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Medical Image Segmentation Based on the SVM&K-NN based Edge Stop Function

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Abstract: Edge-based active contour models are successful in segmenting images with intensity in homogeneity but it fail when images are poorly defined boundaries. Such as medical images. The conventional Edge stop function (ESF) use only gradient information it fails to stop gradient magnitude to rectify this problem, we formulate a group of ESFs for edge based active contour models to segment the images with poorly defined boundaries. In our proposed work, which includes gradient information and probability scores from a standard classifier. The distance regularized level set, and k-nearest neighbour's and SVM are used to experimenting the medical images.

Keywords: Index Terms—Edge-based active contour, edge-stop function, gradient information, image segmentation, probability score.

I. INTRODUCTION

For Medical Image analysis, image segmentation plays vital role in computer vision. There is several methods have been used but no one is universally applicable [2]. Energy minimization was important thing in image segmentation, the level set method (LSM) has much attention to segmenting an object [3]. There is two methods are used in image segmentation model it can be classified as edge based model (or) region based model. [4]. In Images, where the intensities change gradually in the vicinity of a poorly defined boundary two edge stop function (ESF) fails to stop the contour. To blown away the traditional ESF in edge based active contour model, we develop a group of ESF that utilize probability scores instead of the predicted class tables from a classifier. Since the scores fall in [0,1], This is similar to fuzzy segmentation [5].

II. CONSTRUCTION OF NEW ESFs

InournewESFscanbeconstructedfromanyclassificationalgorithmandappliedtoanyedge-basedmodelusinganLSM.Herewe can use K-NN, SVM Algorithm

A.Level Set Methods for Image Segmentation

Level set method can be effectively used to solve problems during evolution of curves. The level set function ϕ (x,y,t=0), whose zero level set corresponds to curve with the curve as a boundary the whole surface can be divided into an internal region of the curve. The signed distance function (SDF) on the surface $\phi(x,y,t=0)=d$ ----1

Where the value of d is the shortest distance between two point of x on the surface and the curve. In the whole evolutional process of two curve its points will fit into the following formula.

$$\phi(x,y,t=0)=0 \qquad \text{---2}$$

The common movement formula of level set is

$$\phi_t + F\,|\,\nabla\phi\,|=0 \qquad \text{----3}$$

Where F denotes the speed of evolution and ∇is the gradient operator. The resulting evolution of the level set function is the gradient flow that minimizes the overall energy functional. The energy function

$$E(\phi)=\mu P(\phi)+\varepsilon_{g,\lambda,v(\phi)}=\mu\int_{\Omega}\frac{1}{2}(|\nabla\phi|-1)^{2}\,dxdy+\lambda\int_{\Omega}g\delta(\phi)|\nabla\phi|dxdy+v\int_{\Omega}gH(\phi)dxdy \qquad \text{---- 4}$$

Where ▯> 0 is a parameter controlling the effect of penalizing the deviation of ϕ from a signed distancefunction, and g is the edge indicator function defined by

$$g=\frac{1}{1+|\nabla G_{\sigma}*I|^{2}}$$

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Where *I* is an image, and G is the Gaussian kernel with standard deviationσ .

B. Probability Scores from Classification Algorithms:

(i) ***K-NN***: In the fuzzy K -NN, the final classification is not strictly assigned to a certainclass only. Let $X_R = \{x_i\}_{i=1}^{m_R}$beareference set and$W = \{w_i\}_{i=1}^{m_R}, w_i = (w_{i,1}, w_{i,2}, \dots \dots w_{i,l})$be a set of l dimensional vectors where l is the number of classes. For $1 \leq i \leq l\ m_R$ and $1 \leq j \leq l$, the value of w_i, j is a membership value of g i-th object to class j . For a particular xto be classified, theset k of indices corresponding to the classes of the K-nearest neighbours of x inX_R is obtained. Instead of majority votingas in the original *K*-NN, rule generates the fuzzy decision-vector. [8]

$$g = \frac{1}{k}\sum_{s \epsilon K} w_s$$

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(ii) ***Support Vector Machine***: This Classification is performed using a sign function class (x) = sgn h(x) where h (x) is the separating hyperplane for the two classes. For linearly separable data in dimension d, the hyperplane is expressed by

$$h(x) = w_o^T x + b_0$$

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Where $w_0 \in R^d$ is the optimal weight vector, $X \in R^d$ is the data and b_0 the optimal bias. A mapping of the data into a higher dimensional space through function φ (x) is introduced. Finding an explicit φ is often difficult, instead we use kernel $K(x, x_i)$ is used to compute directly the dot product which is expressed by

$$h(x) = \sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b_0$$

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whereα_i is the estimated SVM parameter, and $y_i \in \{+1, -1\}$is the desired class for the corresponding . The value of h(x) is , the SVM evaluation score and the sign is the predicted class. Evaluation scores from classifiers generally fall in the range [0,1] or ($-\infty$ $+\infty$). [9]

C. Fuzzy Edge – Stop Function

The conventional ESFs in (4) have a drawback when applied to an image containing an object with poorly defined boundaries. The contour may fail to stop at the desired boundary because of the gradual change in gradient. The binary classification of an image into background (class 0) and foreground (class 1) can be solved using a classifier. Probability scores which lie in the range of [0,1] can be obtained by applying a classification algorithm to all the pixels. In the vicinity of the object boundary, the scores change from 1 to 0 (or vice versa) through a smooth transition. We use the fuzzy ESF $\rho(s) : [0, 1] \rightarrow [0,1]$

$$\rho(s) = (2(s - 0.5))^2$$

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where s is the probability score for the foreground. The plot of p(s) , shown in Fig. 1(a), has its global minimum at s= 0.5 and can be utilized to identify the object boundary.

It is worth noting the properties of ρinequ (9): the domain as well as the range lie in [0,1], $\lim_{s \to 1} \rho(s) = 1$; it is monotonically decreasing in [0,0.5] and monotonically increasing in [0.5,1]. Any other functions having similar characteristics also can be employed asρ (s) , e.g.,

$$\rho(s) = (\cos \pi s)^p,\ 0 \leq s \leq 1,\ p = 2, 4, 6 \ \dots.$$

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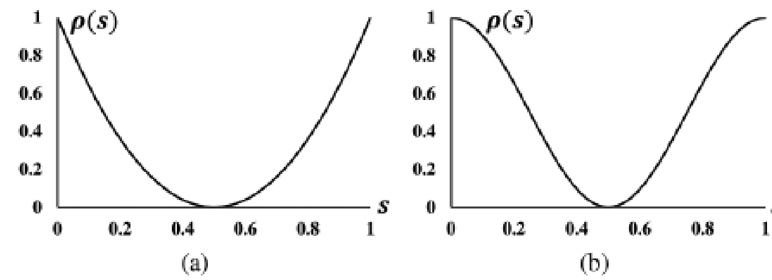


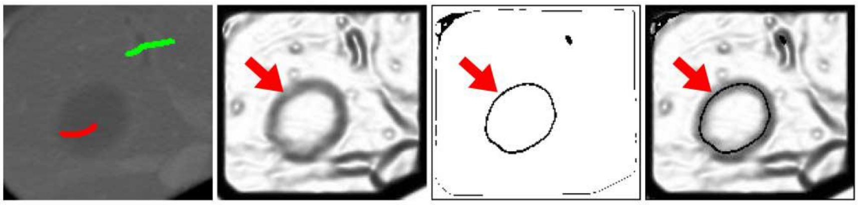
Fig.1: Function ρ based on (a) Eq. (10). minimum at s=0.5

Fig. 1(b) shows function ρ for p =2

Subsequently, the fuzzy ESF is used to regularize function g in (4) to obtain g_{new}which can be simply expressed by

$$g_{new} = g\rho \qquad \text{-----11}$$

A smoothing step, e.g., applying the Gaussian kernel, may be required for highly noisy images to prevent the contour from stopping prematurely. The fuzzy ESF, ρ , will forceg_{new} to be close to 0 when $\rho$is very close to zero even though g is much higher than 0, So the image intensity drops gradually. Consequently,g_{new} will be close to 0 which will stop a contour at the desired boundary.



(a) (b) (c) (d)

Fig 2: Liver tumor image with(a) user initializations and the map of (b) g, (c),ρ and (d) g_{new}. The tumor boundary is indicated by the arrow.

III. RESULT AND DISCUSSIONS

A. Experimental Setup

To assess the effectiveness of the proposed work, many medical images includes objects with poorly defined boundaries are tested. The images come from different patients. The medical images are computed tomography (CT) scans of liver tumor (3 images).The resolution for CT, images are 512 x 512. We implement the proposed ESFs in Matlab and utilize the DRLSE implementation in the form of an edge-basedactive contour model with parameter values from [7]. The default parameter values are$\mu = 0.04$, $\varphi = 1.5$,$=1.5$, and $\sigma = 2.5$. The value of λ is set to 3 for the liver tumor and 5 for the brain tumor. The numberof neighbor's, k , in the fuzzy k-NN algorithm is set to a large value to allow fuzziness in the vicinity of the boundaries.We use k = 99 for all the experiments to cover exactly one hundred different membership values and generate smooth transitions between the background and foreground. The kernel function in the SVM is linear with scale parameter =1. For comparison purposes, two common quantitative measurements are used, the Jaccard index (JI) and the Dice coefficient which is also known as the similarity index (SI). Letting Aand B be the segmentation result and the ground truth, respectively,JI is calculated by (A ∪ B) / (A ∪ B) and SI is by (2 ❘A∩ B❘) / (❘A❘ + ❘B❘).

B. Maps of g

Maps of g can be used to visualize how our proposed ESFs work. A sample of a CT liver tumor image is used (Fig. 2(a)). The traditional $\varphi - 1$ map, which utilizes only gradient information,is generated based on (4) and shown in Fig. 2(b). At the same time, applying a classification algorithm, e.g., the SVM, to the image will produce the evaluation score of each pixel. Subsequently, the evaluation score is converted to a probability score. The fuzzy ESF (ρ) from (9) is applied to the probability score and the resulting map is shown in Fig. 2(c). Pixels with a high likelihood to be background or foreground have higher p values and look brighter. Finally, the g_{new} map (Fig. 2(d)) based on (11) is used as the ESF of the edge-based active contour model.

Proposed Method (K-NN) **Proposed Method (SVM)**

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Chan –Vese's Method **Li et al's Method**

Fig:3 Segmentation results for the liver tumor using the general settings for each modality.

C. Segmentation Results

The proposed method converges faster compared to Li *et al.*'s method and gives moreaccurate segmentations. It is well known that region-based activecontour models and C-V's method do not perform wellwith inhomogeneous images.

It is clear that function *p* plays an important role when a poorly defined boundary is present. It generates a minimum value when the scores are at the decision boundary. Further more, retaining the gradient information is beneficial at clear boundaries since there are no fuzzy values. Function g_{new} incorporates both of these advantages to give accurate segmentation results. An edge based active contour model is generally sensitive to initialization. In addition, a probability score is sensitive to training data.

TABLE I COMPARISON OF SEGMENTATION ACCURACY

Expt.	**Method**				**C-V's Method**		**Li et al.'s Method**	
	k-NN		**SVM**					
	JI	SI	JI	SI	JI	SI	JI	SI
1	0.92	0.95	0.93	0.96	0.90	0.91	0.36	0.47

IV. CONCLUSION

We have proposed a framework to construct a group of robust ESFs for edge-based active contour models which can be used to detect poorly defined boundaries. The framework utilizes edge-based information from image gradient values aswell as probability scores from a classifier. Our framework is sufficiently flexible to be applicable to other edge-based active contour models that use ESFs and can be constructed from any classifier. Experiments on medical images using the DRLSE in the form of an edge-based active contour model as well as the *K*-NNand the SVM confirm the effectiveness of our framework.

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