

An enhanced variational level set method for MRI brain image segmentation using IFCM clustering and LBM

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Abstract

Today's technological advances in medical imaging have given rise to efficient diagnostic procedures. Segmentation identifies and defines individual objects with various attributes such as size, shape, texture, spatial location, contrast, brightness, noise, and context. Deformable segmentation methods are Active contours, which are used to match and track images of an atomic structure by determining constraints derived from the image data. Level set method is an integral part of active contour family, considerable work towards level set methods has identified two main disadvantages i.e., initialization of controlling parameters and time complexity. In this paper, the methodology employed proposes an enhanced Variational level set methodology for Magnetic Resonance (MR) brain image segmentation with heterogeneous intensity. Core concept of IFCM is based on Intuitionistic fuzzy set. Both the values of membership and non membership values for the purpose of labelling are utilized together. As the result of experimentation reveals the efficiency of the recommended IFCM algorithm and Lattice Boltzmann Method (LBM) to overcome the drawbacks of Level Set methods by using the energy function to reduce the processing time which addresses the time complexity issue. The proposed system combines of both IFCM and LBM to form a novel approach. The system is tested on a large set of MRI brain images, extensive research and experiments were carried over on the standard dataset and the results are found to be improved in identification of tumor size detection with respect to time complexity.

1. Introduction

Advancements in biomedical imaging applications have led to the rise of a vital approach of automatic segmentation for MRI images. The procedure of Segmentation is used to delimit the boundary of anatomical structures and the other regions of their interest [21]. The process of magnetic resonance imaging (MRI) medical imaging involves a process of scanning to create detailed images of the body's interior organs, which helps in medical examination and other medical purposes. Currently the techniques used for medical imaging are X-ray, CT scan and MRI [19]. Gathered data through medical analysis uses various methods and it's used in areas such as medicine, health, bioinformatics, molecular imaging and nanotechnology etc. Image segmentation is the main purpose of medical image processing which aims at observing specific group of pixels whereby a group of pixels represent a region, a region can be recognized according to the correlation with constituent parts like color, intensity to identify and locate the boundaries in an image. The characteristics such as image modality, partial volume effect, geometry of anatomy, presence of artifacts and noise makes the process of medical image processing complex. Specific areas of applying image segmentation process in medical imaging are to locate tumors and other pathologies. Through the process of segmentation, various processes like intensity detection, boundary value analysis and abnormality identification are executed for diagnosing the stage of the tumor. In the Literature survey, many researchers have proposed segmentation methods. Canny [23] extended Fuzzy C-means algorithm for edge detection in the process of segmentation. Zhou et al., [18] presented a Fuzzy C-means algorithm based on mean shift, i.e., which is similar to level set

algorithm. Zanaty et al., [16] proposed a substituent method for measuring Euclidean distance in standard FCM by using a new method kernelized distance metric (KFCM). Combination of Spatial FCM (SFCM) and Level Set method yields better results in the process of image segmentation. Aruna kumar and Harish [11] implemented a blend of spatial information with distance as kernel metric calling it as Spatial Kernel FCM (SKFCM), which produced robust results thus naming this clustering algorithm as Robust Spatial Kernel FCM (RSKFCM). Level Set Method (LSM) helps in finding of shapes and boundaries efficiently in a medical image. Paragios [19] introduced constraints based on the knowledge by dealing with Level Set Methods local deformations. Enthralled by the efficient performance of the RSKFCM method, SudharshanDuth [8] proposed a hybrid method to initialize the parameters of level set function based upon Robust Spatial Kernel Fuzzy C-Means (RSKFCM) algorithm. Balla et al., [14] proposed a novel method which focuses at the evolving curve which stops the active contour at the current pixel's membership degree, to fall inside or outside. Zhan et al., [13] presented a strong method which utilized improved variational LSM procedure to make corrections in the bias field and for segmenting the magnetic resonance (MR) images with heterogeneous intensities by using Gaussian distribution. Using 2-phase formulation of level set approach for image segmentation yielded accurate results. Chen et al., [9] presented a archetypal which was based originally on speedy fuzzy function and shape-intensity joint Bhattacharya measure of distance to analyze the distance between both, the probability density of local area and the internal and external contour's curve in the process of segmentation calling it as integrated active contour model.

Wang et al., [7] proposed a method for composite image segmentation by integrating local statistical analysis and the

overall similarity measurement for constructing the energy function by utilizing by Level Set Method. Aruna Kumar et al., [6] proposed a new approach for Segmentation of MRI brain images using evolutionary computation technique which is based on the genetic algorithm based on RSKFCM. RSKFCM genetic algorithm initializes the centers of a cluster and attains the global minima of the objective function. Reshma Hiralal and Hema Menon., [4] surveyed and reviewed already existing methods for segmentation of brain MRI images techniques for detecting similarities between different tissue structures, number of homogeneous regions, image slices and orientation present in the brain image. Kiran et al., [3] proposed an algorithm which utilizes Variational Mode Decomposition (VMD) for hyper spectral data which included the process of classification, which was constructed upon sparse representation. VMD method, crumbles the experimental dataset into various categories as separate bands which utilizes scarcity algorithm Orthogonal matching pursuit used for classification. Vinod Kumar and Nishanth Jain [1] presented an Intuitionistic Fuzzy C-Means (IFCM) approach which aims to categorize pixels of an image into various set of clusters. These clusters were used to segment the central liver lesion from an ultrasound image of the liver. The main advantage of IFCM method is that the centroids are in uniform dissemination overcoming the non-uniform dissemination of centroids. This method was also equated with edge based Active contours proposed by Chan-Vese (CV) method. Ching-Wen Huang et al., proposed a new neighborhood algorithm by integrating intuitionistic fuzzy c-means clustering with a genetic algorithm (NIFCMGA) which retains the benefits of an intuitionistic fuzzy c-means to maximize its advantages and to cut down the noise which is influenced from neighborhood membership by simultaneously selecting the optimum parameters of the projected clustering algorithm [5]. Hanuman Verma et al., suggested a variant based upon Fuzzy C-means algorithm calling it as a Intuitionistic fuzzy c-means (IFCM) which integrates the benefits from intuitionistic fuzzy sets theory. They named this approach as improved intuitionistic fuzzy c-means (IIFCM), by considering the local spatial information in an intuitionistic fuzzy way. IIFCM preserves the image details and its sensitive to noise, but it doesn't require any parameter tuning. By using this method of segmentation the results were tested on synthetic MR brain images to demonstrate the efficacy and its superior performance of IIFCM algorithm when compared to all the other existing methods of segmentation [2]. This proposed method was based on modified Fuzzy C-means, with its flavors as IFCM and Lattice Boltzmann Method. LBM is capable of handling the drawback of larger time consumption as the image curvature is discretely calculated and it also supports parallel programming. LBM acts as an alternative solver for Variational Level Set Equations. In this proposed paper we make use of IFCM and LBM for segmentation of medical images. IFCM is a flavor of standard FCM algorithm, which considers both membership and non membership value. The traditional methods consumes more CPU time for solving Variational Level Set Equations. To solve Variational Level Set Equation (VLSE) an alternative approach proposed here is Lattice Boltzmann Method (LBM). LBM is a statistical framework for modelling Boltzmann particle dynamics on 2-D or 3-D lattice, to produces accurate results by overcoming the drawbacks of traditional methods. It was first designed to resolve the challenges of macroscopic fluid dynamics and this method proved to be accurate in space and time up to second order. LBM has two advantages like parallelizability and simplicity as it is indigenous and explicit in nature. The rest of the paper is organized as follows: Section 2 consists of a brief background about IFCM and its algorithm, variational level set method and Lattice Boltzmann method. Section 3 introduces the proposed algorithm with its mathematical analysis. Section 4 consists of experimentation and its results and Finally, Section 5 consists of concluding remarks of this work.

2. Background

Intuitionistic fuzzy C-Means (IFCM)

Fuzzy C-Means algorithm is established on traditional method of fuzzy set, in which membership value of a feature varies between '0' and '1'. However the reality is, gradation of non-membership of a feature in a fuzzy set doesn't complement to the membership degree, due to presence of hesitation. Hesitation occurs due to lack of awareness in outlining the membership function. To address the hesitation in fuzzy set, Atanassov developed an Intuitionistic Fuzzy Set (IFS), which is the enhanced version of Fuzzy Set. The IFS gives mathematical model to deal with the ambiguity arising from the inherent uncertainty and insufficiency of imperfect information. Intuitionist Fuzzy C-Means is built upon IFS. The objective function of IFCM is as stated below:

$$J(U, V) = \sum_{j=1}^c \sum_{i=1}^n \mu_{ij}^p d_{ij}^2 \quad (1)$$

In the above equation, μ_{ij} acts as the intuitionistic fuzzy membership degree of i^{th} pixel to j^{th} cluster, p is the fuzzy coefficient. $d_{ij} = d(x_i, v_j)$ describes the distance measure between cluster center v_j and pixel x_i , v_j means j^{th} cluster center, x_i means i^{th} pixel, c represents no of cluster centers and n represents total no of pixels. μ_{ij} is the combination of fuzzy membership function (u_{ij}) and hesitation degree (π_{ij}) which can be computed as:

$$\mu_{ij} = u_{ij} + \pi_{ij} \quad (2)$$

The fuzzy membership (u_{ij}) and hesitation degree (π_{ij}) is computed as:

$$u_{ij} = \frac{1}{\sum_{s=1}^c \left[\frac{d_{ij}^2}{d_{is}^2} \right]^{\frac{1}{(p-1)}}} \quad (3)$$

$$\pi_{ij} = \frac{1 - u_{ij}}{1 + \lambda u_{ij}} \quad (4)$$

Where λ is constant $\lambda > 0$. The center of the cluster is computed by the following equation given below:

$$v_j = \frac{\sum_{i=1}^n \mu_{ij} x_i}{\sum_{i=1}^n \mu_{ij}} \quad (5)$$

Cluster centers are always reorganized instantaneously with the membership degree. The IFCM optimizes the objective function by instantly reorganizing the membership degree and cluster center until to meet Convergence Criteria value $\varepsilon = 0.0001$ i.e., then, $\max |J^{(t)} - J^{(t-1)}| < \varepsilon$.

Level set method (LSM)

A statistical technique for tracking various interfaces and shapes is known as Level Set Method (LSM). LSM methods advantage is that it automatically handles topological changes of the tracked shapes as it uses implicit representation for active contours. In segmentation of 2D images, a closed curve in LSM is represented

as ‘0’ level set of the function level set. Each curves evolution begins from an arbitrary starting contour and evolves the contour by LSE which can be realised as a convection–diffusion equation:

$$\frac{\partial \theta}{\partial t} + \vec{V} \cdot \nabla \phi = a \Delta \phi \quad (6)$$

In the above mentioned equation, $\nabla \phi$ and $\Delta \phi$ are the gradient and the Laplacian of ϕ respectively. The terminology $a \Delta \phi$ represents artificial viscosity (Sethian suggested replacing it with $ak |\Delta \phi|$ which is better for handling the evolution of lower dimensional interfaces [10]), and k represents the curvature of the distance function. The LSE can therefore be written as:

$$\frac{\partial \theta}{\partial t} + \vec{V} \cdot \nabla \phi = ak |\Delta \phi| \quad (7)$$

Enhanced variational level set method

The main aim objective of Variational level set method is to maintain the level set function closer to its signed distance function and by which we eliminate the entire process of re-initialization. Variational level set method can be used to test various types of medical images such as X-rays, ultrasound images and Magnetic Resonance Imaging images because it’s very flexible in handling sharp edges and cusps of the brain tissue, and it’s flexible to the topological changes in the boundary of brain images. In the segmentation process of MR images, the dynamic curve in active contour instantly moves close to the direction of the object boundary. This is attained by using external energy function which moves the zero level curves in the direction of the boundaries in the interested region. We need to consider a few parameters such as Gaussian distribution’s standard deviation, the weighted area term parameter, internal energy parameter and weighted length term parameter. Every parameter records an important role in the evolution of LSM. Selection of these parameter values should be done very carefully; as the consistency of level set equation has to be maintained in variational level set method to obtain accurate results. Internal energy part is a parameter that controls the effect of penalizing the deviation ϕ from a signed distance function. The time step ranges from step τ and the coefficient μ must satisfy $\tau\mu < 0.2$ in order to maintain stability in level set evolutions. For $\tau\mu < 0.2$, small μ will take longer time to completely segment the image. Variational level set method is used to represent Gaussian distribution to assess the bias field and to segment the medical images with heterogeneous intensities. To describe varied medical images:

$$I = a \cdot j + n \quad (8)$$

Where I measures image intensities, b is the unknown bias field, J is the original signal to be restored, and n is additional noise. Estimation of unknown bias field is our objective by estimating the original signal from the measured image I . It is assumed here that original image J and the bias field b have the below listed properties:

Property 1: bias field b is varying slowly in the entire domain of an image.

Property 2: Original image intensity J is almost a constant within each issue of a class, i.e.,

$$J(x) \approx c_i \text{ for } x \in \Omega_i, \text{ with } x \in \Omega_i, \{\Omega_i\}_i^N = 1 \text{ being a partition of } \Omega \quad (9)$$

Let $U_i(x)$ be the local intensity means in the partition $\Omega_i \cap O_x$. From (Property 2) in the section which is mentioned above, we can prove that $U_i(x)$ can be approximated by $b(x)c_i$:

$$U_i(x) = \frac{\sum_{y \in \Omega_i \cap O_x} I(y)}{|\Omega|} \approx \frac{\sum_{y \in \Omega_i \cap O_x} a(y)J(y)}{|\Omega|} \approx \frac{\sum_{y \in \Omega_i \cap O_x} a(x)c_i}{|\Omega|} = a(x)c_i \quad (10)$$

In the above mentioned equation, $|\Omega|$ is the no of pixels in $\Omega_i \cap O_x$. Which is similar to other numerical methods of medical Image segmentation [15], the $I(y)$ is presumed to follow the below Gaussian distribution in sub region $\Omega_i \cap O_x$:

$$\tilde{p}_{i,x}(I(y)) = \frac{1}{\sqrt{2\pi}\sigma_i(x)} \exp\left(-\frac{(a(x)c_i - I(y))^2}{2\sigma_i(x)^2}\right), i=1,2. \quad (11)$$

Where $\tilde{p}_{i,x}(I(y))$ is the abbreviated form of $\tilde{p}_p(I(y) | y \in \Omega_i \cap O_x)$, is the possibilities thickness in region $\Omega_i \cap O_x$. $\sigma_i(x)$ and $a(x)c_i$ are the standard deviation and local intensity mean respectively. In contrast to [10] the local mean $U_i(x)$ is substituted by $a(x)c_i$, in the equation. According to the new equation obtained, this descriptor can identify the intersecting node of bias correction and for medical image segmentation with heterogeneous intensities. By Bayesian formula and maximum posteriori possibilities (MAP) approach [10, 28], the below objective function for each point x with an image in the domain Ω can be described as:

$$E_x = \sum_{i=1}^N \int \Omega_i - K(x-y) \log \tilde{p}_{i,x}(I(y)) dy, \quad (12)$$

To minimize E_x for each points of x , the integral of E_x is minimized over Ω , and the required level set function represents each partition $\{\Omega_i\}_i^N = 1$. Bias correction and the whole objective energy function utilized for segmentation of medical images, which can be expressed as follows:

$$F(\phi, a, u_1, u_{2,1}, \phi_2) = - \int K(x-y) \log \text{Property1}, x(I(y)) H_\epsilon((y)) dy dx - \int \left(\int K(x-y) \log \text{Property2}, x(I(y)) 1 - H_\epsilon((y)) dy \right) dx + \nu \int |\nabla H_\epsilon(\phi(x))| dx + \mu \int p(|\nabla \Phi|) dx, \quad (13)$$

The length term to smoothen the contour and the level set regularization term are the third term and the last term in equation 13, to penalize the deviation of the level set function ϕ from the signed distance function [17]. $H(x) = \frac{1}{2} [1 + \arctan(\frac{x}{\epsilon})]$ is smoothing function n approximation of the heavy side function. Accordingly, if we set $\sigma_i(x)$ in Eq. (14) to $\frac{1}{\sqrt{2}}$, our method is

similar to method proposed by Li et al. [15]. Including the values of local variance in the local region descriptor, the obtained method’s results are found to be more precise and accurate. The minimiser of F at every variable is found by setting up another variable. By fixing $c_i, \sigma_i, i=1,2$, and a , minimization of the energy functional F in Eq. (14) in accordance to ϕ can be obtained by resolving the gradient descent flow equation:

$$\frac{\partial \Phi}{\partial t} = -\delta_\epsilon(\Phi)(e_1 - e_2) + \delta_\epsilon(\Phi) \text{div}\left(\frac{\nabla}{|\nabla \Phi|}\right) + \mu(\text{div}(d_p |\nabla \phi|) \nabla_\phi), \quad (14)$$

Where $\delta_\epsilon(x) = H_\epsilon(x) = \frac{1}{\pi} \left(\frac{\epsilon}{\epsilon^2 + x^2} \right)$, $\text{div}(\cdot)$ is the divergence operator, d_p is a function defined by $d_p(s) = p'(s)s$ and $e(1)$ and $e(2)$ are the functions as follows:

$$e_i = \int_{\Omega} \omega(x-y) \left[\log(\sigma_i(x)) + \frac{(I(y) - a(x)c_i)^2}{2\sigma_i(x)^2} \right] dy. \quad (15)$$

By fixing up ϕ , σ and C , here we detect an ideal bias field which minimizes F :

$$a = \frac{\sum_{i=1}^2 (I c_i M_i(\phi)) * K ./ \sigma_i}{\sum_{i=1}^2 (c_i^2 M_i(\phi)) * K ./ \sigma_i} \quad (16)$$

Using the similar optimal process which is already used in Equ (9), the global means C_i and local variance σ_i^2 can be written as:

$$c_i = \frac{\int (a * K) I M_i(\phi) dx}{\int (a^2 * K) M_i(\phi) dx} \quad (17)$$

and

$$\sigma_i^2(x) = \frac{\int K(y-x) (I(y) - a(x)c_i)^2 M_i(\phi(y)) dy}{\int K(y-x) M_i(\phi(y)) dy} \quad (18)$$

For minimizing the energy, the level set ϕ , bias field b , global means and local standard deviations are updated by using Eqs. (15)-(19) alternately in each iteration. After the final iteration, we will be able to compute the corrected image J with $J = I ./ \tilde{a}$, where \tilde{a} is the optimal bias field.

Lattice boltzmann method

A numerical framework is LBM for modelling Boltzmann particle dynamics on a 2D or 3D lattice, which was designed first to resolve the various challenges of macroscopic fluid dynamics. Advantages of LBM are parallelizability and simplicity due to local and explicit nature. The problem of implicitly calculating the curvature using LBM can resolve the drawback of larger time consumption and this algorithm supports parallel programming. D2Q9 method, in which the 2D image is partitioned into eight links with its neighbours and one link for the cell itself [10]. Using the Bhatnagar, Gross and Krook model [28], the LBM equation can be evaluated as follows:

$$f_i(\vec{r} + \vec{e}_i, t+1) = f_i(\vec{r}, t) + \frac{1}{T} [f_i^{eq}(\vec{r}, t) - f_i(\vec{r}, t)] \quad (19)$$

Where τ represents the relaxation time determining the kinematic viscosity \mathcal{G} of the fluid by:

$$\mathcal{G} = \frac{1}{3} \left(\tau - \frac{1}{2} \right) \quad (20)$$

and f_i^{eq} is the equilibrium particle distribution defined as

$$f_i^{eq}(\rho, \vec{u}) = \rho \left(A_i + B_i (\vec{e}_i \cdot \vec{u}) + C_i (\vec{e}_i \cdot \vec{u})^2 + D_i (\vec{u})^2 \right) \quad (21)$$

where A_i to D_i are constant coefficients depending on the geometry of the lattice links, ρ and \vec{u} are the macroscopic fluid density and velocity, respectively, computed from the particle distribution as

$$\begin{aligned} \rho &= \sum_i f_i \\ \vec{u} &= \frac{1}{\rho} \sum_i f_i \vec{e}_i \end{aligned} \quad (22)$$

For modelling typical diffusion computations, the function for equilibrium can be rewritten as follows: [13]

$$f_i^{eq}(\rho, \vec{u}) = \rho A_i \quad (23)$$

In scenarios of D2Q9 model, $A_i=4/9$ for the zero link, $A_i=1/9$ for the axial links, and $A_i=1/36$ for the diagonal links. Now, the relaxation time τ is determined by the diffusion coefficient γ defined as :

$$\gamma = \frac{2}{9} (2\tau - 1) \quad (24)$$

As represented by using [19], for solving parabolic diffusion LBM can be used, which can be improved by the Chapman-Enskog expansion:

$$\frac{\partial \rho}{\partial t} = \gamma \nabla \cdot \nabla \rho \quad (25)$$

In our case, the external force can be included as given below:

$$f_i \leftarrow f_i + \frac{2\tau - 1}{2} B_i (\vec{F} \cdot \vec{e}_i) \quad (26)$$

Therefore, (9) is represented as

$$\frac{\partial \rho}{\partial t} = \gamma \nabla \cdot \nabla \rho + F \quad (27)$$

Replacing ρ by the signed distance function ϕ , the LSE can be recovered.

3. Proposed method

Level set method is a part of the active contour family. Level set methods have shown tremendous results for medical image segmentation. The main drawbacks of Level set methods are the results depends on the initialization of controlling parameters and time complexity. Gaussian distribution is used as the descriptor of local intensities is utilized in this method to extend Li et al., model [15]. Variational LSM do has fewer parameters such as regular deviation of Gaussian distribution, weighted length term parameter, weighted area term parameter and internal energy parameter. Every parameter plays an important role in evolution of LSM and it also supports in maintaining the stability in evolution of LSE. For internal energy part, there is parameter that controls the effect of penalizing the deviation ϕ from a signed distance function. Actual step up of the time intervals range from τ and the coefficient μ must satisfy $\tau\mu < 0.2$ in order to maintain stability in evolution of level set evolution. For $\tau\mu < 0.2$, small μ takes a longer time to completely segment the image which plays an effective role in achieving results as accurate as possible. Interestingly, the parameter weighted graph of weighted area term α may be +ve or -ve depending up on the relative position of the initial contour to the interest of object. The positive α results makes the initial contour to shrink inwards and negative α results causes the initial contour to expand outwards. By this, the actual value of standard deviation can affect the outcome of the concluding contour. The concluding contour of edge-indicator depends upon the Gaussian distribution of the image which is inputted. Gaussian distribution is the basic statistical analysis; it's also referred as normal distribution. The standard deviation value reflects on the width of the bell. With a Small value or large value in standard deviation leads to narrow bell and high peak or if it's high then it represents wide bell and low peak in generating the final contour. In the proposed method we overcome the drawbacks of initialization of parameters and to reduce the compute time taken by the system. To overcome these two drawbacks we used Intuitionistic Fuzzy C-Means (IFCM). IFCM is based on Intuitionistic Fuzzy Set, which considers both membership and non membership value to decide the label. To overcome the second drawback we make use of Lattice Boltzmann Method (LBM).

The steps of the algorithm carry a greater importance for achieving the segmentation result:

The computational steps are as follows:

Step 1: Fix and initialize the distance function and class centroid values v_1 and v_2 . Initialize B with zeros.

Step 2: Calculate Level set functions and using (2)

Step 3: Calculate v_1 and v_2 with (14)

Step 4: Calculate B with the equation (17)

Step 5: Calculate the external force using (27)

Step 6: Involve the external force as grounded by (27)

Step 7: By using LBM, determine the convection-diffusion equation.

Step 8: Collect $f_i(\vec{r}, t)$ values at each point by equation (6), which utilizes an instant distance value at each point.

Step 9: Discover the evolution of the contour

Step 10: In the case where segmentation process has not been done, then increase the value of λ and return to Step 5.

4. Experimental results

MRI brain images taken for experimentation consists of three different categories: T1-weighted, proton density (pd)-weighted and T2-weighted. Normal images of brain are acquired from the Brainweb database [4]. In this research work, we utilise the transversal slice map, the slice thickness is 1 mm and the size is 217 x 181 pixels. We here use the same weighting exponent $m=2.0$, and a 3x3 square brain image pixels for implementation. We used Matlab R R2013a for simulating all the algorithms.

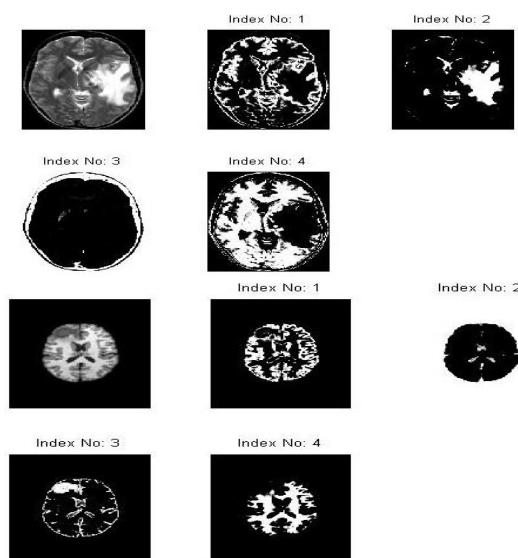


Fig. 1: Initial segmentation using IFCM

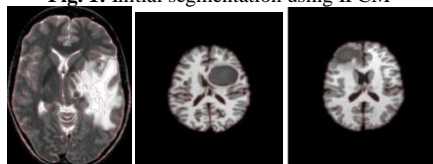


Fig. 2: Final segmentation using proposed method

Figure 1 depicts the initial segmentation results using method of IFCM. Figure 2 depicts the proposed methods segmentation result. In summary, the proposed method gives a good segmentation result. Since, IFCM incorporate spatial information and uses kernel metric, it shows less vulnerability to varied noise types. Thus it's appropriate to utilize variational level set evolution for the process of image segmentation.

5. Conclusion

In this research work, we present a hybrid approach for segmentation of medical images. The proposed method is based

on Variational level set method, whose goal is to maintain the level set function closely to a signed distance function, thus completely eliminating the process of re-initialization in the process of medical image segmentation, here active contours always move in the direction of the boundary of an object which can be attained by using the external energy function which moves the zero level curves towards the boundary of the interested region. The proposed method utilizes IFCM algorithm to initialize the controlling parameters of level set and LBM method to reduce the time complexity. Performance evaluation of the proposed method has been done on MRI brain images and the outcomes were confirmed to be efficient.

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