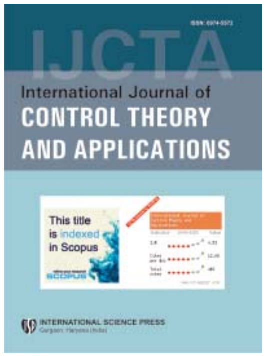

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Efficiency Analysis of Phase Field Model in Segmentation of Brain CT Images

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Abstract: Although there are a remarkable amount of segmentation methods available, the need for a more accurate and robust segmentation technique still exists especially when it comes to computer-aided analysis and reconstruction of medical images. This paper elucidates an efficient quantitative and qualitative segmentation analysis of both parametric as well as geometric contour models with the recent phase field model. Here an effort is made to find the segmentation method which is best suited and could be adopted for brain CT images in the perspective of 3D reconstruction. The metrics used for comparative analysis include accuracy, sensitivity, specificity, mean square error and peak signal to noise ratio. Phase field model proves to be most effective.
Keywords: *Image segmentation, phase field function, geometric active contour model, level set.*

1. INTRODUCTION

A radical change in the history of medical imaging was experienced since the discovery of CT scanner and the digital computer. CT is a 2D reconstruction of a cross section of a patient which provides good contrast between different kinds of tissues. Extracting various features of the CT slices in order to build meaningful regions is segmentation. Segmentation is usually considered the pre-processing step for image analysis and interpretation. Also, for more accurate 3D reconstruction of a specific portion/organ from a set of 2D slice data either from CT/ MRI, we require a perfect segmentation technique.

A promising image analysis tool for refinement of object boundary is the active contour model or the snake model. They find wide applications in segmentation, motion tracking, shape modeling etc. It is a set of connected points guided by external constraint forces, internal forces between points of contour and image forces so as to interactively pull it towards lines and edges by minimizing the energy function [1]. The external constraints are the user defined forces applied to the contour. Image forces pull the snake towards the optimal boundaries. The internal energy corresponds to the continuity and curvature term. This iterative energy minimization method is simple but exhibits poor concavities. Moreover, the initial contour must be close to the original boundary. These problems were addressed in Gradient Vector Flow (GVF) which introduced a new class of external forces [3] which detects boundary concavities, exhibits large capture range and are insensitive to initialization. These problems have been taken care of in [12,13] which improve GVF snake convergence.

Parametric deformable models and geometric deformable models are the two types of deformable models and the above said models come under parametric snake model which represents curves and surfaces explicitly. Geometric deformable models represent curves and surfaces implicitly as a level set function and topological changes are efficiently handled here. [2] Geodesic active contours were introduced as a geometric model with energy minimization functional. A modification to the variant of Geodesic model is given in [4] which consider all the level sets as energy minimizing contours. This segments multiple objects simultaneously.

Moreover, another fast and intuitive contour model which shows snakes as a cubic spline is the B-spline Snakes [5]. Cubic spline snakes suffer from slow convergence speed. The regularization term is eliminated thereby overcoming the difficulty in calculating the weight factors of the internal energy terms. This proves to be stable even under noisy environments. [6] proposed a new model for active contour boundary delineation known as active contours without edges using the Mumford Shah functional, curve evolution and level sets. It can detect boundaries without the need for gradient unlike the other methods. This being an iterative process detects interior contours even if the initial contour is placed anywhere in the image. An edge-driven bidirectional geometric flow for boundary extraction was proposed by Nikos et.al in [7]. By combining the geodesic active contour and GVF external force, this has proved to exhibit robust and fast convergence.

Another variant to deformable snakes is the adaptive snakes [8].Here, the edge points are associated with strokes and they are classified as inlier or outlier each associated with a confidence degree which is updated using Expectation Maximization algorithm. Dynamic directional gradient vector flow in [9] presents better segmentation techniques for edges of different directions by calculating gradients and external force fields in both x and y direction. Moreover, [10] presents a precise comparative analysis on some of the deformable models and its level set methods both quantitatively and qualitatively.

Distance Regularized Level Set Evolution (DRLSE) is a variation provided to level set which develops irregularities during evolution. The level set is derived with a distance regularized term that helps in minimizing the energy functional and an external energy term that controls the motion of zero level set to the desired boundary [11]. Reinitialization and therefore the induced numerical errors are avoided.

In [16], the authors have proposed a phase field approximation for fast and accurate segmentation of medical images based on modified Allen-Cahn (AC) equation and its numerical solution. AC equation [14] is used to model mean curvature flow problems. Phase field method is an alternative to mean curvature flow. Phase field methods find wide application in differential geometry and phase transitions. The numerical solution to this AC equation can be easily obtained using a multigrid method.

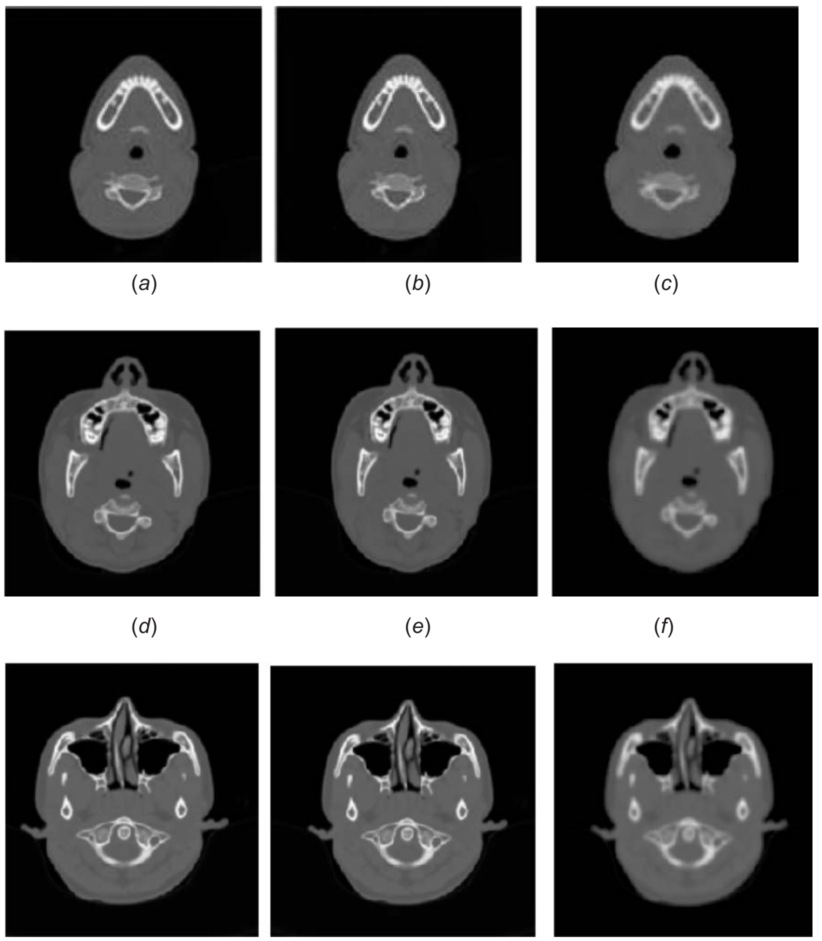
There is still a lot of research work related to snake models applied to medical as well as non-medical images. This paper mainly concentrates in segmenting brain CT images by applying the phase field function. This method not only segments regions with greater accuracy and minimum mean square error but also provides better signal to noise ratio. The paper is organized as follows: Section II explains the preprocessing step. Section III explains the iterative phase field segmentation process. Section IV deals with comparison of iterative phase field segmentation with other contour models, along with segmentation results and performance evaluation tables. Section V and VI comprise discussion and conclusion.

2. PREPROCESSING

Preprocessing is the process of improving the quality of the image for better analysis. Brain CT slice data is a DICOM image and Connected Component Labeling is used for removing the regions that are not part of the object of interest. Also the image is normalized and smoothed using Gaussian filter before segmentation. The original DICOM images are of size 256 x 256 and Fig. 1 shows the original, normalized and Gaussian smoothed image for slice no.2, 20, and 33.

3. ITERATIVE PHASE FIELD SEGMENTATION (IPFS)

A phase field model is a mathematical model for solving interfacial problems [14, 17, 18, 19]. Here the phase field or order parameter (ϕ) is used to separate one phase from other. The initial guess for this segmentation is given in the form of a characteristic function covering the object of interest. After preprocessing, the edge stopping function is calculated from the gradient image. The edge stopping function plays a very important role because this stops the evolution when the contour reaches the edge. [15] explains segmentation using the phase field function and reconstruction of (tibia and fibula) human bone with these segmented slice data. The geometric active contour model based on mean curvature motion given by the following evolution equation is in (1).



(*a*) (*b*) (*c*)

(*d*) (*e*) (*f*)

(*g*) (*h*) (*i*)

Figure 1: (*a*), (*d*), (*g*) original slice data, (*b*), (*e*), (*h*) normalized image, (*c*), (*f*), (*i*) smoothed image

$$\frac{\partial\varphi(x,t)}{\partial t} = g(f_0(x))\left(-\frac{F'(\varphi(x,t))}{\in^2}+\Delta(x,t)\right)+\beta g(f_0(x))F(\varphi(x,t))$$

$$x \in \Omega,\ 0 < t \leq T \qquad (1)$$

where,

$\in$ is a constant called phase transition width

β is a parameter

Δ_d is discrete five point laplacian operator
$f_0(x)$ is the normalized value of the given image $f(x)$
$g(f_0(x))$ is the edge stopping function
$\varphi(x, t)$ is the phase field function
$F(\phi) = 0.25(\phi^2 - 1)^2$ is the double well potential function
The discrete edge function is given as,

$$g(f_0)_{ij} = \frac{1}{1 + (G_\sigma * f_0)^2_{x,ij} + (G_\sigma * f_0)^2_{y,ij}} \tag{2}$$

where, $(G_\sigma * f_0)_{x,ij} = [(G_\sigma * f_0)_{i+1,j} - (G_\sigma * f_0)_{i-1,j}]/(2h)$

and $(G_\sigma * f_0)_{y,ij} = [(G_\sigma * f_0)_{i,j+1} - (G_\sigma * f_0)_{i,j-1}]/(2h)$

G_σ is the Gaussian function and h is the uniform mesh size. The double well function becomes zero for –1 and + 1 values of ϕ and $F(\phi)$ takes 0.25 for $\phi = 0$. Zero Neumann boundary condition is used. Equation (1) is discretized [16] as,

$$\frac{\varphi^*_{ij} - \varphi^n_{ij}}{\Delta t} = g_{ij}\Delta_d\, \varphi^*_{ij} + \beta g_{ij}\, F(\varphi^n_{ij}) \tag{3}$$

Equation (3) is solved using multigrid method.

The equation $\varphi_t = g\dfrac{\varphi - \varphi^3}{\in^2}$ is solved using separation of variables and the solution is given in Equation (4) with the initial condition $\varphi^n = \varphi^*$.

$$\varphi^{n+1}_{ij} = \frac{\varphi^*_{ij}}{\sqrt{e^{\frac{-2\,g_{ij}\Delta t}{\in^2}} + (\varphi^*_{ij})^2\left(1 - e^{\frac{-2\,g_{ij}\,\Delta t}{\in^2}}\right)}}$$

Initial value of phase field function is assigned to be 1 for values inside the square contour and –1 for values outside the square contour. The square contour can be placed close to the object of interest by any initialization technique to speed up the evolution. $\in$ is important and it is a measure of the transition region between two gray scale states. According to the initial value of the φ, $F(\varphi)$ takes to zero and after further iterations, φ takes zero value on the boundary, – 1 outside and + 1 inside the boundary. Equation (3) and (4) helps in evolving the contour beyond the non-convex and disconnected regions with Δt as the time step.

4. COMPARISON WITH OTHER CONTOUR MODELS

Iterative Phase Field Segmentation being a contour model, is been compared with other contour models in literature. The compared contour models are the Active Contour Model (ACM), Chan Vese (CV), Geodesic Active Contour Model (GACM), DRLSE and Region Based ACM (RACM). The segmented results along with original and manually segmented image for slice 2 are shown in Fig. 2.

The parameters used for evaluation [20] are
Accuracy (ACC)
Sensitivity (SEN)
Specificity (SPEC)
Hammoude distance (HamD)
Mean Square Error (MSE)
Peak Signal to Noise ratio (PSNR)

Accuracy: It is the proportion of true results (both true positives and true negatives) in the population.
Sensitivity: It is the proportion of positives measured as such.
Specificity: It is the proportion of actual negatives which are correctly identified as such.

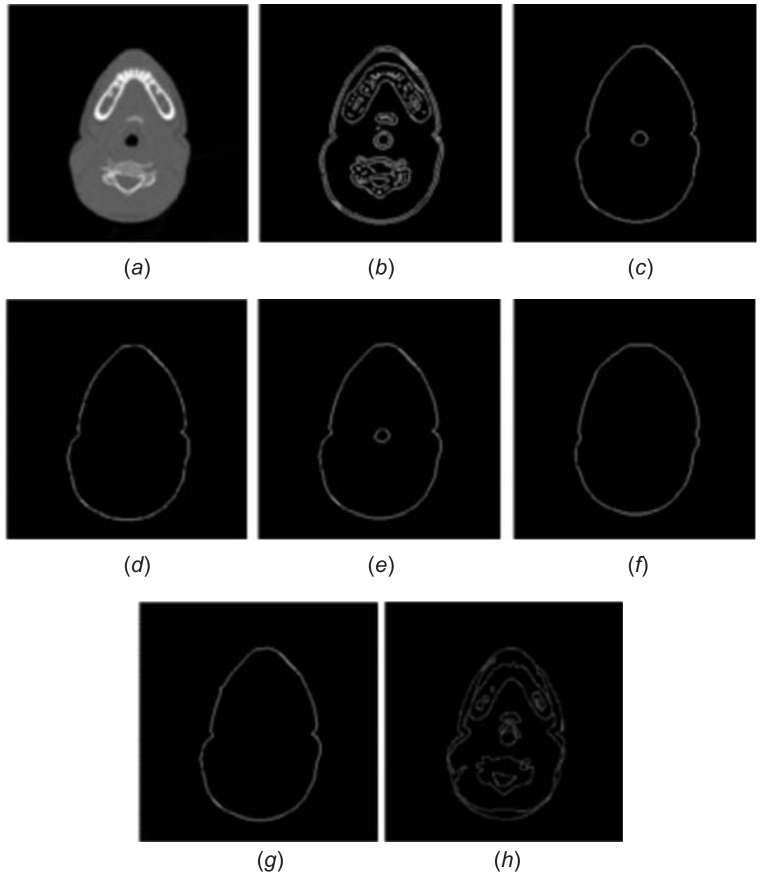


Figure 2: Segmentation results (*a*) original image (*b*) IPFS (*c*) ACM (*d*) GACM (*e*) CV (*f*) DRLSE (*g*) RACM (*h*) manual segmented image

Hammoude distance: It makes a pixel by pixel comparison enclosed by the two boundaries.
MSE: It measures the average of the square of the difference between the segmented and the original image.
PSNR: It is a measure of reconstruction quality.

Table 1, 2, 3 shows the individual evaluation table for 3 slices namely slice 2, slice 20 and slice 33 of brain CT image which shows improved performance using IPSF segmentation in terms of accuracy ,specificity and PSNR along with reduced MSE and HamD.

Table 1
Performance evaluation for Slice 2

For slice 2	*ACC*	*SEN*	*SPEC*	*HamD*	*MSE*	*PSNR*
IPFS	91.666	69.626	93.063	9.524	0.083	58.922
ACM	78.426	76.407	78.554	29.206	0.216	54.791
GACM	78.543	95.650	77.458	29.458	0.215	54.815
CV	79.207	95.650	78.164	28.289	0.208	54.952
DRLSE	76.946	100.00	75.484	32.479	0.231	54.503
RACM	79.001	95.957	77.926	28.657	0.210	54.909

Table 2
Performance evaluation for Slice 20

For slice 20	*ACC*	*SEN*	*SPEC*	*HamD*	*MSE*	*PSNR*
IPFS	89.630	71.970	91.034	12.297	0.104	57.973
ACM	72.194	71.224	72.271	41.534	0.278	53.689
GACM	72.420	91.568	70.897	41.995	0.276	53.725
CV	73.135	91.403	71.683	40.457	0.269	53.839
DRLSE	69.223	98.550	66.891	49.669	0.308	53.249
RACM	72.528	96.126	70.652	41.975	0.275	53.742

Table 3
Performance evaluation for Slice 33

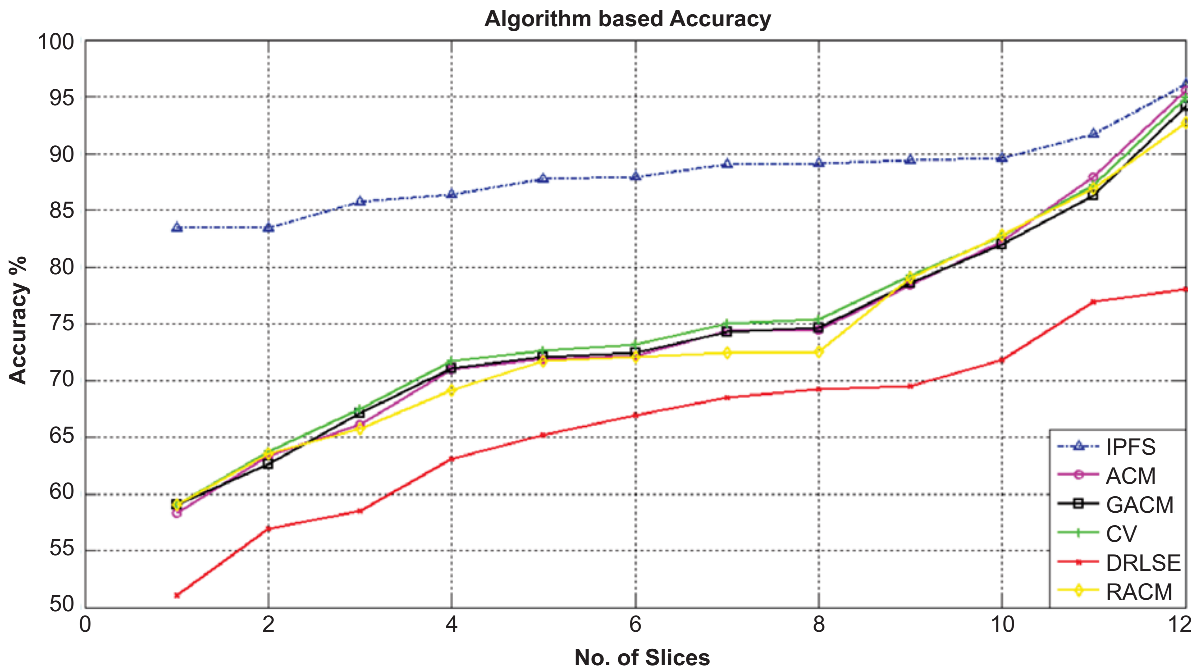
For slice 33	*ACC*	*SEN*	*SPEC*	*HamD*	*MSE*	*PSNR*
IPFS	89.037	78.144	90.135	13.390	0.110	57.731
ACM	74.419	70.815	74.782	37.657	0.256	54.052
GACM	74.295	88.073	72.906	38.813	0.257	54.031
CV	74.999	86.907	73.798	37.295	0.250	54.151
DRLSE	69.495	99.933	66.425	50.555	0.305	53.287
RACM	72.057	95.619	69.681	44.146	0.279	53.668

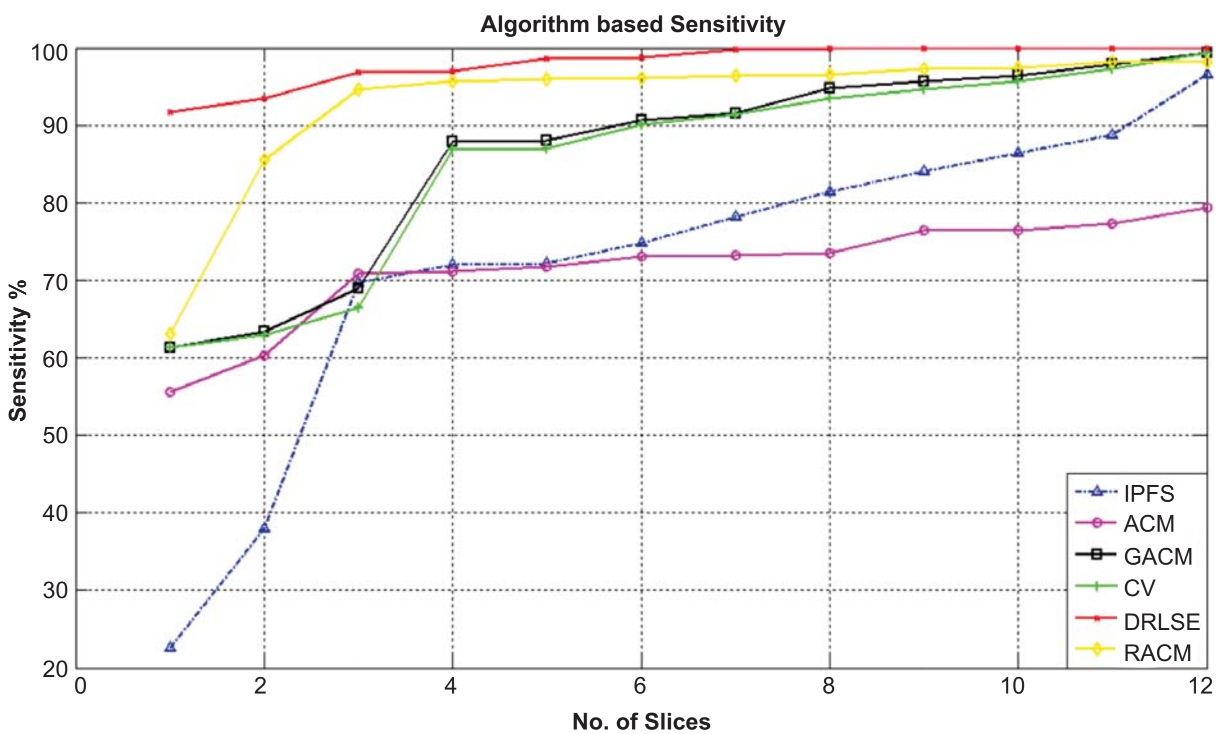
5. DISCUSSION

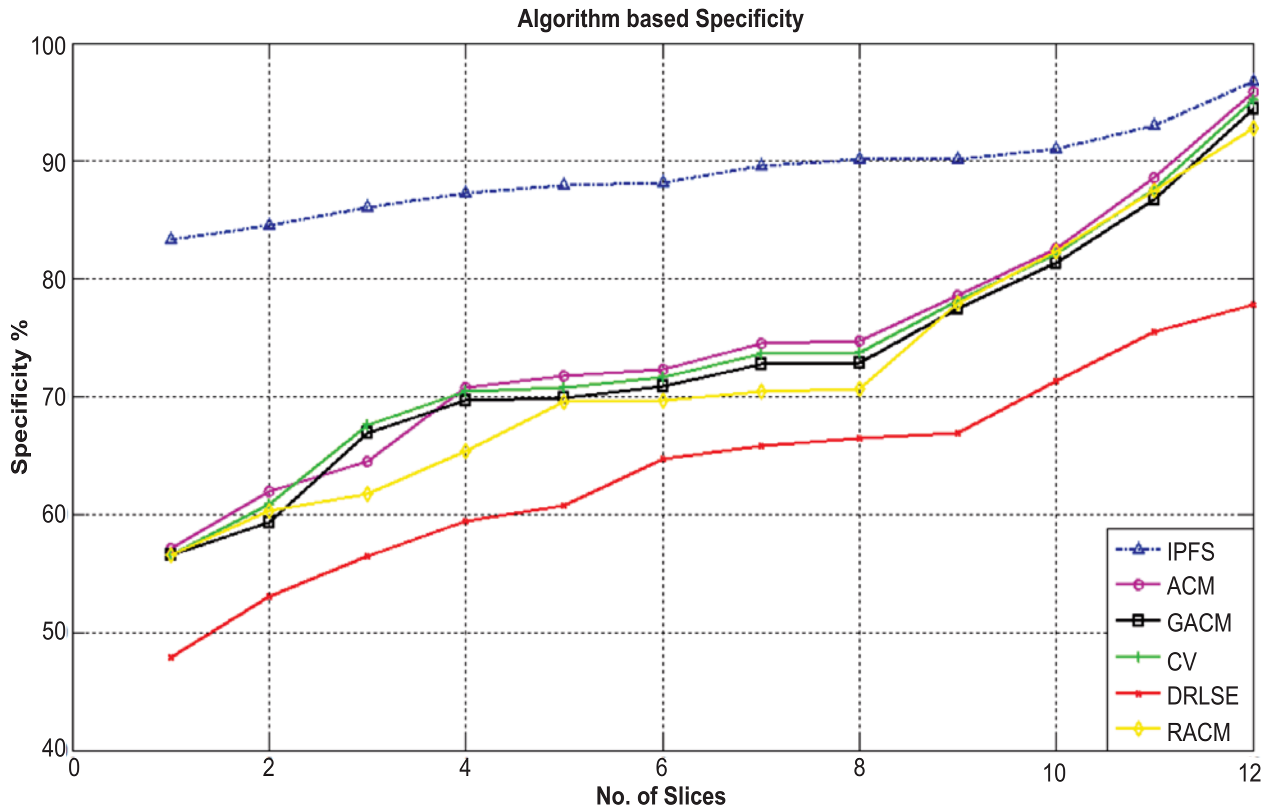
Table 4
Average Performance evaluation for segmentation of different contour models for a set of 12 slices

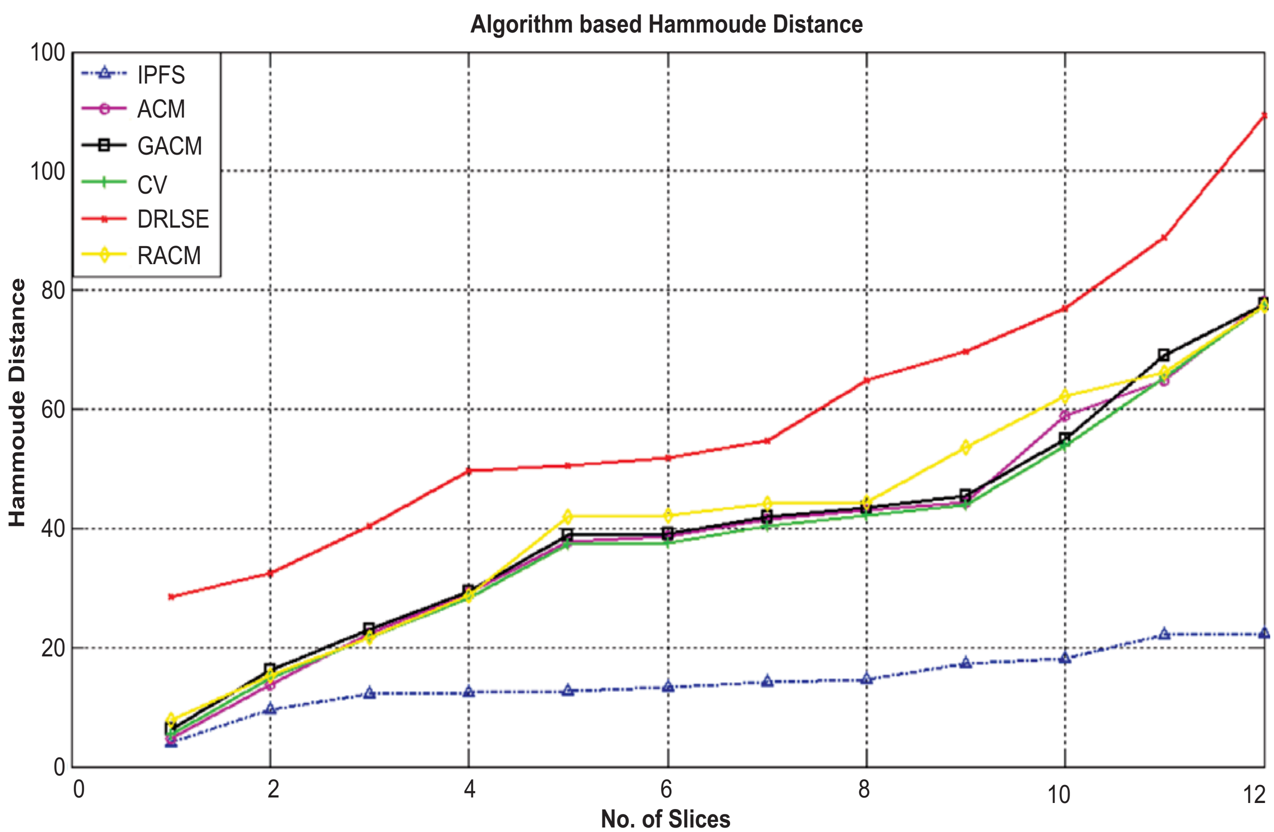
Average of 12 Slices	*ACC*	*SEN*	*SPEC*	*HamD*	*MSE*	*PSNR*
IPFS	88.290	72.021	89.008	14.442	0.117	57.688
ACM	74.640	71.600	74.436	39.761	0.254	54.628
GACM	74.510	86.321	73.252	40.432	0.255	54.500
CV	75.182	85.536	74.051	39.003	0.248	54.665
DRLSE	66.308	97.996	63.842	59.824	0.337	52.968
RACM	73.972	92.930	72.076	42.114	0.260	54.372

In IPSF segmentation, the edge information in the image is determined by the gradient and the inverse of gradient is the edge stopping function. It is multiplied with the potential or free energy functional. Also, the laplacian of the phase field function is multiplied with the edge stopping function. Equation (3) shows these two terms which help in evolving the contour beyond non-convex and disconnected regions iteratively. The values in the performance evaluation Table 4 are the average of each segmentation method performed on 12 slices chosen randomly from the database. Out of all the contour models chosen for segmentation, IPFS proves to be efficient for brain CT images as indicated by the parameters. A graphical plot of all the 12 slices vs. the parameters used for evaluation for all the segmentation algorithms is shown in Fig. 3. The CT brain data sets have been collected from well equipped medical scan center utilizing Siemens SOMATOM Sensation 64 slice CT scanner (cardiac imaging with rotating time of 0.33s and isotropic spatial resolution of 0.24 mm). The manual segmentation has been verified by a neurologist who has 20 years of experience in his field. The algorithms have been implemented using MATLAB.






Algorithm based Specificity
Specificity %
No. of Slices
IPFS
ACM
GACM
CV
DRLSE
RACM
100
90
80
70
60
50
40
0
2
4
6
8
10
12


Algorithm based Hammoude Distance
Hammoude Distance
No. of Slices
IPFS
ACM
GACM
CV
DRLSE
RACM
100
100
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20
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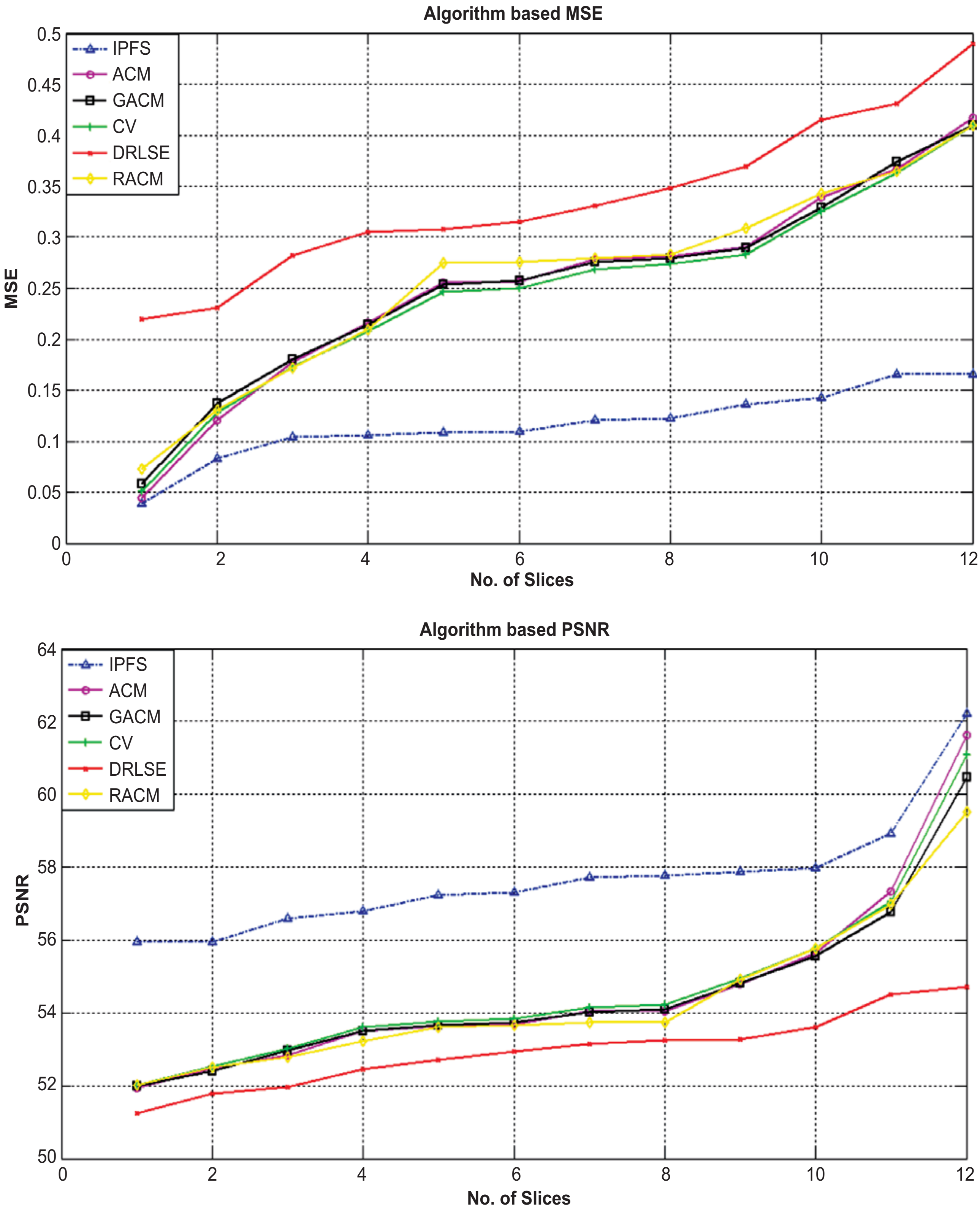

Figure 3: Graphs showing the performance analysis of contour models with respect to measurement parameters for all the 12 slices

6. CONCLUSION

Segmentation techniques, especially for medical images, need to provide very accurate results since they aid in diagnosis and analysis of abnormalities. From the comparative analysis, it is seen that phase field modeling concept when applied to brain CT segmentation proves to be very effective than other contour models for detecting edges or boundaries. It is observed to provide better accuracy (atleast 15% higher) and minimal Mean Square Error in comparison to other models. Hence, for appropriate reconstruction of brain from segmented slice data, use of iterative phase field segmentation will enhance the result.

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