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Fast Evolution of Curve Based On Chan-Vese Model for Specific Images

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Abstract--*In image processing, segmentation is an important intermediate step for object recognition. It is a fundamental task in image analysis responsible for partitioning an image into multiple sub-regions based on a desired feature. One such technique is through Curve Evolution and one of the applications of Geometric Curve Evolution is Active Contours.*

In the research work being reported in this paper an attempt has been made to enhance Chan-Vese [1] Algorithm faster by taking different planes (red, green and blue) of an image. The plane in which the contour evolves fastest gets automatically selected and rest of the algorithm will work on that particular plane. Experimental results are presented on various domains like biomedical images, artificial images and painted images. Also, the contour evolves differently in different planes.

Key Terms- *active contour, objects, object recognition, segmentation, standard deviation*

I. INTRODUCTION

Segmentation is an intermediate step in all high level object-recognition tasks. For example, if we want to locate the face of a particular person in an image of a crowd, we should first determine that which parts of the image correspond to human faces. Active Contours have been widely used as attractive image segmentation methods because they always produce sub-regions with continuous boundaries. For instance, starting with a curve around the object to be detected, the curve moves toward its interior normal and has to stop on the boundary of the object. An object in image processing is an identifiable portion of an image that can be interpreted as single unit.

The active contour model is more and more used in image segmentation because it relies on solid mathematical properties and its numerical implementation uses the level set method to track evolving contours. The motion of the curve is driven by the image itself. The driving force is obtained by defining a potential in the image that shall be small near objects contours.

If β is a grey level image, the external potential is defined at each point of the image and is of the type

$$\mathbf{g(x)} = \frac{\mathbf{1}}{\mathbf{(1+|DG\sigma*\beta|2)}}$$

where G is a gaussian with standard deviation s. The term appearing in the denominator is the gradient of a regularized version of the image (* denotes convolution.)

Active contours can be classified as parametric active contours and geometric active contours according to their representation and implementation. Geometric active contours were in use now a days, which provide solution to tackle the problem of topological changes required in curve evolution. In [5] a precise relationship between the geometric and parametric active contours has been developed which includes spatially-varying coefficients, both tension and rigidity, and non-conservative external forces. Geometric deformable models implemented using level set methods have advantages over parametric models due to their intrinsic behavior, parameterization independence, and ease of implementation.

Active contour models are also used for 2D and 3D biomedical images formulated using the level set method [6].These models can also be generalized to segmentation of images with more than two segments.

Snakes are also active contour models [7]-they lock onto nearby edges, localizing them accurately. Snakes were used extensively in image processing applications, particularly to locate object boundaries. An improved region-based active contour/surface model for 2D/3D brain MR image segmentation is introduced in [8].The model combines the advantages of both local and global intensity information, which enable the model to cope with intensity in homogeneity.

In [9] a graph cut based active contour without edges segmentation model has been discussed to track pedestrian in thermal images. The deformable model is based on the Mumford- Shah piecewise constant energy formulation.

An algorithm for automated segmentation of white matter in brain MRI images was proposed [11] which can be used to create connected representations of the gray matter in the cerebral cortex of the brain. Automating the postmortem identification of deceased individuals based on dental characteristics is receiving increased attention especially with the large number of victims encountered in mass disasters.

In [10] a novel formulation framework of the minimal surface problem, called Active Geometric Functions (AGF), is proposed to reach truly real-time performance in segmenting 4D ultrasound data.

II. THE MODEL

The original idea of active contours was given by Kass, Witkin and Terzopoulos. We have chosen a model for active contours to detect objects in a given image, based on techniques of curve evolution, Mumford–Shah functional [3] for segmentation and level sets [2].

Chan-Vese approach involves geometric active contour model (based upon Mumford – Shah Functional). The model begins with a contour in the image plane defining an initial segmentation and then contour is evolved according to evolution equation. The basis of Chan-Vese algorithm is a Fitting Energy Functional [1]. The goal of algorithm is to minimize this fitting energy for a given image and corresponding will define segmentation.

In general form it is written as follows:

$$F(\phi) = \mu\left(\int_\Omega |\nabla H(\phi)| dx\right)^p + \upsilon\int_\Omega H(\phi)dx$$

$$+\lambda 1\int_\Omega |I- C1|^2 H(\phi)dx$$

$$+\lambda 2\int_\Omega |I-C2|^2(1-H(\phi))dx$$

μ, υ, λ_1, λ_2 and p are parameters selected to fit a particular class of images.
Here,
H=Heavy side function
I is the image to be segmented
Ω =domain of that image
C1 and C2 are averages of the image I in the regions where $\phi>=0$ and $\phi<0$ respectively.

In the above equation the first term can be thought as a penalty on the total length of the edge contour for a given segmentation. The second term is a penalty on the total area of the foreground region found by the segmentation. The third term is proportional to the variance of the image gray level in the in the foreground region. The fourth term does the same for background region. Usually, we take $\lambda_1=\lambda_2=1$ but if we set $\lambda_1=2$, $\lambda_2=1$ then our final segmentation will have a more uniform foreground region at the expense of loss of uniformity in background.

The contour ultimately segments the image into foreground and background. Chan- Vese [1] algorithm evolves this contour via a level set method. The function (I,i,j) (the level set function where (i,j) are co-ordinates in the image and t is time). The segmentation is given by two regions$\{\Phi>0\}$ and $\{\Phi<0\}$. Some PDE (Partial Differential Equation) is used to evolve level set function.

III. RESULT AND ANALYSIS

In the research work being reported in this paper, four planes red, green, gray and blue have been taken and standard deviation corresponding to each plane is calculated by keeping the number of iterations and size of each image fixed. It is found that the contour evolves faster in the plane having highest value of standard deviation. This is because the energy in different planes attracts the contour differently. The position of the initial curve can be anywhere in the plane, and it does not necessarily surround the objects to be detected.

It is shown that the images (fig 3 & fig 4) in which the red, blue and green components are present almost equally are having almost same values for standard deviation. In case of painted images (fig.1) the red plane is having highest value of standard deviation. The contour is evolving fast covering objects minutely as compare to blue and green planes.
The astronomical image (fig.2) is having more blue component and a little amount of red component. Hence, contour is evolving faster in blue plane covering large number of objects as compare to other planes. Also the standard deviation of blue plane is larger than red and green planes.

Actual Size of all images in the following figures is same i.e 512 x 512 pixels

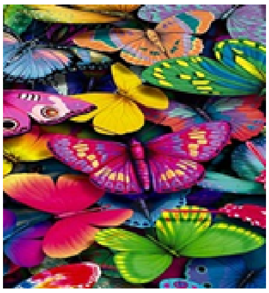

Fig1: Painted Image- order of evolution of contour is R>G>Gr>B.

Fig:1(a) Red Plane

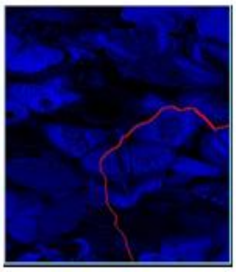

Fig:1(b) Blue Plane

Fig:1(c) Green Plane

Fig:1(d) Gray Plane

Fig 3: Synthetic Image- Evolution of curve is equal in all planes i.e B=G=R=Gr.

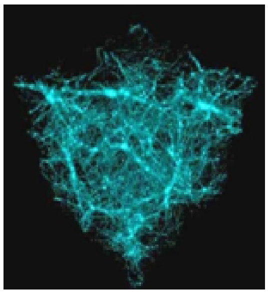

Fig2: Astronomical Image- order of evolution of contour is B>G>Gr>R.

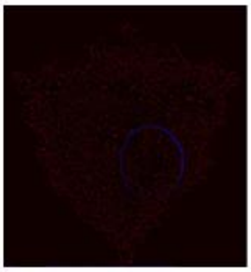

Fig:2(a)Red Plane

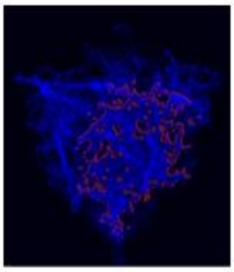

Fig:2(b)Blue Plane

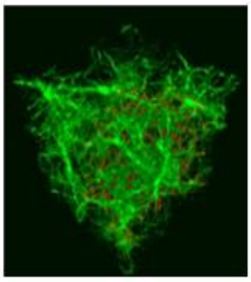

Fig:2(c)Green Plane

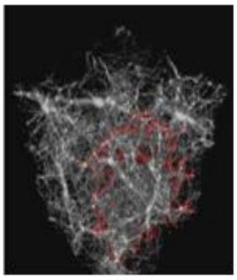

Fig:2(d)Gray Plane

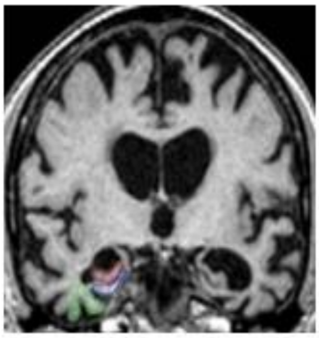

Fig 4: Biomedical Image-Evolution of curve is almost same in all the respective planes


Fig3(a):Red Plane Fig3(b):Blue Plane


Fig3(c):Green Plane Fig3(d):Gray Plane

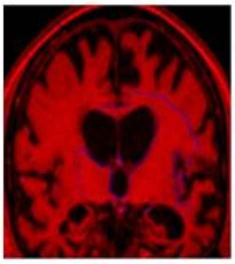
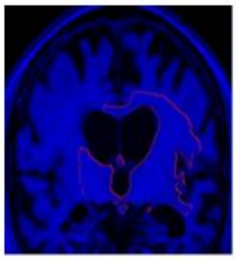

Fig4(a):Red Plane Fig4(b):Blue Plane

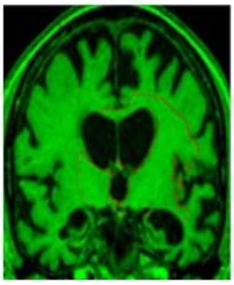
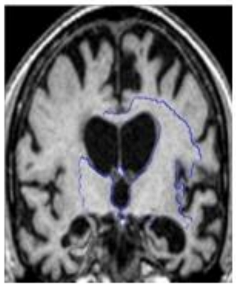

Fig 4(c):Green Plane Fig:4(d)Gray Plane

Table I: **Standard Deviation vs. Contour Evolution in Different Planes**

S.N0.	**Type of image**	**Order of evolution**	**Standard Deviation**			
			Blue (B)	**Green (G)**	**Red (R)**	**Gray (Gr)**
1.	Painted Image	R>G>Gr>B	56.062	68.230	80.148	57.761
2.	Astronomical Image	B>G>Gr>R	53.979	53.939	13.217	39.474
3.	Biomedical Image	B>G>R>Gr	71.460	71.457	71.425	71.398
4.	Synthetic Image	B=G=R=Gr	71.339	71.339	71.339	71.339

IV. CONCLUSION & FUTURE SCOPE

Chan-Vese algorithm has been enhanced for specific application in image segmentation. It has also been shown that the proposed algorithm is effective on a wide variety of images in red, green and blue planes. Chan-vese presented a modified model for vector images [12] but its computation is expensive as different planes require λ1, λ2 and c1 and c2 (region averages) values to be computed separately.

For those types of images where there is not much difference in three component values (red, green, blue) proper plane can be selected for fast evolution without losing segmentation. In particular, the images where one or two components of color are negligible we can make use of standard deviation to select the plane which has fastest evolution. Thereby, reducing unnecessary computation like in astronomical image, red component is significantly small and thus ignorable. Hence saving much computation as compare to Chan–Vese model for vector images.

More efficient method can be used to find that how a contour can be evolved in different planes fastly and covering a large number of objects in a particular image. Still there is a need to work on real time applications.

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