ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 6, Issue 8, August 2017

ENTROPY BASED CONSTRAINT METHOD FOR IMAGE SEGMENTATION USING ACTIVE CONTOUR MODEL

M.Nirmala
Department of ECE
JNTUA college of engineering, Anantapuramu
Andhra Pradesh,India

Abstract: Over the past existing image segmentation methods based on the Active Contour Models. These active contour models makes evolution of the contours are very sensible to initializing the contour and inefficient in dealing with the intensity inhomogeneous and noisy images. To overcome these drawbacks we proposed a method called active contour model using entropy based constraint. Entropy based constraint can be defined as relative entropy. This can be provides the global guidance for evolving the contour. This can be help to reach global optima. Existing method RSF having the energy function .That energy function contained the parameter required for the segmentation. In that energy function we have the region scalable fitting model it gives the local region information not giving the global optima for segmentation for that we are using the entropy based constraint along with region scalable fitting it can give global optima for image segmentation. Make the contour robust to initialization ,intensity heterogeneous and noise. This method renders better results than RSF model.

Key words: Active contour model, entropy based constraint, relative entropy, level set method.

I. INTRODUCTION:

The Active Contour models have been mostly used in the areas of image processing and computer vision for the segmentation of the images. And some other applications are remote sensing, medical imaging (ultra sonogram) ,cancer detection. Aim of these models is to contours reach the boundaries object of through minimization of the energy function. Based on the representation of the contours there are two types of contours .parametric active contours and geometric active contour. Parametric active contours (PAC) can used as parameterized curve It is very sensible for the initializing of the contour. And not converges for concavities of the object. Geometric Active Contour (GAC) have lot of advantages than the parametric active contour(PAC).Geometric active contours can be used for different topology rather than specific shapes depend upon our requirement. For desirable GACs Level set function used from the both the views of edges and regions for the segmentation of the images specially for images having difficult structure. Level set method has lot of disadvantages .It can be defined as propagation tool for image segmentation. It can be reinitialized to a SDF(signed distance function) make the stable contour it will take more time .Another one is many of the region based level set methods based on the intensity homogeneity, which leads the misclassification when the regions having large amount of noise and intensity inhomogeneous. However, the region descriptor is difficult to defining for different types of images. Third one is the, the edge based level set functions can handles the noise in a nice manner and the images having intensity inhomogeneous. But it has disadvantaged that when the objects containing week boundaries, they have boundary leakage problem. These problems depend up on the size shape and location of the object. These drawbacks make the limited usage of the level set method.

To overcome the above problems we have suggested a new method called is Active contour model for image segmentation using entropy based constraint method. This method can be defined as the Relative entropy .Relative entropy measuring the difference between the intensity distribution prior of foreground and background and the contour-segmented regions. This entropy based constraint provides a global guidance for the evolution of the contour. Using this method we achieved the global optima. Actually energy function has the region scalable fitting term which provide information of the local region .Along with region scalable fitting we are using the entropy based constraint term to achieve the global optima for segmentation. While minimizing the energy contour reach the object boundary. It has fast convergence than the previous method and robust to noise and the initializing the contour Section 2 of this paper provides introduction of the Active contour model for image segmentation using the entropy based constraint method. Here we have formulation of the energy and energy minimization and section 3 defines the experimental results and comparing the result with the previous method. Section 4 contains the summary of the paper

II. Active contour model for segmentation using the entropy based constraint method:

We are considering the two cases for the segmentation of the image. We are defining Ω Є R^2 be the image domain I: Ω → R be the input gray image. Segmentation of the image achieved by finding out the contour of image.

C: R → Ω contour which separate image domain into two sub regions Ω1=outside(C) defined outside of the contour, Ω2=inside(C) inside of the contour .We are forming the energy while minimizing the energy we achieve the segmented contour region.

i. Formulation of the energy function:

Image energy defined as the features of the image. Total energy of image defined as the sum of the external and the internal energy of the image. Internal energy defined as the controlling of the deformations. External energy defined as the fitting of the contour on image. External energy also contains the constraint forces introduced by user.

$\mathbf{E_{total}=E_{internal}+E_{external}}$

$\mathbf{E_{internal}= vE_{smooth}+\mu E_{regular}}$

v,μ are positive constants parameters.

$\mathbf{E_{regular}}$ this term can be used to avoid discontinues in the level set method and maintaining the regularization of the contour to make contour more stable and accurate. Level set function can be denoted at the **ø.** Level set method provide the flexibility and convenience for the implementation of the contour. To avoid reinitializing the contour we kept level set method as SDF.SDF is a level set function that give the shortest distance of nearest points on interface. Level set function satisfies the property $|\nabla ø| = 1$

$$E_{regular} = \int \frac{1}{2}(|\nabla\phi(x)|-1)^2 dx$$

$\mathbf{E_{smooth}}$ term can be used for the smoothing of the sub regions it can the defined contour length. For the evolution of the contours considering the Heaviside function H to differentiate the inside the contour and outside the contour. That is defined as if H=0 for level set function **ø**<0 and H=1 for the level set function **ø**>0.

H can be defined as the

$$H_\varepsilon(\phi) = \frac{1}{2}[1+\frac{2}{\pi}\arctan(\frac{\phi}{\varepsilon})]$$

$$\delta_\varepsilon(\phi) = H_\varepsilon'(\phi) = \frac{\varepsilon}{\pi(\varepsilon^2+\phi^2)}$$

δ_ε would be the derivative of H_ε , ε be the positive parameter

$\mathbf{E_{external} = E_{data} = E_{RS} + E_{EC}}$

External energy used for the fitting of contour. External energy consists of both the terms region scalable fitting term and entropy based constraint term.

ii. Region scalable fitting model:

This RSF model can be used to getting the information present in the local region

$$E^{RS} = \int \sum_{i=1}^{2} \lambda_i \int_{\Omega_i} K_\sigma(x-y)\,|I(y)-f_i(x)|^2\, dy dx$$

λ_1 , λ_2 positive constant parameters and $f_1(x)$,$f_2(x)$ are two fitting functions of average intensities in, region Ω_1, region Ω_2. We are considering image domain Ω and considering the point x present in the image domain.

Considering the point y surrounding point x .If the point y present near point x intensity of the point is fine .Otherwise if the point y large distance from point x the intensity of point is approaches to zero. For this condition we are multiplying kernel function and adding weight to each intensity function. Considering the nonnegative kernel function $K : \Re^n \rightarrow [0, +\infty)$.

$K(u) \geq K(v)$, if $|u| < |v|$, and $\lim_{u\to\infty} K(u) = 0$. This can be defined as the localization property of kernel function. For the better performance we are considering the Gaussian kernel having scalable parameter σ>0.kernel function defined as K_σ (x-y).

$$K_\sigma(x-y) = \frac{1}{(2\pi)^{n/2}\sigma^n}\exp(-\frac{|x-y|^2}{2\sigma^2})$$

k(x-y)>3σ the Gaussian kernel becoming zero. For that we are considering kernel function .k(x-y)≤3σ.

Size of the regions can be maintained by scale parameter σ. For noisy images large σ can be preferred.

Usage of the kernel function the model become anti – noise and handles intensity heterogeneous. Result of the segmentation depend on the initializing the contour such as size , shape. If the initial point distance from boundary there is shape deviation because of this reason we did not exact segmentation they fall in Local region they didn't come out of from that location. this is the drawback of the region scalable fitting model. To avoid this drawbacks we go for entropy based constraint method.

iii. EC(Entropy based constraint) method:

This method allows global guidance for avoiding the local optima and to achieve global optima for segmentation. This method can be defined as the "difference between the region intensity distribution P which is getting from evolution of the contour and prior intensity distribution Q from both foreground and background". P and Q can be defined as

$$P(\Omega_i) = P(I(x) \mid \mu_i, \sigma_i) \quad \text{i=1,2}$$

$$Q(\Omega_i) = Q(I(x) \mid \mu_i, \sigma_i), \quad \text{(i € o,b)}$$

σ,μ are mean and variance with respect to the foreground and background.

Probability distribution function of P,Q are defined as

$$P(I(x) \mid \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(I(x)-\mu_i)^2}{2\sigma_i^2}\right), \quad x \in \Omega_i$$

$$Q(I(x) \mid \mu_o, \sigma_o) = \frac{1}{\sqrt{2\pi}\sigma_o} \exp\left(-\frac{(I(x)-\mu_o)^2}{2\sigma_o^2}\right), \quad x \in object$$

$$Q(I(x) \mid \mu_b, \sigma_b) = \frac{1}{\sqrt{2\pi}\sigma_b} \exp\left(-\frac{(I(x)-\mu_b)^2}{2\sigma_b^2}\right), \quad x \in background$$

E_{EC} constraint energy is minimum means we are achieving the global optima when $P \approx Q$.

If there is a gap between them we can scale as relative entropy it defined as energy

$$E^{EC} = \sum_{i=1}^{2} \beta_i K_i(P \| Q)$$

$$= \int \sum_{i=1}^{2} \beta_i P(I(x) \mid \mu_i, \sigma_i) \log \frac{P(I(x) \mid \mu_i, \sigma_i)}{Q(I(x) \mid \mu_{0i}, \sigma_{0i})} dx$$

iv. Minimization of the energy function:

We need to minimize the energy function to achieve the boundaries of the object based on the Heaviside function which are denoted in above equations .We are using gradient descent(or) steepest descent method .These method satisfy the euler-lagrange equations

$$\int K_\sigma(\mathbf{x}-\mathbf{y}) M_i^\epsilon(\phi(\mathbf{y}))(I(\mathbf{y}) - f_i(\mathbf{x}))d\mathbf{y} = 0, \quad i = 1,2.$$

M1=Hε, M2=1-Hε

Achieving the global optima means gradient amplitude .Gradient amplitude is the negative derivative of the energy function it can be defined as

$$\frac{\partial\phi}{\partial t} = -\frac{\partial E}{\partial\phi} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) - \delta_\varepsilon(\phi)(\beta_1 g_1 - \beta_2 g_2)$$

$$+\nu\delta_\varepsilon(\phi) div\left(\frac{\nabla\phi}{|\nabla\phi|}\right) + \mu\left(\nabla^2\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right)$$

When we have minimum energy means the contour move towards boundaries of the object.

III. Comparative Result:

Parameters that we are used in ACEC are μ=1, v=0.01*255^2 β_1,= β_2,=0.5 $\lambda_1 = \lambda_2 = 1$. ε=1. $\Delta t = 0.5$, σ=3.

Parameter μ adjusting the length penalty which balancing the fitting of input image more accurately when smaller value .v is taken as less than zero we get the better result.

For the evaluating the precision of the segmentation we are using Jaccard Coefficient (JC), and False positive Rate (FPR). For accuracy of segmentation we have false positive rate values lower than 1. And JC values approximately 1.

Table 1: Result For the ACEC model

False positive rate	accuracy	JC values
0.0114	0.9923	0.984
0.006	0.987	0.97
0.0115	0.990	0.980
0.0268	0.9826	0.965

False Positive Rate can be defined as $E1=(R_2/R_1)/R_2$,False Negative Rate can be defined as $E2=(R_1/R_2)/R_1$. R_1, R2 can be defined as the average pixel intensities in the inside contour and outside of the contour.

True positive rate =1-FPR, True negative rate=1-FNR.

ISSN: 2278 – 909X
International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 6, Issue 8, August 2017

Accuracy = TP+TN/TP+TN+FP+FN

JC=TP/TP+FP+FN. when comparing these values with previous RSF model it gives better performance and improved accuracy of the segmentation. We take different input images.

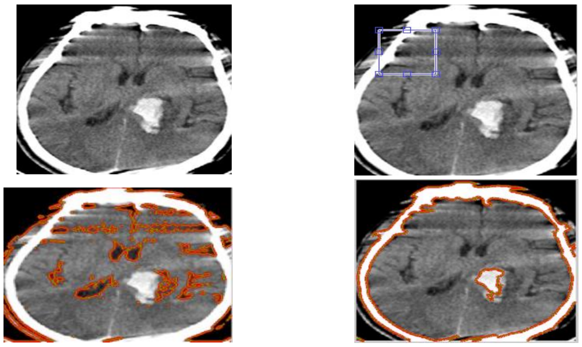

Fig1:segmentation result of image 1: (a) is input image ,(b) is initializing contour. (c) is Result of RSF model. (d) is result of entropy based constraint method

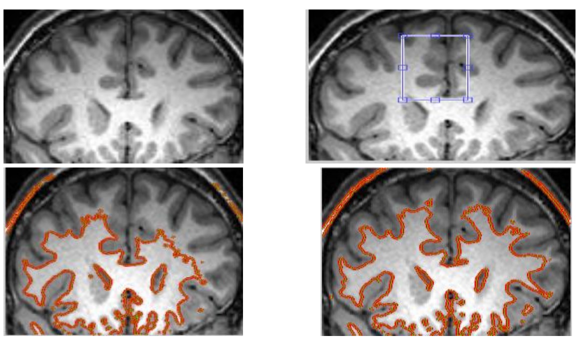

Fig 2: segmentation result of image 2: image (a) is input image (b) is initializing contour , (c) is Result of RSF model. (d) is result of entropy based constraint method

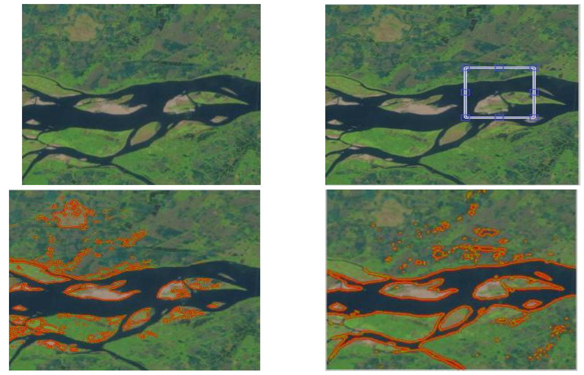

Fig3: segmentation result of image 3: (a) is input image ,(b) is initializing contour. (c) is Result of RSF model.(d) is result of entropy based constraint method

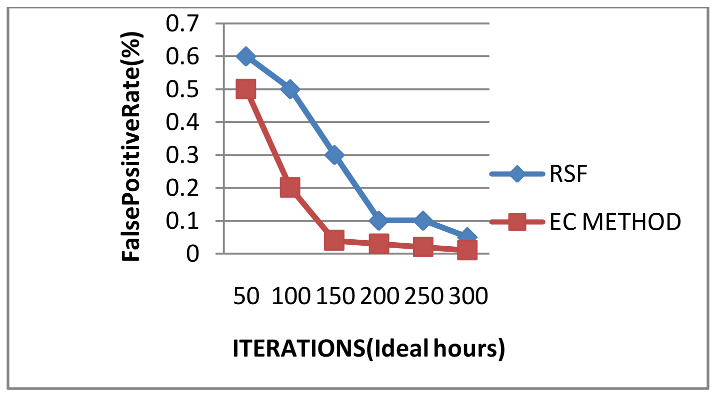

Fig 4: Graph (a) represents the graph between FPR and Iterations for the image1.here FPR values are low for EC method.

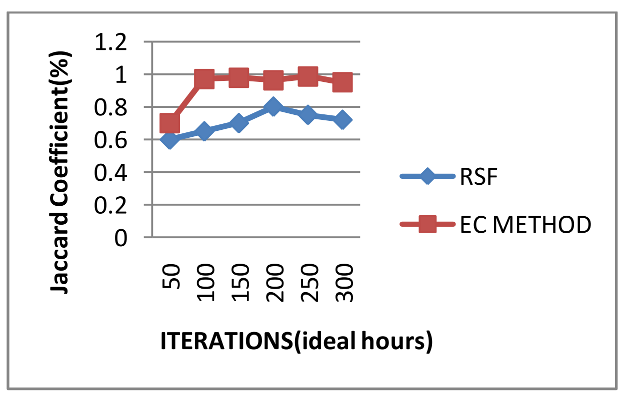

Fig4:graph (b) represents graph between JC and iterations for image 1

Here JC values are approximately 1 for EC method

IV. CONCLUSION:

Conclusion of this paper is EC method (entropy based constraint) give better result than the RSF model. This EC method require less number of iterations as compared to the previous method(RSF).EC method has the capability to handle the intensity inhomogeneous regions and also handle the images contain heavy noise. Robustness to the initialization of the contour. This EC method work faster than the RSF model in this way we are getting the advantages of the EC method for segmentation.

REFERENCES

[1] Yufei Chen , Haiquan Liang, Xiaodong Yue , Qiangqiang. Zhou, "Active contour model with entropy based constraint," IEEE conference publications SAI Computing Conference Pages: 259 - 263, 2016,july

[2] C. Li, R. Huang, Z. Ding, J. C. Gatenby, D. N. Metaxas, J. C. Gore, "A Level Set Method for Image Segmentation in the Presence of Intensity In homogeneities with Application to MRI," IEEE Transactions on Image Processing, vol. 20, pp. 2007-2016, July 2011.

[3] C. Li, C. Xu, C. Gui, M. D. Fox, "Distance Regularized Level Set Evolution and Its Application to Image Segmentation," IEEE Transactions on Image Processing, vol. 19, pp.3243-3254, December 2010

[4] C. Li, C. Y. Kao, J. C. Gore, Z. Ding, "Minimization of Region-ScalableFitting Energy for Image Segmentation," IEEE Transactions on Image Processing, vol. 17, pp. 1940-1949, October 2008

[5] V. Caselles, R. Kimmel, G. Sapiro, "Geodesic Active Contours,"International Journal of Computer Vision, vol. 22, pp.61-79, February 1997.

[6] X. Zhou, X. Huang, J. S. Duncan, W. Yu, "Active Contours with Group Similarity," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2013, pp. 2969-2976

[7] W. Kim, C. Kim, "Active Contours Driven by the Salient Edge Energy Model," IEEE Transactions on Image Processing, vol. 22, pp. 1665-1671, April 2013.

[8] Y. Wang, L. Liu, H. Zhang, Z. Cao, S. Lu, "Image Segmentation Using Active Contours With Normally Biased GVF External Force," IEEE Signal Processing Letters, vol. 17, pp. 875-878, October 2010.

[9] A. Mishra, A. Wong, "KPAC: A Kernel-Based Parametric Active Contour Method for Fast Image Segmentation," IEEE Signal Processing Letters, vol. 17, pp. 312-315, March 2010

[10] R. Ronfard, "Region-based Strategies for Active Contour Models,"International Journal of Computer Vision, vol. 13, pp.229-251, October 1994.

[11] H. Wang, T. Huang, Z. Xu, Y. Wang, "An Active Contour Model and Its Algorithms with Local and Global Gaussian Distribution Fitting Energies," Information Sciences, vol. 263, pp.43-59, April 2014

[12] T. Chan, L. Vese, "Active Contours without Edges," IEEE Transactions on Image Processing, vol. 10, pp. 266-277, February 2001