International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-6, April 2020

Level Set Segmentation of Oil Spills from Earth Observatory Images Via Spatial KFCM Clustering

Ramudu Kama, Ganta Raghotham Reddy

Abstract: ***In this paper, we present a novel technique called spatial kernel fuzzy clustering with adaptive level set approach for Oil spill image segmentation. The proposed method is diversified into two stages; in the first stage the input is pre-processing by Spatial Kernel Fuzzy C-Means clustering (KFCM) to improve the clustering efficiency and less sensitive to noise. In the second stage, it necessary to use the level set method to refine the previous stage segmentation results. The performance of the level set segmentation is subjected to proper initialization and optimal formation of directing parameters. The controlling parameters of level set evolution are also projected after the results of kernel fuzzy clustering. The proposed method, spatial kernel fuzzy adaptive level set algorithm is enhanced the local minima problem. Such developments enable level set handling and more strong segmentation. The results confirm its effectiveness for oil spill images over the conventional CV model i.e number of iterations, Computational time and PSNR***

Keywords: ***Oil Spill Image Segmentation, adaptive Level set Equation, spatial kernel fuzzy clustering.***

I. INTRODUCTION

A well-studied problem in computer vision is the fundamental task of segmenting or partitioning an image into disjoint regions with applications ranging from medical image analysis, quality control, or military surveillance and tracking. Although the general segmentation problem involves separating N distinct partitions, a piecewise assumption of two sets is generally made. That is, the image is assumed to be comprised of two homogeneous regions, often referred to as "Object" and "Background". The goal of segmentation is to accurately capture these regions. Specifically, the use of active contours has been proven to be quite successful in accomplishing this task. [1-6] There are many advantages of region-based approaches when compared to edge-based methods including robustness against initial curve placement and insensitivity to image noise.

Revised Manuscript Received on April 30, 2020.
***** Correspondence Author
Ramudu Kama*, Department of ECE , KITS,Warangal-15, Email: ramudukama@gmail.com
Dr.G.Raghotham Reddy, Department of ECE , KITS,Warangal-15, Email: grrece9@gmail.com

© The Authors. Published by Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP). This is an open access article under the CC-BY-NC-NDlicense (http://creativecommons.org/licenses/by-nc-nd/4.0/)

However, techniques that attempt to model regions using global statistics are usually not ideal for segmenting heterogeneous objects. In cases where the object to be segmented cannot be easily distinguished in terms of global statistics, region-based active contours may lead to erroneous segmentations. The construction of this image causes it to be segmented improperly by a standard region-based algorithm, but correctly by an edge-based algorithm. Heterogeneous objects frequently occur in natural and medical imagery. To accurately segment these objects, a new class of active contour energies should be considered which utilizes local information, but also incorporates the benefits of region-based techniques. Segmentation is to Partition an image into disjoint, connected components that are homogeneous w.r.t. intensity, texture or certain probabilistic measures.

Active contour Method is evolving contours towards boundaries of interest by designed forces (e.g. edge, region Information or prior knowledge). Active contour models have a consistent mathematical description; their solutions satisfy certain minimum principles.

Edge based Rely on edge information (high magnitude of image gradient) Limitation – sensitive to noise, artifacts, may leak through gaps on boundary Region based: Make use of information on regional statistics from image intensities. Limitation – high noise level, intensity homogeneity, complex intensity distribution Combination of edge based and region based.

There are two well-established concepts in image segmentation: pixel classification and tracking variational boundary [7]. The first one assumes that the pixels in each subclass have nearly constant intensities, which is true for the anatomical structures with similar physiological properties. Such algorithms may detect multiple components concurrently, but they are susceptible to environmental noise and image inhomogeneity. In contrast, methods that track variational boundaries make use of both intensity and spatial information. Therefore, a subclass has to be homogeneous and enclosed in a specific variational boundary. When applied to oil spill image segmentation, neither of them is universally robust due to intrinsic noise and artifacts [7–11].

In this paper, we propose a kernel fuzzy clustering with adaptive level set algorithm for oil spill image segmentation.

The new algorithm is significantly improved in the following aspects. Firstly, kernel fuzzy clustering incorporates spatial information during an adaptive optimization, which eliminates the intermediate morphological operations. Secondly, the controlling parameters of adaptive level set segmentation are now derived from the results of kernel fuzzy clustering directly.

Thirdly, a new strategy, directed by kernel fuzzy clustering, is proposed to regularize adaptive level set evolution, which is different from other methods. Finally, we also verified the kernel fuzzy adaptive level set algorithm on oil spill images.

Spillage of oil either in oceans by illegal discharges from ships may shows adverse effects on the natural resources, marine environment and the economic health of the area at stake. Thus, there should be an operational process to detect, track, and monitor oil spills and to predict their drift. Synthetic Aperture Radar (SAR) is the most efficient satellite sensor for oil spill monitoring of the world's oceans.

The dark areas in the SAR images are the areas indicating oil spills because the oil dampens the capillary waves on the sea surface. The presence of the glitter induces speckle in SAR is not only reduces the interpreter's ability to resolve fine detail, but also makes automatic segmentation of such images difficult. Segmentation of such images using conventional level set methods makes the process cumbersome and may lead to improper results. In this paper we considered such kind of images as test images for segmentation using Adaptive level set method with Spatial KFCM clustering.

This paper will be organized as follows. Section II will give information regarding spatial kernel fuzzy clustering Section III is about Adaptive levelset background ie Previous work done by C-V model. Section IV gives the detailed information about our proposed algorithm. In section V experimental results and discussion and finally section VI depicts the conclusion of this research work are given below.

II. SPATIAL KFCM CLUSTERING

A. Introduction

In fuzzy clustering, the centroid and the scope of each subclass are estimated adaptively in order to minimize a pre-defined cost function .It is here by appropriate to take fuzzy clustering as a kind of adaptive thresholding. Kernel Fuzzy C means (KFCM) is one of the most popular algorithms in fuzzy clustering, and has been widely applied to medical problems [12-16].

The classical FCM and KFCM algorithms originate from the k-means algorithm seeks to assign N objects, based on their attributes, into k clusters (K≤N). For medical image segmentation, N equals the number of image pixels Nx x Ny. The desired results include the centroid of each cluster and the affiliations of N objects. Standard k-means clustering attempts to minimize the cost function

$$J=\sum_{m=1}^{K}\sum_{n=1}^{N}\left\|i_n-v_m\right\|^2, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where i_n is the specific image pixel, v_m is the centroid of the mth cluster and $\|.\|$ denotes the norm. The ideal results of k-means algorithm maximize the inter-cluster variations, but minimize the intra –cluster ones.

In k-means clustering, every object is limited to one and only one of k clusters. In contrast, an FCM utilizes a membership function μ_{mn} to indicate the degree of membership of the nth object to the mth cluster, which is justifiable for medical image segmentation as physiological tissues are usually not homogeneous. The cost function in an KFCM is similar to eq. (1)

$$J_m(U,V)\equiv 2\sum_{i-1}^{c}\sum_{k-1}^{n}u_{ik}^{m}\left(1-k(x_k,v_i)\right). \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Minimizing Eq. under the constraint of, $u_{ik}, m>1$. We have

$$u_{ik}=\frac{\left(1/\left(1-K(x_k,v_i)\right)\right)^{1/(m-1)}}{\sum_{j=1}^{c}\left(1/\left(1-K(x_k,v_i)\right)\right)^{1/(m-1)}} \ldots\ldots\ldots\ldots\ldots (3)$$

$$v_i=\frac{\sum_{k=1}^{n}u_{ik}K(x_k,v_i)x_k}{\sum_{k=1}^{n}u_{ik}^{m}K(x_k,v_i)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4)$$

Here we now utilize the Gaussian kernel function for straight forwardness. If we use additional kernel functions, there will be corresponding modifications in Eq. (3) and (4) In fact, We can be analyzed as kernel-induced new metric in the data space, which is defined as the following

$$d(x,y)\underline{\underline{\Delta}}\left\|\phi(x)-\phi(y)\right\|=\sqrt{2\left(1-K(x,y)\right)} \ldots\ldots (5)$$

And it can be proven that $d(x,y)$ is defined in Eq. (5) is a metric in the original space in case that $K(x,y)$ takes as the Gaussian kernel function. the data point x_k is capable with an additional weight $K(x_k,v_i)$, which measures the similarity between x_k and v_i and when x_k is an outlier i.e., x_k is far from the other data points, then $K(x_k,v_i)$ will be very small, so the weighted sum of data points shall be more strong.

The full explanation of KFCM algorithm is as follows:

B. KFCM Algorithm:

Step 1: Select initial class prototype $\{v_i\}_{i=1}^{c}$.

Step 2: Update all memberships u_{ik} with Eq. (3).

Step 3: Obtain the prototype of clusters in the forms of weighted average with Eq. (12).

Step 4: Repeat step 2-3 till termination. The termination criterion is $\|V_{new}-V_{old}\|\le\varepsilon$.

Where $\|.\|$ is the Euclidean norm.

V is the vector of cluster centers ε is a small number that can be set by user (here ε =0.01).

Where l(>1) is a parameter controlling the fuzziness of the resultant segmentation. The membership functions are subjected to the following constraints:

$$\sum_{m=1}^{C}\mu_{ik}=1;0\le\mu_{ik}\le 1;\sum_{n=1}^{N}\mu_{ik}>0 \quad \text{……………..} (6)$$

The membership functions μ_{ik} and the centroids v_i are updated iteratively.

$$u_{ik}=\frac{\left(1/\left(1-K\left(x_k,v_i\right)\right)\right)^{1/(m-1)}}{\sum_{j=1}^{c}\left(1/\left(1-K\left(x_k,v_i\right)\right)\right)^{1/(m-1)}} \quad \text{……………} (7)$$

$$v_i=\frac{\sum_{n=1}^{N}\mu_{mn}^{l}i_n}{\sum_{n=1}^{N}\mu_{mn}^{l}} \quad \text{………………………………….} (8)$$

The standard FCM and KFCM algorithms is optimized when pixels close to their centroid are assigned high membership values, while those that are far away are assigned low values.

One of the problems of standard FCM and KFCM algorithms in image segmentation is the lack of spatial information [21, 22].Since image noise and artifacts often impair the performance of FCM segmentation, it would be attractive to incorporate spatial information into an KFCM. Cai et al. [5] proposed a generalized KFCM algorithm that adopts similarity factor to incorporate local intensity and spatial information. In contrast to the above preparatory weighting, it is also possible to utilize morphological operations to apply spatial restrictions at the post-processing stage [9].

C. Incorporating Spatial Information in KFCM Clustering

Chuang et al. [17] proposed another spatial KFCM algorithm in which spatial information can be incorporated into fuzzy member- ship functions directly using

$$\mu_{ik}=\frac{\mu_{ik}^{p}h_{ik}^{q}}{\sum_{k=1}^{C}\mu_{ik}^{p}h_{ik}^{q}} \quad \text{…………………………………}(9)$$

Where p and q are two parameters controlling the respective contribution. The variable h_{ik} includes spatial information by

$$h_{ik}=\sum_{k\in N_n}\mu_{ik} \quad \text{…………………………………..}(10)$$

Where N_n denotes a local window centered on the image pixel n. The weighted μ_{ik} are the centroid v_i are updated as usual according to eqs. (4) and (5).

III. LITERATURE ON LEVEL SETS

The level set method was initiated by Dervieux and Thomasset [11][12] in the late 1970s, but their work did not draw much attention. Later in 1987 Osher and Sethian [10], came up with the idea of tracking moving interfaces which became well known and had an impact in various domains such as computational geometry, fluid dynamics, image processing and computer vision. It can be used efficiently to address the problem of curve or surface propagation in an implicit manner. The central idea is represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface when applied to the zero level set. The basic and most versatile level set models are represented in proceeding topics

Chan Vese (C-V) model

Chan and Vese presented model a special case of Mumford-Shah functional. Let *I* be the given image with c_1 and c_2 the mean intensities inside and outside the contour respectively. For a given image $I(x,y)$ in the domain Ω. Let C be the evolving curve in Ω driven by the inward and outward forces acting with reference to object as shown in figure 1. The level set function ϕ will have the value greater than zero inside the curve, less than zero when it is outside and it is zero on the curve C.

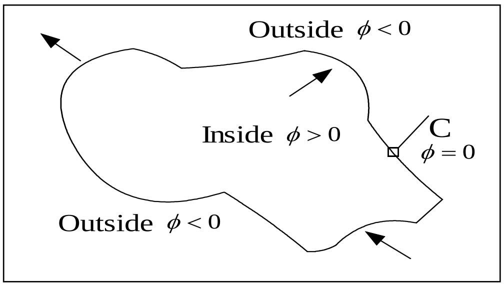

Figure.1 Curve' C' propagating in directions as represented with arrows

$$\phi(x,y)=\begin{cases}1 & inside(c)\\ -1 & outside(c) \quad x,y\in\Omega\\ 0 & otherwise\end{cases}$$

The *C-V* model is formulated by minimizing energy functional and by adding some regularizing terms is as follows.

$$E(c_1,c_2,C)=\lambda_1\int_{inside(c)}\left|I(x,y)-c_1\right|^2 dxdy + \lambda_2\int_{outside(c)}\left|I(x,y)-c_2\right|^2 dxdy, \quad x,y\in\Omega \quad \text{…}(11)$$

C is the evolving curve and can be represented as ϕ . Keeping ϕ fixed and minimizing the energy $E(c_1,c_2,\phi)$ with respect to the constants c_1 and c_2, it is easy to express these constants as the function of ϕ by

$$c_1(\phi)=\frac{\int_\Omega I(x,y)\cdot H(\phi)dxdy}{\int_\Omega H(\phi)dxdy}$$
$$c_2(\phi)=\frac{\int_\Omega I(x,y)\cdot\left(1-H(\phi)\right)dxdy}{\int_\Omega\left(1-H(\phi)\right)dxdy} \quad \text{…………………}(12)$$

Where $H(\phi)$ the Heaviside function is is given as

$$H(\phi)=\begin{cases}1, & if\ \phi\geq 0\\ 0, & if\ \phi<0\end{cases}$$

Heaviside function $H(\phi)$ is greater than zero then the curve has nonempty interior in Ω and $1-H(\phi)$ is greater than zero for the curve nonempty exterior in Ω. By including the length and area energy terms in the Eq. 6 and solving for minimizing them the corresponding variational level set formulation is

$$\frac{\partial\phi}{\partial t}=\delta(\phi)\left[\mu\nabla\left(\frac{\nabla\phi}{|\nabla\phi|}\right)-v-\lambda_1(1-c_1)^2+\lambda_2(1-c_2)^2\right] \quad (13)$$

Where λ_1,λ_2,μ and v are fixed parameters such that $\lambda_1,\lambda_2>0$ and $\mu,v\geq 0$. And μ, v are used for controlling the smoothness of zero level set and increasing the propagation speed respectively.
∇ is gradient operator and $\delta(\phi)$ is the Dirac function given as

$$\delta(\phi)=\frac{d}{d\phi}H(\phi)$$

IV. PROPOSED SPATIAL KFCM WITH LEVEL SET

Both Spatial KFCM algorithm and adaptive level set approach that can be applied to problems of any dimension. However, if we constrain them to satellite images it is possible to take advantage of the specific circumstances for better performance.

The proposed new version kernel fuzzy clustering with adaptive level set approach is there by proposed for an automated medical image segmentation.. It begins with spatial kernel fuzzy clustering, whose results are utilized to initiate adaptive level set segmentation, estimate controlling parameters and regularize level set evolution The new version kernel fuzzy adaptive level set approach automates the initialization and parameter configuration of the level set segmentation, using spatial fuzzy clustering. It employs an KFCM with spatial restrictions to determine the approximate contours of interest in a image. The enhanced adaptive level set function can accommodate KFCM results directly for evolution[18-21].

Suppose the component of interest in an KFCM results is $R_k:\{r_k=\mu_{ik}, n=X*N_y+y$

It is then convenient to initiate the level set function as

$$\phi_0(x,y)=-4\varepsilon(0.5-B_k)\ \ldots\ldots\ldots\ldots\ldots\ldots(14)$$

Where ε is a constant regulating the Dirac function [17,23]. The Dirac function is then defined as follows:

$$\delta_\varepsilon(x)=\begin{cases}o, |x|>\varepsilon\\ \frac{1}{2\varepsilon}[1+\cos(\pi x/\varepsilon)], |x|\leq\varepsilon\end{cases}\ \ldots\ldots\ldots\ldots\ldots\ldots (15)$$

Bk is a binary image obtained from

$$B_k=R_k\geq b_0\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (16)$$

Where $b_0(\varepsilon(0,1))$ is ian iadjustable ithreshold iBenefitted ifrom ispatial ifuzzy iclustering, iBk ican iin isome isense iapproximate ithe icomponent iof iinterest, iwhich ican ibe ireadily iadjusted iby ib0.

It iis iattractive ito idetermine ithese icontrolling iparameters iadaptively ifor ithe ispecific imedical iimage. iGiven ithe iinitial ilevel iset ifunction if0 ifrom ispatial ikernel ifuzzy iclustering ias iin iEq.(19),it iis iconvenient ito iestimate ithe ilength il iand ithe iarea iα iby

$$l=\int_1\delta(\phi_0)dxdy\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (17)$$

$$\alpha=\int_1 H(\phi_0)dxdy\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (18)$$

Where the Heaviside function H (ϕ_0) is

$$H(\phi_0)=\begin{cases}1,\phi_0\geq 0\\ 0,\phi_0<0\end{cases}\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots (19)$$

We observe that level set evolution will be faster if the component of interest is large. In this case, the ratio

$$\varsigma=\alpha/l\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (20)$$

will also be large. It is there by reasonable to assign the time step τ as ς in the proposed special kernel fuzzy adaptive levelset algorithm. The penalty coefficient μ will be set as

$$\mu=0.2/\varsigma\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(21)$$

The new special kernel fuzzy levelset algorithm takes the degree of member- ship of each image pixel μ_k as the distance to the specific component of interest Rk. An enhanced balloon force is proposed here to pull or push the dynamic interface adaptively towards the object of interest:

$$G(R_k)=1-2R_k\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(22)$$

The resultant balloon force $G(R_k)(\varepsilon[-1,1])$ is a matrix with a variable pulling or pushing force at each image pixel. In other words, the levelset function will be attracted towards the object of interest regardless its initial position. Then, the evolutionary equation (Eq.(15)) is transformed into

$$\xi(g,\phi)=\lambda\delta\phi div(g\frac{\nabla\phi}{|\nabla\phi|})+gG(R_k)\delta\phi\ \ldots\ldots(23)$$

V. SIMULATION RESULTS AND DISCUSION

The experiments and performance evaluation were carried on oil spill images from different modalities. The proposed method spatial KFCM with adaptive level set segmentation was implemented with MATLAB 2019b.

The experimental results were obtained by oil spill images for segmentation using spatial kernel fuzzy clustering algorithm.

From figures 1 to 5 and figures 6 to 10 shows the simulation results on Image 1 and 2 respectively using SKFCM clustering method, assuming the input index number is 2, after it shows the two types of clustering segmented images with 200 iterations.

Retrieval Number: F4540049620/2020©BEIESP
DOI: 10.35940/ijitee.F4540.049620
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Simulation results on Image 1:

Figure (1): Spatial KFCM clustering with assuming index number 2 (a) Original Oil spill image (b) First clustering index no.1 (c) Second clustering index number 2

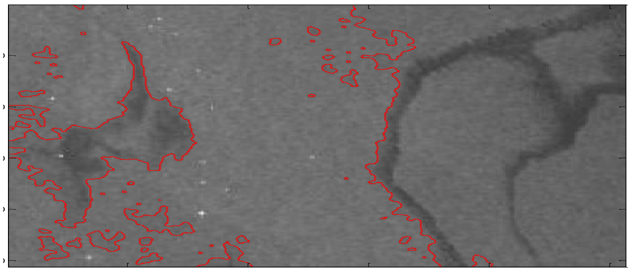

Figure 2.Previous Method (CV model) for 200 iterations, red color indicates the final segmentation.

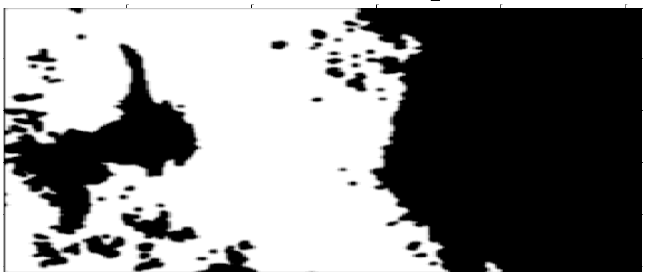

Figure 3.Segmented regions of Oil spill image for previous method (CV Model).

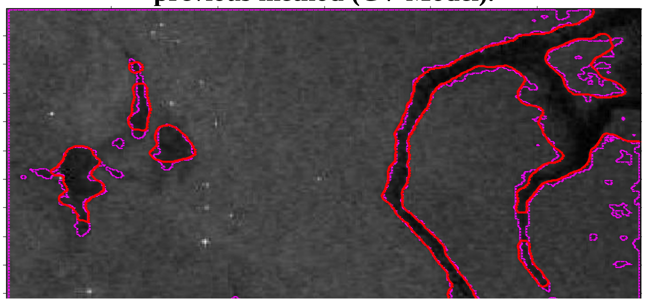

Figure 4. Proposed Method for 200 iterations (magenta indicates the initial segmentation, red color indicates the final adaptive level set segmentation

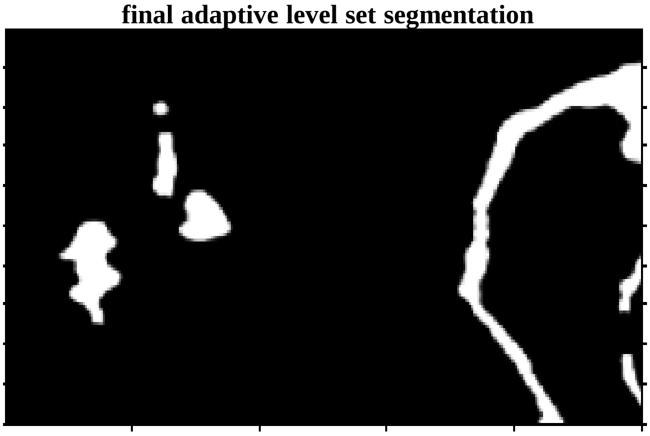

Figure 5. Segmented regions of Oil spill image for proposed method.

Simulation Results on Image 2:

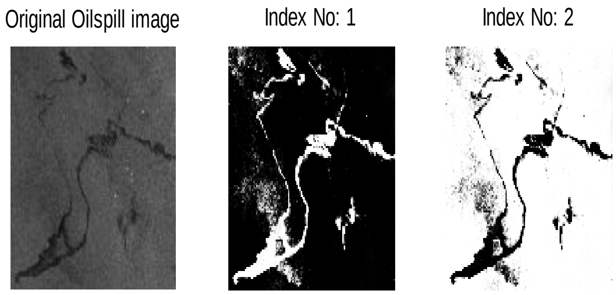

Figure 6. Spatial KFCM clustering with assuming index number 2 (a) Original Oil spill image (b) First clustering index no.1 (c) Second clustering index number 2

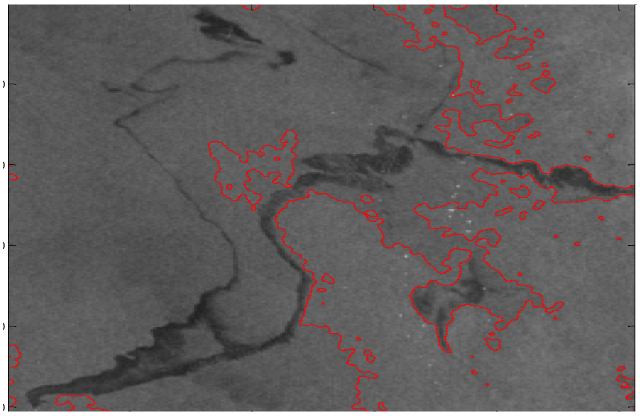

Figure 7. Previous Method for 200 iterations, red color indicates the final segmentation (CV Model)

Figure 8. Segmented regions of Oil spill image for previous method (CV Model).

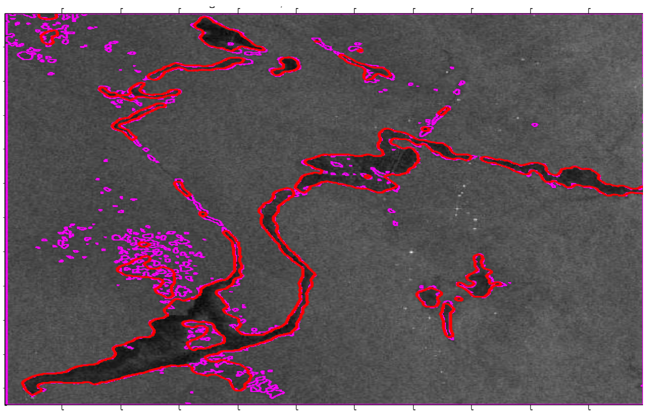

Figure 9. Proposed Method for 200 iterations (magenta indicates the initial segmentation, red color indicates the final adaptive level set segmentation

Figure 10.Segmented regions of Oil spill image for proposed

Table I: Performance table of existing C-V Model

Images	Previous method (CV Model)			
	Computational time	Iterations	PSNR(dB)	
			Index 1	Index 2
Image 1	10.78sec	200	0.869	0.866
Image 2	12.68sec	200	3.246	3.129

Table II: Comparative analysis of proposed method

Images	Proposed Method (SKFCM with adaptive level set)			
	Computational time	Iterations	PSNR(dB)	
			Index 1	Index 2
Image 1	8.06sec	200	4.8469	4.8771
Image 2	9.86sec	200	6.3473	6.4239

VI. CONCLUSION

In this paper, we proposed a novel approach called Spatial KFCM with Level Set Evolution for robust and automatic segmentation of oil spills regions.

This image segmentation model has been successfully implemented on the images of NASA earth observatory Images, which are available open source dataset and results reveal the less computational time, speed and accuracy of convergence by re-initialization free level set method. The sample images of Oil spills under consideration appear as consisting of regions with homogeneous intensities appearing as a blend of dark areas.

The adaptive level set evolution process based on the SKFCM clustering performed and gives the good segmentation results leading to the identification of the regions indicating spillage with great accuracy and profoundness leading over existing active contour model.

REFERENCES

1. A. Kass and D. Terzopoulos, "Snakes: active contour models," *IJCV* , pp. 321–331, 1987.
2. V. Caselles, R. Kimmel, and G. Sapiro, " Geodesic active contours," *Int. J. Comput. Vis.* 22, pp. 61–79,
3. A. Blake and M. Isard, *Active Contours*, Springer, Cambridge, 1998.
4. R. Ronfard "Region Based Strategies for Active Contour Models", International Journal Of Computer Vision, Vol.13, No. 2, pp.229-251 1994
5. X. Bresson, S. Esedo¯glu, P. Vandergheynst, J.-P. Thiran, and S. Osher, "Global Minimizers of The Active Contour/Snake Model, UCLA CAM Report 05-04," 2005.
6. S.Zhu and A.Yuille.'' Region Competition:Unifying Snake, region growing and Bayes/MDL for multiband image segmentation"IEEE Transactions on Pattern Analysis and Machine intelligence,18(9):884-900,sep-1996.
7. D.L.Pham, C.Xu, J.L.Prince ,Current methods in medical image segmentation, Annual Review of BiomedicalEngineering2(2000)315–337.
8. T.F.Chan,L.A.Vese, Active contours without edges, IEEETransactionsonImage Processing 10(2001)266–277.
9. P.Martin, P.Refregier, F.Goudail, F.Guerault, Influence of the noise model on level set active contour segmentation, IEEE Transactions on Pattern Analysis and MachineIntelligence26(2004)799–803.
10. K.S.Chuang,H.L.Hzeng,S.Chen,J.Wu,T.J.Chen,Fuzzy c-means clusteringwith spatial informationforimagesegmentation,ComputerizedMedicalImaging and Graphics30(2006)9–15.
11. W.Cai,S.Chen,D.Zhang,Fastandrobustfuzzy c-means clusteringalgorithms incorporating localinformationforimagesegmentation,PatternRecognition 40 (2007)825–838.
12. P.A.Yushkevich,J.Piven,H.C.Hazlett,R.G.Smith,S.Ho,J.C.Gee,etal.,User- guided 3Dactivecontoursegmentationofanatomicalstructures:significantly improved efficiencyandreliability,NeuroImage31(2006)1116–1128
13. G.D.Giannoglou,Y.S.Chatzizisis,V.Koutkias,I.Kompatsiaris,M.Papadogiorgaki, V.Mezaris,etal.,Anovelactivecontourmodelforfullyautomatedsegmentation of intravascularultrasoundimages :invivovalidationinhumancoronaryarteries, ComputersinBiologyandMedicine37(2007)1292–1302
14. B.N.Li,C.K.Chui,S.H.Ong,S.Chang,IntegratingFCMandlevelsetsforlivertumor segmentation,in:Proceedingsofthe13th InternationalConferenceonBiomedical Engineering,(ICBME2008),IFMBEProceedings23.(2009)202–205.
15. J.S.Suri,K.Liu,S.Singh,S.N.Laxminarayan,X.Zeng,L.Reden,Shaperecovery algorithmsusinglevelsetsin2-D/3-Dmedicalimagery:astate-of-the-artreview, IEEETransactionsonInformationTechnologyinBiomedicine6(2002)8–28.
16. N.Paragios,A levelset approach for shape-driven segmentation and tracking of left ventricle ,IEEETransactionson MedicalImaging22(2003)773–776.
17. K.S.Chuang, H.L.Hzeng, S.Chen,J.Wu, T.J.Chen, Fuzzy c-meansclusteringwithspatial information for image segmentation, Computerized Medical Imaging and Graphics, 30(2006), 9–15.
18. W.Cai,S.Chen,D.Zhang,Fastandrobustfuzzy c-means clusteringalgorithms incorporating localinformationforimagesegmentation,PatternRecognition 40 (2007)825–838.
19. W.K.Lei,B.N.Li,M.C.Dong,M.I.Vai,AFC-ECG:anadaptivefuzzyECG classifier, in: Proceedingsofthe11th World CongressonSoftComputinginIndustrial Applications (WSC11),AdvancesinSoftComputing39.(2007)189–199.
20. Kama Ramudu and Tummala Ranga Babu "Segmentation of Tissues from MRI Bio-medical Images Using Kernel Fuzzy PSO clustering based Level Set approach" Current Medical Imaging Reviews: An International Journal, Vol.14, Issue 3, June 2018, ISSN (print):-1573-4056 & ISSN (online):-1875-6603, pp: 389-400
21. Kama Ramudu and Tummala Ranga Babu "Layers and Dark sand dunes segmentation of MARS satellite Imagery Using Level Set Model" IETE Journal, Vol.56, Issue 2, 2015, (ISSN:- 0974-7338), pp: 59-67

AUTHORS PROFILE

Ramudu Kama, received his Bachelor of Engineering degree in Electronics & Communications from V.R.Sidhartha Engineering College, Vijayawada, AcharyaNagarjuna University, Guntur. He obtained his M.Tech in Digital Communication Engineering from, Kakatiya University, Warangal.Currently he is Assistant Professor in the department of ECE at Kakatiya Institute of Technology and Science, Warangal, Telangana, INDIA. His Research Interest is Biomedical Image Processing and He published 28 International Journals and Conference till date in the field of Image Processing. He is a Member of IETE, and ISTE.

Dr.Ganta Raghotham Reddy received his Bachelor of engineering degree in Electronics & Communications from Gulbarga University; He obtained his M. Tech in Digital Communication Engineering from Maulana Azad National Institute of Technology (MANIT), Bhopal; He obtained his PhD degree from Osmania University, Hyderabad, Telangana, India. Currently he is Professor in the department of Electronics and Communication Engineering, Kakatiya Institute of Technology and Science (KITS), Warangal, A.P. India. His areas of research include Image and Signal processing. Member of IETE, ISTE and IEEE.