of fitting energy, ultimately analyzing the data with a level set framework.*
Keywords: *Bias correction, Gaussian distribution, inhomogeneities, level set , MR image*

I. INTRODUCTION

Many clinical and research applications of MR imaging rely on segmentation in order to delineate different intensity distributions in each image.The major problem for brain MR image segmentation is not noise rather, intensity inhomogeneities, also named as bias field.The observed MRI signal J is the product of the true signal I generated by the underlying anatomy and spatially varying field factor B, and an additive noise N

$$J=(I+N).B$$

The bias field is smooth. The smoothness of B can be assured in the frequency domain. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analogy image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled.

.

II. HEADINGS

1.Introduction
2.Heading
3.Intendation And Equation
3.1Modules
3.1.1.Image segmentation based on local means
 3.1.1.1. Bias correction based on local means
3.1.2.Image segmentation based on local distribution
3.1.3.Bias correction based on local distribution
 3.1.3.1 Energy minimization in level set framework
 3.1.3.2.The gradient flow

3.2.Application Of Proposed Method
3.2.1 MR Image
3.2.2 Application on real-world images
3.2.3 Robustness of our method
4.Figures
5.Conclusion
References

III. INDENTATIONS AND EQUATIONS

3.1.Modules

3.1.1.Image segmentation based on local means

It is generally assumed that the bias field is smooth or slowly varying. Ideally , the intensity I of each tissue sould take a specific value ci, which represents the measured physical property. We assume that the image I and the bias field B have the two different properties, i.e., the bias field B is slowly varying over the entire image domain and the image intensity I is fairly constant within each class of tissue. As mentioned previously, the measured data J in the whole image are not separable based on their intensity values. Our previous method is based on an observation that intensities in a relatively small region are separable. The method defined an objective function to classify the data in the neighbourhood Ly into N clusters using a k-means clustering method.

$$\varepsilon_{\gamma} = \sum_{i=1}^{N} \int_{\wedge y \cap \Omega_i} \omega(x-y)|j(x)-B(y)-c_i|^2 dx$$

3.1.1.1. Bias correction based on local means

The cluster values to be optimized, and it is a non-negative weighting function such that R and Lx = 1. r is the radius of Ly . In the method, the weighting function is chosen as the Gaussian kernel. The ultimate goal is to find an optimal set of partitions for the entire image domain O, the bias field B, and the constants ci. The minimization of a single objective function for a point y does not accomplish this goal. The method minimizes for the entire points y. This can be achieved by minimizing the integral of over O. Therefore, the energy is written as y.

$$\varepsilon_{means} = \int_{\Omega} (\omega(x-y)|j(x)-B(y)-c_i|^2 dx)$$

3.1.2.Image segmentation based on local distribution

To effectively exploit information on local intensities, in need to characterize the distribution of local intensities via partition of neighbourhood. The neighbourhood Ly can be segmented by using the framework a maximum posteriri probability be the posteriori probability of the subregions Oi\Ly gives the gray values gives thegray values.

According to the Bayes rule:

$$p(x \in \Omega_i \cap \wedge_y |I(x)|) = \frac{p(I(x)|x \in \Omega_i \cap \Lambda_y|}{p(I(x))}$$

Assuming that the pixels within each region are independent, the QQMAP can be achieved by finding the maximum of N=1.

Taking algorithm, the maximization can be converted to the minimization can be converted to the minimization of the following energy.

$$\varepsilon_y^{'} = \sum_{i=1}^{N} -\omega(x-y)\log p_{i,y}(I(x))dx$$

3.1.3.Bias correction based on local distribution.

There are various approaches to model the probability densities Þ including a full Gaussian density, or nonparametric Parzen estimator. Most image segmentation methods assume a global model for the probability of each region. As we know, there exist quite a few spatially different substructures with different functions within each tissue class in the human brain. For instance, the cortex, caudate, and putamen are anatomically different substructures in the brain, but they all belong to gray matter (GM). Due to the inherent regional differences in imaging-related properties across substructures, the intensities in different substructures, even in the same tissue class, are also more or less different. Consequently, these global methods have difficulties in the presence of intensity inhomogeneity and intensity diversification in one same tissue. In this paper, we use traditional Gaussian distribution to

$$p_{i,y}(I(x)) = \frac{1}{\sqrt{2\Pi\sigma_{i,y}}} \exp\left(\frac{(I(x)-u_i(y))^2}{2\sigma_{i,y}^2}\right)$$

where u, s are local intensity means and standard deviations, respectively. Then, the ultimate goal is to minimize

$$\varepsilon_{local} = \int_{\Omega} \sum_{i=1}^{N} \int_{\Omega i} -\omega(x-y)\log p_{i,y}(J(x)-B(y))dxdy$$

3.1.3.1 Energy minimization in level set framework

In this paper, we consider the case of N= 2, the multi-phase case can be solved with a similar procedure. In this case, the image domain is partitioned into two regions corresponding to the object and background. We assume that these two regions can be represented by the regions separated by the zero level contour of function f.

. By using a Heaviside function H, the energy E local can be expressed as

$$\varepsilon_{local} = -\int \sum_{i=1}^{N} \left[\int \omega(x-y) \log p_{i,x}\big(J(x) - B(y)\big) M_i(\phi(x)) dx \right] dy$$

3.1.3.2.The gradient flow

When N =2, the image domain is partitioned into two regions corresponding to the object and background. We assume that these two regions can be represented by the regions separated by the zero level contour of function f, the equation can be written as

$$B(y) = \frac{\sum_{i=1}^{N} \lambda_i \int \omega(x-y) \frac{J(x) - u_i(y)}{\sigma_i^2(y)} M_i(\phi) dx}{\sum_{i=1}^{N} \lambda_i \int \omega(x-y) \frac{1}{\sigma_i^2(y)} M_i(\phi) dx}$$

In numerical implementation each iteration, according to the equation, the variables u are updated such that for fixed f and B, we find an optimal u that minimizes E. The object and background have the same intensity means but different variances. Using the initial contour, the intermediate results of the piecewise constant (PC) model is presented. It can be seen that the PC model, which assumes that an image consists of statistically homogeneous regions fails to extract the object boundary. In our previous method, the local intensity means of object and background are rather close and the local intensity variance information is not taken into account, which results in an inaccurate decision on object boundary.

3.2.Application of proposed method

3.2.1 MR Image:

It shows the result for a 3T MR cardiac image, which has obvious noise. With the effect of the noise, the PC model cannot obtain an accurate result, which is based on the local intensity means information too. With the effect of strong noise and weak edges, the LBF method cannot obtain accurate result. Using the same initialization, the intermediate results of our method are presented. Compared to the PC model and LBF model, our method can delineate the boundary more precisely. It shows the result for a 3T bias corrupted MR cardiac image, which also has weak edges and the result of LBF model. Due to the low image contrast in the right side of the image, the LBF model failed to extract the whole object boundaries. The model can segment while estimating the bias field. However, the model only uses the local intensity means and cannot obtain accurate results. Interestingly, our method successfully extracts object boundaries which have the corrected image and the estimated bias field. We also evaluated the performance of the algorithm on a set of in vivo medical images with intensity inhomogeneity. In these vessel images, some vessel boundaries are quite weak. Our method successfully extracts the object boundaries for these images, respectively.

3.2.2 Application on real-world images

The original images and initial contours, and our approach are shown from the left column to the right column. Our method successfully extracts the object boundaries for these images.

It presents the results for other two real-world images. The first row shows the result of rice image corrupted by intensity inhomogeneity. The original images and initial contours, the results for the LBF model, our model and the estimated bias field are shown from the left column to the right column. It can be seen that the new contours can emerge during the evolution to extract multiple object boundaries. The second row shows the results of an image which is corrupted by intensity inhomogeneity due to nonuniform illumination, often seen in camera images. Our method successfully extracts the object boundaries for these images.

3.2.3 Robustness of our method

We compared our method to Wells et al and Leemput et al.on more than 100 simulated images obtained from some of them corrupted with bias field without noise and the others with both. The average coefficients of variance values for the two kinds of images are listed in Table 1. It can be seen that the coefficient of variation (CV) values of our method are lower than those of Wells' and Leemput's methods, which indicates that the bias corrected images obtained in our method are more homogeneous than those of the other two methods. It can be seen that the entropy of our method is lower than those of Wells and Leemput's methods, which indicates that the bias corrected images obtained in our method are more homogeneous than those of the other two methods. Quantitative evaluation was performed by computing the coefficient of joint variations (CJV) [38] between gray (GM) and white matter (WM) of the brain, which were segmented in all images. CJV is computed from standard deviations s and mean values m of the voxel intensities belonging to the two matters which is presented on both synthetic and real images.

$$CJV(GM,WM) = \frac{\sigma(GM) + \sigma(WM)}{|\mu(WM) - \mu(GM)|}$$

The model can segment while estimating the bias field. However, the model only uses the local intensity means and cannot obtain accurate results. Interestingly, our method successfully extracts object boundaries which has the corrected image and the estimated bias field. We also evaluated the performance of the algorithm on a set of in vivo medical images with intensity inhomogeneity. In these vessel images, some vessel boundaries are quite weak.

IV. FIGURES

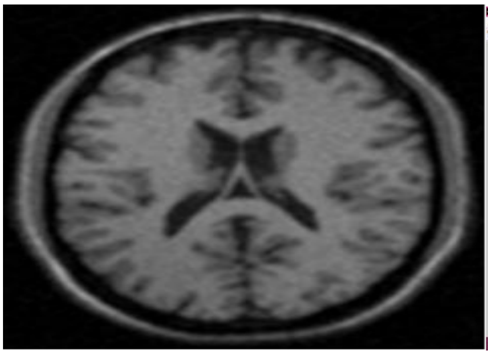

Fig.4.1 shows the input image of brain

Fig.4.2 shows the output image of brain

V. CONCLUSION

In this paper, we propose a new region-based active contour model in a variational level set formulation for bias correction and segmentation. We define an energy functional with a local intensity fitting term, which is dominant near object boundaries and responsible for attracting the contour toward object boundaries. Our model can estimate intensity inhomogeneity, handle noise efficiently, and also allows flexible initialization. Another advantage of our method is that it can be applied to some texture images in which the texture patterns can be distinguished from the local intensity variance. In addition, the regularity of the level set function is intrinsically preserved by the level set regularization term to ensure an accurate computation avoiding expensive reinitialization procedures. Comparison with some of the popular methods proves the effectiveness of our approach over standard applications.

REFERENCES

Journal Papers:

[1] M. Jungke, W. Seelen, G. Bielke, M. Grigat, P. Pfannenstiel, , 1987, pp. 471–481."*A system for the diagnostic use of tissue characterizing parameters in NMR-tomography, in: Information Processing in Medical Imaging*".

Books:

[2] U. Vovk, F. Pernus, B. Likar, , IEEE Trans. Med. Imag. 26 (3) (2007) 405–421."A review of methods for correction of intensity inhomogeneity in MRI"

Chapters in Books:

[3] G. Collewet, A. Davenel, C. Toussaint, S. Akoka, , Magn. Reson. Imag. 20 (4) (2002) 365–373" *Correction of intensity nonuniformity in spin-echo t1-weighted images, Magn. Reson".*

.Theses:

[4] M. Tincher, C. Meyer, R. Gupta, . Med. Imag. 12 (2) (1993) 361–365. D. Williams," *Polynomial modeling and reduction of RF body coil spatial inhomogeneity in MRI, IEEE Trans*"

Proceedings Papers:

[5] B. Brinkmann, A. Manduca, R. Robb, IEEE Trans. Med. Imag. 17 (2) (1998) 161–171." *Optimized homomorphic unsharp masking for MR grayscale inhomogeneity correction"*