A Survey of Image Segmentation Based On Multi Region Level Set Method

Suraj.R[1], Sudhakar.K[2]

[1]*P.G Student, Computer Science and Engineering, Hindusthan College Of Engineering and Technology, Tamilnadu, India*

[2]*Assistant Professor, Computer Science and Engineering, Hindusthan College Of Engineering and Technology, Tamilnadu, India*

***Abstract*−Image segmentation has a long tradition as one of the fundamental problems in computer vision. Level Sets are an important category of modern image segmentation techniques are based on partial differential equations (PDE), i.e. progressive evaluation of the differences among neighboring pixels to find object boundaries. Earlier method used novel level set method (LSM) for image segmentation. This method used edges and region information for segmentation of objects with weak boundaries. This method designed a nonlinear adaptive velocity and a probability-weighted stopping force by using Bayesian rule. However the difficulty of image segmentation methods based on the popular level set framework to handle an arbitrary number of regions. To address this problem the present work proposes Multi Region Level Set Segmentation which handles an arbitrary number of regions. This can be explored with addition of shape prior's considerations. In addition apriori information of these can be incorporated by using Bayesian scheme. While segmenting both known and unknown objects, it allows the evolution of enormous invariant shape priors. The image structures are considered as separate regions, when they are unknown. Then region splitting is used to obtain the number of regions and the initialization of the required level set functions. In the next step, the energy requirement of level set functions is robustly minimized and similar regions are merged in a last step. Experimental result achieves better result when compare with existing system.**

***Keywords* − Active contour, Bayesian criterion, finite difference, image Segmentation, level set, and partial differential equation.**

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments called as set of pixels, which are also known as super pixels. The typical use of image segmentation is to locate objects and boundaries (lines, curves, etc.) in images. Image segmentation assigns a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image. Pixels of a region are similar with respect to some characteristic, such as color, intensity, texture, etc. Adjacent regions differ significantly with respect to the same characteristics. In the case of medical imaging, the set of contours produced after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

If an image has been pre processed appropriately to remove noise and artifacts, segmentation is often the solution for understanding the image. The Image segmentation group the regions according to similar characteristics or features shared among them.

Image segmentation may use any technique, such as, statistical classification, edge detection, segmentation based on PDE, thresholding, region detection, clustering or any combination of these techniques. Most of the segmentation techniques are either region-based or edge-based.

> *Region-based*: Region-based techniques rely on common patterns in intensity values within a group/cluster of neighboring pixels. The group/cluster is referred to as the region, and the main objective of the segmentation algorithm is to group regions according to their anatomical or functional roles.
>
> *Edge-based:* Edge-based techniques rely on discontinuities in image values between distinct regions, and the main aim of the segmentation algorithm is to accurately demarcate the boundary separating these regions.

Segmentation has two objectives. The first objective is to decompose the image into parts for further analysis. In simple cases, the environment might be well enough controlled so that the segmentation process reliably extracts only the parts that need to be analyzed further. For example, an algorithm was presented for segmenting a human face from a color video image. The segmentation is reliable, provided that the person's clothing or room background does not have the same color components as a human face. In complex cases, such as extracting a complete road network from a greyscale aerial image, the segmentation problem can be very difficult and might require application of a great deal of domain building knowledge.

The second objective of segmentation is to perform a change of representation. In an image, the pixels must be organized into higher-level units that are either more meaningful or more efficient for further analysis (or both). A critical issue is whether or not segmentation can be performed for many different domains using general bottom-up methods that do not use any special domain knowledge. The segmentation methods have potential use in many different domains. The prospects of having a single segmentation system work well for all problems appear to be dim. Experience has shown that an implementer of machine vision applications must be able to choose from a toolset of methods and perhaps tailor a solution using knowledge of the application.

II. LITERATUR SURVEY

Several general-purpose algorithm and techniques have been developed for image segmentation. These techniques must be combined with a domain's specific knowledge in order to effectively solve the domain's segmentation problems.

Using a partial differential equation (PDE)-based method and solving the PDE equation by a numerical scheme, the image can be segmented. Curve propagation is a popular technique in the PDE based method, with great number of applications to object extraction, object tracking, stereo reconstruction, etc. The core idea is to gradually develop an initial curve towards the lowest potential of a cost function, and its definition must reflect the task to be addressed. The minimization of the cost functional is very important as for most inverse problem and it introduces certain smoothness constraints on the results, which can be expressed as geometrical constraints on the evolving curve.

In this paper [8], we propose an energy functional which is a modified version of the Chan–Vese model [1], and which has a stationary global minimum that results in a bimodal segmentation of the image based on the colors. In [1], Chan and Vese have proposed a model that implements the Mumford–Shah functional [6] via the level set function for the purpose of bimodal segmentation. The segmentation is performed by an active contour model which uses the information inside regions rather than the gradients on the boundaries. Through a level set function φ the segmented regions are represented.

In this paper, we propose a new level set-based partial differential equation (PDE) for the purpose of bimodal segmentation. This equation is derived from an energy functional which is a modified version of the fitting term of the Chan–Vese model. The energy functional is designed to obtain a stationary global minimum, i.e., the level set function which evolves by the Euler–Lagrange equation of the energy functional has a unique convergence state. The existence of a global minimum makes the algorithm invariant to the initialization of the level set function, whereas the existence of a convergence state makes it possible to set a termination criterion on the algorithm. Chan and Vese have proposed a model that implements the Mumford–Shah functional via the level set function for the purpose of bimodal segmentation. The segmentation is performed by an active contour model which uses the information inside regions rather than the gradients on the boundaries.

The minimizer of the energy sometimes becomes a local minimizer. For example, the inside region of an object cannot be detected, if the initial contour is initialized to enclose the object. However, when the zero level set settles on the outer boundary of the object, there is no sign change in the next time step, and the algorithm stops running, leaving the inside regions non detected. This is due to the fact that there is no decrease in the energy in the next time step. For this reason, Chan and Vese choose a non-compactly supported smooth strictly monotone approximation of the Heaviside function, so that inside regions can be detected. However, with the approximation of the Heaviside function, the energy functional has no minimizer φ at all. Even after the zero level contour stops moving, the value of φ(r) (on both sides of the zero level contour) keeps moving to ∞ or $-\infty$. Due to the continual increase in the magnitude of the value of φ(r), it becomes difficult to set a termination criterion on the algorithm.

In the first part of this paper [13], we present a curve evolution approach to minimizing the original Mumford–Shah functional, thereby obtaining an algorithm for simultaneous image smoothing and segmentation. In contrast to anisotropic diffusion algorithms, however, the smoothing is linear, with edge preservation based upon a global segmentation as opposed to local measurements based upon the gradient. The development of this model is based upon both estimation-theoretic and geometric considerations. However, each gradient step involves solving an optimal estimation problem to determine piecewise smooth approximations of the image data inside and outside the active contour. We obtain these estimates by solving a linear partial differential equation (PDE) for which the solution inside the active contour is decoupled from the solution outside the active contour. This PDE, which takes the form of a Poisson equation, and the associated boundary conditions come directly from the variational problem of minimizing the Mumford–Shah functional assuming the set of discontinuities (given by our active contour) to be fixed. In the second part of this paper, we generalize the data fidelity term by substituting a spatially varying penalty for the traditional constant one. This “missing data” problem arises regularly in archived or high speed motion picture films, damaged paintings, and remote sensing and medical images with data dropouts due to speckle and sensor data gaps. By applying this missing data technique in a structured manner, we then develop a novel approach for simultaneous image magnification, segmentation, and smoothing, thereby providing a new application of the Mumford–Shah functional. This technique constitutes a more global approach to interpolating magnified data than traditional bilinear or bi cubic interpolation schemes, while still maintaining sharp transitions along region boundaries. Furthermore, the curve length penalty in our Mumford–Shah based flow tends to prevent the blocky appearance of object boundaries which is a symptom of replication-based schemes.

One key factor in diffusion tensor imaging (DTI) analysis [16] is a proper choice of diffusion tensor distance that measures the similarity or dissimilarity between the tensors and is particularly important in the aforementioned tasks. In the following, we will present a brief overview of different tensor distance measures used in DTI analysis and various techniques currently in vogue in using tensor-based information for segmenting DTI. In general, any kind of matrix norm can be used to measure the distance between two 2-tensors. The stopping criterion in this case is chosen as a decreasing function of the trace of the sum of the structure tensors formed from individual elements of the given tensor in the tensor field. This amounts to taking the Frobenius norm of the tensors in the tensor field formed by the gradient magnitude of the individual channels/components of the given tensor. This scheme is a gradient based active contour (snake) whose performance is lacking in absence of significant gradient in the data. Moreover, the norm used here is not invariant to affine transformations of the input coordinates on which the original tensor field is defined. Affine invariance is a desirable property for the segmentation scheme when dealing with data sets obtained from different hardware.

The paper [17], provides a new unified tensor level set method for image segmentation, which is region-based. This model provides a new tensor, which is the order of three that can extract the features of pixels like the local geometrical features, such as orientation and gradient, and average gray scale value. The region-based level set method is represented from scalar to tensor by defining a weighted distance. Level set methods used in [2] [3] (Early region-based) just use a scalar to represent a pixel, which is a basic unit in an image. Then, methods [14],[18],[15],[16] uses a symmetrical matrix, and the LST is used to represent the basic unit of an image (a pixel) when this method is applied on texture images, but this method does not consider the gray scale values of pixels which is considered as an important feature. None of the above methods provide a comprehensive representation of images. To build a unified tensor representation of a pixel Gabor features are introduced. The representation of pixels using tensor method provides more information such as average gray value, gradient, and orientation of pixels and is relatively overall. When building this method, the unified tensor representation consists of three steps.

1) To build a robust model and to make it withstand against noise, Gaussian filter bank is used to smooth the initial image, and then, from the smoothed image the gray scale value of pixels are represented in the form of matrix.
2) The gray scale value of pixels extracted from the image to be segmented is embedded in to the unified tensor representation.
3) The Gabor features are used to represent the gradient and orientation of images.

By assumption, consider the field T is composed of two homogenous regions and further assume that the object that needs to be detected from the field is with the similar value. The function of energy is defined as,

$$E(C) = Eg + Ee.$$

Ee is known as a fitting error, Eg is known as the length of the curve. The energy is decreased and the fitting term is minimized together to obtain the segmentation result. This process is represented as a formula,

$$Inf_c \{E(C)\}.$$

The paper [17] presents a new image segmentation method that applies an edge-based level set method in a relay fashion. It segments an image in a series of nested sub regions that are automatically created by shrinking the stabilized curves in their previous sub regions. The final result is obtained by combining all boundaries detected in these sub regions. Although the relay mode was also used in [13], our method employs an edge-based method [9] in relays instead of the region-based method. To make this method automatically execute, a curve-shrinking procedure and an automatic curve initialization are designed. The sub regions are created according to the boundaries detected in the previous sub region, and this way ensures a full segmentation for images. This method evolves a level set function until it stabilizes and then continuously evolves it after executing a tiny shifting. This “evolving-to-stable” procedure is repeated until the area inside the curve equals zero. The proposed method applies an edge-based level set method [7] in a relay fashion on a series of nested sub regions to obtain a full segmentation. Each sub region is automatically created and included in to the previous sub region. The zero level curves are namely the boundaries detected in the associated sub region. Having boundaries in all sub regions, we obtain synthetic boundaries of the given image.

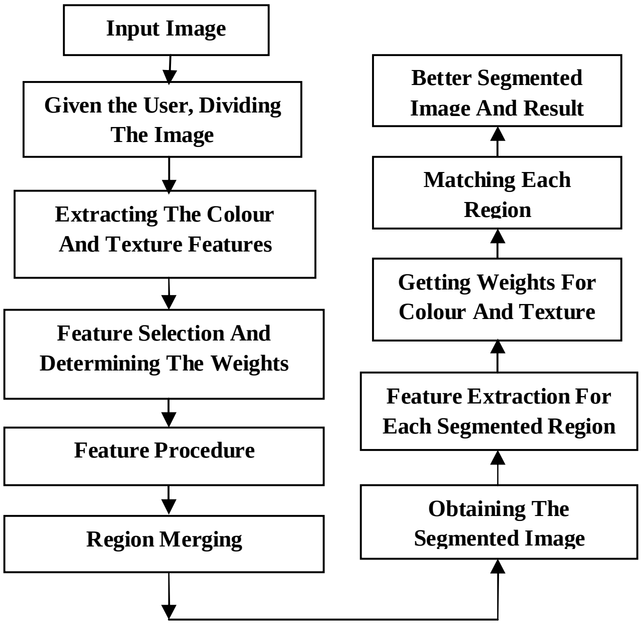

Fig: Architecture Diagram

III. PROPOSED METHODOLOGY

The PDE is a kind of Hamilton–Jacobi equation, and it is usually obtained by applying Euler–Lagrange equation to the pre-defined energy functional. Differing in the representation of evolving curves, popular ACMs can be divided into two categories, i.e., explicit models and implicit models. Explicit models define the evolving curve by parametric equations, and implicit models define it by a Lipchitz continuous function on the image domain [10],[11]. This function enables ACMs to handle the topological changing of curves.

The proposed method has following advantages: 1) compared with the LSMs [4], [5], [12], an adaptive direction function is designed to automatically determine the direction of curve evolution, and it makes the method more insensitive to curve's initial position; 2) this function provides a nonlinear evolution speed to avoid the occurrence of boundary leakage at weak boundaries; and 3) a probability-weighted stopping force is designed to provide the capability of suppressing the influence of false boundaries, i.e., the edges far from objects. By combining these functions with a penalty term from [14], we proposed a novel nonlinear adaptive LSM for image segmentation. To overcome the aforementioned drawbacks, we propose a novel LSM for image segmentation by designing a nonlinear adaptive velocity and a probability-weighted stopping force. It consist of the modules,

1. Adaptive Direction Function
2. Probability-Weighted Stopping Function
3. Nonlinear Adaptive LSM
4. Performance evaluation.

IV. CONCLUSION

Image segmentation has a promising future as the universal segmentation algorithm and has become the focus of contemporary research. This method utilizes global statistical features to automatically determine the direction of curve evolution; utilizes a sigmoid function to provide a nonlinear speed that accelerates the convergence and avoids boundary leakage; and finally weights the stopping function with the probability to improve the segmentation performance on false boundaries and noisy images.

REFERENCES

[1] T. F. Chan and L. A. Vese, "Active contours Without edges", *IEEE Trans. Image Process.*, vol. 10, no. 2, pp. 266–277, Feb. 2001

[2] B. Wang, X. Gao, D. Tao, and X. Li, "A unified tensor level set for image segmentation," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 40, no. 1, pp. 857–867, Feb. 2010.

[3] T. F. Chan, B. Y. Sandberg, and L. A. Vese, "Active contours without edges for vector-valued images," *J. Vis. Commun. Image Represent.*, vol. 11, no. 2, pp. 130–141, Jun. 2000.

[4] M. Rousson, T. Brox, and R. Deriche, "Active unsupervised texture segmentation on a diffusion based feature space," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2003, pp. 699–704

.

[5] Y. Chen, D. Tseng, "Medical image segmentation based on Bayesian level set method," in *Proc. Med. Imag. Info.*, 2007, pp. 25-34.

[6] D. Mumford and J. Shah, "Optimal approximations by piecewise smooth functions and associated variational problems," *Commun.Pure Appl. Math.*, vol. 42, no. 5, pp. 577– 685, May 1989.

[7] C. Li, C. Xu, C. Gui, and M. D. Fox, "Level set evolution without re-initialization: A new variational formulation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recog.*, San Diego, CA, Jun. 2005, pp. 430–436.

[8] S. Lee and J. Seo, "Level set-based Bi modal segmentation with stationary global minimum," *IEEE Trans. Image Process.*, vol. 15, no. 9, pp. 2843–2852, Sep. 2006.

[9] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int. J. Comput. Vis.*, vol. 1, no. 4, pp. 321–331, Jan. 1988.

[10] S. Osher and J. A. Sethian, "Fronts propagating with curvature dependent speed: Algorithms based on Hamilton–Jacobi formulation," *J. Comput. Phys.*, vol. 79, no. 1, pp. 12–49, Nov.

1988.

[11] S. Osher and R. Fedkiw, *Level Set Methods and Dynamics Implicit Surfaces*, New York, NY, USA: Springer-Verlag, 2003, chs. 3, 4.

[12] N. Paragios and R. Deriche, "Geodesic active regions and level set methods for supervised texture segmentation," *Int. J. Comput. Vis.*, vol. 46, no. 3, pp. 223–247, Feb. 2002.

[13] A. Tsai, A. Yezze, Jr., and A. S. Willsky, "Curve evolution implementation of the Mumford–Shah functional for image segmentation, denoising, interpretation, and magnification," *IEEE Trans. Image Process.*, vol. 10, no. 8, pp. 1169–1186, Aug. 2001.

[14] D. Tschumperle and R. Deriche, "Diffusion PDEs on vector-valued images," *IEEE Signal Process. Mag.*, vol. 19, no. 5, pp. 16–25, Nov. 2002.

[15] Z.Wang and B. C. Vemuri, "Tensor field segmentation using region based active contour model," in *Proc. Eur. Conf. Comput. Vis.*, 2004, vol. 3024, pp. 304–315.

[16] Z. Wang and B. C. Vemuri, "DTI segmentation using an information theoretic tensor dissimilarity measure," *IEEE Trans. Med. Imaging*, vol. 24, no. 10, pp. 1267–1277, Oct. 2005.

[17] B. Wang, X. Gao, D. Tao, and X. Li, "A unified tensor level set for image segmentation," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol.40, no. 1, pp. 857–867, Feb. 2010.

[18] X. Gao, B. Wang, D. Tao, and X. Li, "A relay level set method for automatic image segmentation," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 41, no. 2, pp. 518–525, Apr. 2011.