

# Fuzzy And Level Sets Based Design Approach Fof Brain Tumor Segmentation

*Ms.Ashwini Thool<sup>1</sup>, Prof. Prashant R. Indurkar<sup>2</sup>, Prof.S.M.Sakhare<sup>3</sup>*

<sup>1</sup>RTM university, Department of Electronics(comm.) Engg  
S.D.College of Engineering, Wardha, India  
[ashwinithool@gmail.com](mailto:ashwinithool@gmail.com)

<sup>2</sup> Professor, Dept. of Extc.  
RTM university, B.D. College of Engineering Sewagram, Wardha, India  
[prashantindurkar@rediffmail.com](mailto:prashantindurkar@rediffmail.com)

Assistant Professor , Dept. of Electronics Engg.  
RTM university, S.D.College of Engineering, Wardha, India  
[shaileshsakhare2008@gmail.com](mailto:shaileshsakhare2008@gmail.com)

**Abstract:** This paper present deals with the implementation of Image enhancement, Linear contrast stretching, filtered image and bias field correction also Estimated that image. Normally the Brain can be viewed by the MRI scan or CT scan. MRI scanned image is used for the entire process. The MRI scan is more comfortable than any other scans for diagnosis. It will not affect the human body, because it doesn't practice any radiation. Modified fuzzy C means (MFCM) and level sets segmentation based methodology is proposed In future method.It allows with high accuracy and reproducibility comparable to segmentation that also reduces the time for analysis also detection of range and shape of tumor in brain MRI Image.

**Keywords:** Magnetic Resonance Image (MRI), Brain tumor,Level set method, K-Means clustering

## 1. Introduction

Image processing tools for enhancement and analysis of Data. Image enhancement deals with the procedures of making a raw image better interpretable for a particular application. In this section, commonly used enhancement techniques are described which improve the visual impact of the raw remotely sensed. Image enhancement techniques can be classified in many ways. Contrast enhancement, also called global enhancement, examples are linear contrast stretch, histogram equalized stretch and piece-wise contrast stretch. Contrary to this, spatial or local enhancement only take local conditions into consideration and these can vary considerably over an image. Examples are image smoothing and sharpening. Contrast enhancement the objective of this section is to understand the concept of contrast enhancement and to be able to apply commonly used contrast enhancement techniques to improve the visual interpretation of an image. Erosion is one of the two basic operators in the area of mathematical morphology, the other being dilation. It is typically applied to binary images, but there are versions that work on grayscale images. The basic effect of the operator on a binary image is to erode away the boundaries of regions of foreground pixels ( white pixels). Thus areas of foreground pixels shrink in size, and holes within those areas become larger.data for the human eye be either an image or a set of features or parameters related to the image. The techniques for image-processing involve treating the image as a two-dimensional signal and then applying standard signal-processing techniques to it. Image processing generally refers to digital image processing, but visual and analog image

processing are also possible. erosions can be made directional by using less symmetrical structuring elements. For example, a structuring element that is 10 pixels wide and 1 pixel high will erode in a horizontal direction only. Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. According to morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest. Erosion is the dual of dilation, i.e. eroding foreground pixels is equivalent to dilating the background pixels.Bias correction is a procedure to estimate the bias field and restore the true signals, thereby eliminating the side effect of the intensity inhomogeneity. Among various bias correction methods, those based on segmentation are most attractive. Tissue segmentation and bias correction are obtained via a level set evolution process. dilation or erosion are influenced both by the size and shape of a structuring element. Noise removal of an image still remains a challenge because noise removal introduces artifacts and causes blurring of the images. To remove noise from the MR image there are several techniques existing. Initially the noise is removed from the MR image using curve let transform. After the noise removal the skull stripping is carried out. MR image consists of both skull and brain tissue region. Usually the tumour will be found in brain region. So, for better evaluation the skull from MR image can be removed in skull stripping. This paper aims at

providing the brain MR image segmentation process which makes the diagnosis and analysis of brain tumour easier.

## 2. Model Formulation

The 2D image  $I : \rightarrow \mathfrak{R}$  is defined on a continuous domain, such that

$$I = bJ + n, \quad (1)$$

where  $J$  is the true image,  $b$  is the intensity inhomogeneity component, and  $n$  is the additive zero-mean Gaussian noise. This is a standard multiplicative model that is used in multiple works on intensity inhomogeneity correction [4]. Similarly as in the model presented by Li et al [2], we assume that the bias field component  $b$  is slowly varying and constant within a small circular neighborhood  $O_y$  ( $b(x) \approx b(y)$ , for  $x \in O_y$ ). The noise  $n$  is minimized by the following fidelity term

$$\sum_{i=1}^N \int_{O_{y_i}} |b(y) - I(x)|^2 dx, \quad (2)$$

where  $N$  is the number of clusters, and  $c_i$  is the center of the  $i$ th class with  $i \in \{1, \dots, N\}$ . The levelset membership function  $M_i(\phi(x))$  is added as a multiplicative term to the clustering energy and it is defined as follows

$$E(\phi, c, b) = \sum_{i=1}^N \int |b(y) - I(x)|^2 M_i(\phi(x)) dx, \quad (3)$$

where  $\phi$  is a levelset function. We consider only the two phase case, where  $N = 2$  and  $M_1(\phi) = H(\phi)$  and  $M_2(\phi) = 1 - H(\phi)$  with Heaviside function  $H$ . The term  $\sum_{i=1}^N \int |b(y) - I(x)|^2 M_i(\phi(x))$  serves both as the data component for regionbased level set function  $\phi$  and the fidelity component for  $b$ . To account for the smoothness of the bias field component, we introduce a smoothing term  $|\nabla b|_{TV}$ , where  $TV$  stands for total variation [15]. Finally, the clustering energy looks as follows

$$E(\phi, c, b) = \alpha \sum_{i=1}^N \int |b(y) - I(x)|^2 M_i(\phi(x)) dx + \beta \int |\nabla b|_{TV}, \quad (4)$$

where  $\alpha$  and  $\beta$  are weighting constants

### B. Levelset Formulation and Minimization Procedure

The variational levelset formulation is defined by

$$F(\phi, c, b) = \mu E(\phi, c, b) + L(\phi), \quad (5)$$

where  $\mu$  is a weighting factor, and  $L(\phi)$  is the regularization term, which is defined by

$$L(\phi) = \int |\nabla H(\phi)| dx. \quad (6)$$

We minimize  $F(\phi, c, b)$  with respect to three parameters for minimization, namely,  $\phi$ ,  $c$ , and  $b$ , given the other two updated in previous iteration. First, we shortly explain the Split Bregman method, proposed by Goldstein, Bresson, and Osher. The Split Bregman method is an efficient technique for solving general L1-regularized problems of the form

$$\arg \min_u \|u\|_1 + \mu \|Au - f\|_2, \quad (7)$$

where  $\_$  and  $A$  are linear operators. The method works by decoupling the L1 and L2 terms using a splitting

$$d = u \quad (8)$$

$$\arg \min_{u,d} \|d\|_1 + \mu \|Au - f\|_2. \quad (9)$$

The constrained problem shown above is converted to an unconstrained problem by introducing a quadratic penalty function.

$$\arg \min_{u,d} \|d\|_1 + \mu \|Au - f\|_2 + \lambda \|d - u\|_2. \quad (10)$$

A vector  $bvk$  (a so-called Bregman vector) is added inside of the quadratic penalty function. Then, we obtain a sequence of unconstrained problems defined by

$$(u_k, d_k) = \arg \min_{u,d} \|d\|_1 + \mu \|Au - f\|_2 + \lambda \|d - u - bv_k\|_2, \quad (11)$$

$$bv_{k+1} = bv_k + u_k - d_k. \quad (12)$$

a) Minimization of  $\phi$ : The minimum of  $\phi$  can be achieved by solving the gradient flow equation

$$\begin{aligned} \frac{\partial \phi}{\partial t} &= - \frac{\partial \mathcal{F}}{\partial \phi} = \\ &= - \delta(\phi) \mu \alpha \left( \int |b(y)c_1 - I(x)|^2 - \int |b(y)c_2 - I(x)|^2 \right) + \\ &= \delta(\phi) \operatorname{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \end{aligned}$$

This functional is non-convex, and its minimization depends on initialization, if the standard gradient descent scheme is used [18]. We use the convexification proposed by Chan et al [18] and search the minimum with respect to  $\phi$  for the following convex functional

$$\min_{0 \leq \phi \leq 1} \int |\nabla \phi| + \mu_1 \int r \phi(x) dx,$$

More details of the convexification procedure are given in the original work of Chan et al [18]. For efficient and fast minimization of this functional, we apply the Split Bregman algorithm.

b) Minimization of  $b$ : The functional  $E$  with respect to  $b$  is very similar to the well-know Rudin-Osher-Fatemi (ROF) functional [15] up to some constant factors, which do not influence the minimization process. The functional looks as follows which is also efficiently minimized with the Split Bregman method (see [3]).

c) Minimization of  $c$ : For fixed  $\phi$  and  $b$  the optimal  $c$  that minimizes the energy  $F$  is explicitly

:

### 2.1 K-means clustering

K-Means is the one of the unsupervised learning algorithm for clusters [11]. Clustering the image is grouping the pixels according to the some characteristics. In this paper input image is converted into Standard format 512 X 512, then find the total no. of pixels using Length = Row X Column. Then covert 2D image into 1D and create no. of clusters depend on user. The k-means algorithm initially it has to define the number of clusters  $k$  [12,13,14]. Then  $k$ -cluster centre are chosen randomly. The distance between the each pixel to each cluster

centres are calculated. The distance may be of simple Euclidean function. Single pixel is compared to all cluster centres using the distance formula. The pixel is moved to particular cluster which has shortest distance among all. Then the centroid is re-estimated. Again each pixel is compared to all centroids.

## 2.2 Fuzzy Clustering

Fuzzy C-Mean (FCM) is an unsupervised clustering algorithm that has been applied to wide range of problems involving feature analysis, clustering and classifier design. FCM has a wide domain of applications such as agricultural engineering, astronomy, chemistry, geology, image analysis, medical diagnosis, shape analysis, and target recognition [19]. The fuzzy logic is a way to processing the data by giving the partial membership value to each pixel in the image [20,21]. The membership value of the fuzzy set is ranges from 0 to 1. Fuzzy clustering is basically a multi valued logic that allows intermediate values i.e., member of one fuzzy set can also be member of other fuzzy sets in the same image. The clusters are formed according to the distance between data points and cluster centres are formed for each cluster. The Algorithm Fuzzy C-Means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method is frequently used in pattern recognition. There is no abrupt transition between full membership and non membership

## 3. Results and Implementation

The proposed method for detecting Bias field in Brain MRI images is implemented and tested using matlab software. The corrected bias image will be given to the skfcm for clustering of bias estimated image and tumour detection.

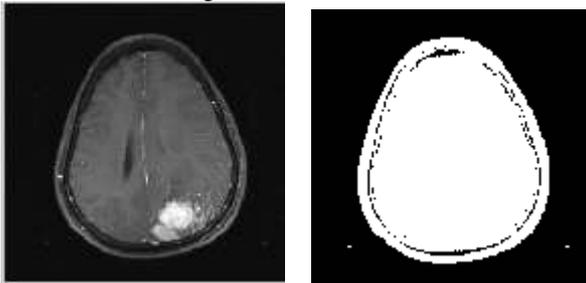


Fig1.A. Input MRI image

Fig2.B BW image

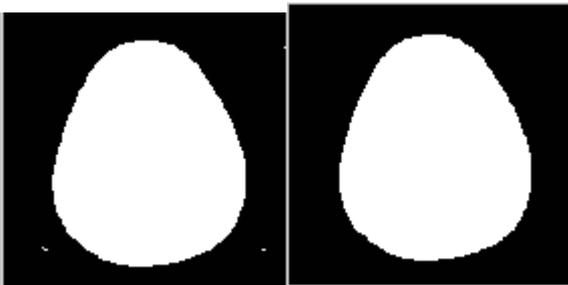


Fig.3.BW holes filled image fig.4.skull image

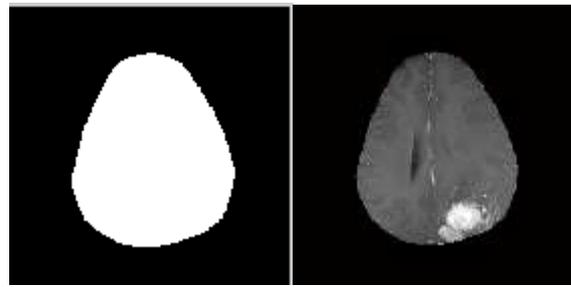


Fig5.Eroded image

fig.6.skull removed image

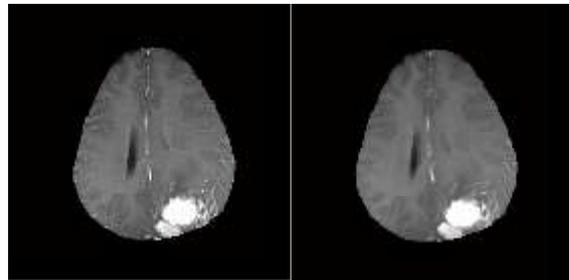


Fig.7 contrast stretched image fig.8 filtered image

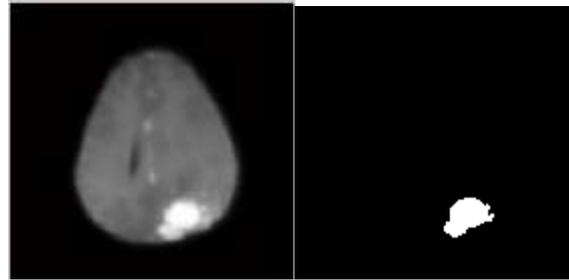


Fig.9 estimated biasfield fig.10.combined segmented image

## 4. CONCLUSION AND FUTURE WORK

There are different types of tumours are available. They may be as mass in brain or malignant over the brain. Suppose if it is a mass then K- means algorithm is enough to extract it from the brain cells. If there is any noise are present in the MR image it is removed before the K-means process. The noise free image is given as a input to the k- means and tumour is extracted from the MRI image And then segmentation using Fuzzy C means for accurate tumour shape extraction of malignant tumour and thresholding of output in feature extraction. Finally approximate reasoning for calculating tumour shape and position calculation. The experimental results are compared with other algorithms. The proposed method gives more accurate result. In future 3D assessment of brain using 3D slicers with Matlab can be developed.

## References

- [1] H. Völzke, D. Alte, C. O. Schmidt et al., "Cohort profile: The study of health in pomerania." *International Journal of Epidemiology*, 2010.
- [2] C. Li, R. Huang, Z. Ding et al., "A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI," *IEEE Trans. on Image Processing*, vol. 20, pp. 2007–2016, 2011.

- [3] T. Goldstein and S. Osher, "The split bregman method for l1-regularized problems," *SIAM Journal of Imaging Sciences*, vol. 2, no. 2, pp. 323–343, 2009.
- [4] U. Vovk, F. Pernus, and B. Likar, "A review of methods for correction of intensity inhomogeneity in mri," *IEEE Trans. on Medical Imaging*, vol. 26, no. 3, pp. 405–421, 2007.
- [5] Z. Hou, "A review on mr image intensity inhomogeneity correction," *International Journal of Biomedical Imaging*, vol. 1, pp. 1–11, 2006.
- [6] R. C. Gonzalez and R. E. Woods, *Digital Image processing*. Prentice Hall International, 2008.
- [7] G. Sapiro, *Geometric Partial Differential Equations and Image Analysis*. Cambridge University Press, 2009.
- [8] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. Wiley Interscience Publication, 2001.
- [9] R. Nock and F. Nielsen, "On weighting clustering," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 28, no. 8, pp. 1–13, 2006.
- [10] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 5, pp. 603–619, 2002.
- [11] A. Makarau, H. Huisman, R. Mus, M. Zijp, and N. Karssemeijer, "Breast mri intensity non-uniformity correction using mean shift," in *Proc. SPIE 7624, Medical Imaging 2010: Computer-Aided Diagnosis*, 2010.
- [12] C. Li, C. Xu, A. W. Anderson, and J. C. Gore, "Mri tissue classification and bias field estimation based on coherent local intensity clustering: A unified energy minimization framework," in *Proceedings of Information Processing in Medical Imaging (IPMI)*, 2009, pp. 288–299.
- [13] M. Lin, S. Chan et al., "A new bias field correction method combining n3 and fcm for improved segmentation of breast density on mri," *Medical Physics*, vol. 38, no. 1, 2011.
- [14] T. Ivanovska, R. Laqua, L. Wang, H. Völzke, and K. Hegenscheid, "Fast implementations of the levelset segmentation method with bias field correction in mr images: Full domain and mask-based versions," in *In Proceedings of IbPRIA 2013: 6th Iberian Conference on Pattern Recognition and Image Analysis*, 2013, pp. 674–681.
- [15] L. Rudin, S. Osher, and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D*, vol. 60, pp. 259–268, 1992.
- [16] X. Bresson, "A short guide on a fast global minimization algorithm for active contour models," 2009.