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Detection of Mountains and Surface Waters from Satellite Images Using Active Contour Model

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Abstract

Snakes or active contours are widely used in computer vision and image processing application mainly for locating the boundaries of the objects or the matter we are considering. In this paper we are trying to use this snake model for detecting the surface water bodies and mountains efficiently. We have developed an active contour model which helps us in detecting the open curves and also introduce the automation of the existing algorithm parameters by trying to make them independent on the image properties. This will be done using various implementation of snakes to detect the sharp as well as blunt peaked mountains and definite edged or fragmented edge water bodies. This will overcome the problems of subjective detection through snake model for specific problem and the problems usually encountered for segmenting a very noisy images such as the satellite images. We have used various implementations like balloon model, modified GVF diffusion snakes, geometric active contours.

Keywords: Active Contour model, multiple objects gradient flow, double thresolding, balloon snakes, diffusion snakes, geometric snakes

I. INTRODUCTION

Satellite image processing like presumed one of most interesting form of imagery, what makes it difficult to process is the fact it contains lots of noise, which stay even after its pre-processing. Various proposed algorithm has been given and our algorithm Active contour model or most widely termed as Snake model was first proposed by Kass at al. Snakes are basically continuous curves within the image domain that moves under a strong influence of the sum of two forces – internal forces which is from the curve itself and external force which is coming from the image itself. Due to this forces there is substantial deformation which helps the snakes to conform a particular shape. Originally the snakes had an existing problem i. e. they have to be given an initial point and it should be nearby to the edge of the object. Another drawback was that it couldn't relate to the boundary concavities or hollow spaces were compromised. To overcome these relatable issues in segmentation Chenyang Xu and Jerry L. Prince proposed the idea of using gradient vector forces which provides the independency of initialisation of the first control points and the boundary concavities can be encountered. Certainly this had its disadvantages, it wasn't efficient enough for cases where there could be chances for overlapping. Improved algorithm [1] provides us the solution to this, which provides us a concrete base for our work to proceed further. In this work they have provided an algorithm where we can use the Active Contouring for the satellite images. The upcoming sections will show that how will resolve the problem which were left as the future scope in [1] starting with our background study.

II. BACKGROUND STUDY

A. Traditional Snake model:

A traditional snake curve is well represented in the form as given in [2]

$$v(s) = (x(s), y(s)) \tag{1}$$

The energy function is then given as:

$$\int_0^1 E_{snake}(v(s))ds = \int_0^1 E_{\text{int}}(v(s)) + E_{image}(v(s)) + E_{ext}(v(s))ds \tag{2}$$

Where E int the internal energy is caused due to the bending and *Eimage* energy of the overall image and *Eext* is the external energy taken from the image data. Internal energy is given by:

$$E_{\text{int}} = \left(\frac{1}{2}\right)(\alpha(s)) \, \|v_s(s)\|^2 + \beta(s)\|v_{ss}(s)\|^2) \tag{3}$$

Where the first order vs(s) will provide us the elasticity and vss(s) the second order term will provide us the measure of the curvature that is whenever the snake is stretched, the first order term will increase and second order term will decrease unless if there is a kink [1] then curvature will increase. The effect of this forces on the overall contour energy is controlled by the coefficients α(s) and β(s) and as suggested by Kass at al. that this will be acting like a membrane on a thin layer much like a plate.

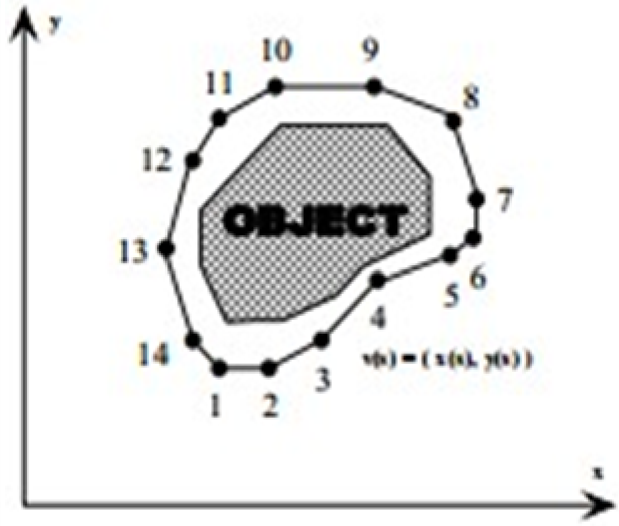

Figure 1-Basic structure of ACM

[1]Let's say the snake can settle on the edges and we have the object in the image ready for detection then consider the image energy as I as the image function then:

$$E_{img}(x, y) = - \| \nabla I(x, y) \|^2 \quad (4)$$

[1]Given a grayscale image I(x, y) viewed as a function of continuous position variables (x, y) the external energies that lead an active contour towards the step edges are given as:

$$E_{ext}^{(1)}(x,y) = - |\nabla I(x, y)|^2 \quad (5)$$

$$E_{ext}^{(2)}(x,y) = - |\nabla[G_\sigma(x, y) * I(x, y)]|^2 \quad (6)$$

Where $G\sigma$ (x, y) is the 2D Gaussian function with the standard deviation σ and gradient operator ∇. If the image is a line drawing, then external energies will be

$$E_{ext}^{(1)}(x, y) = -\ I(x, y) \tag{7}$$

$$E_{ext}^{(2)}(x,y) = -\ G_{\sigma}(x, y) * I(x, y) \tag{8}$$

Since this is in its minimal form, we can call it as balanced snake equation.

Now when we are considering the forces acting upon the image, we have to also consider the external and internal forces. These forces basically does two contradictory functions which helps us out, the internal force will try to prohibit stretching and bending while external force will pull the snake towards the desired image edges:

$$F_{int} + F_{ext}^{(p)} = 0 \tag{9}$$

B. Applying the Gradient Operator to the Snake.

The overall approach for this method [3] is that we have to define a non – traditional external force field, which is the GVF and our balance equation will be the starting point of it. This will provide us two advantages first there is no necessity of initial control points and second it can encounter the concavities. So first we create the edge map and then using the edge map and then we diffuse that with the with gradient vector field. Point to remember is that the edge mapping is of binary or gray level images. This will minimise energy functional in equation 3.

$${}_{x}^{2} \quad {}_{y}^{2} \quad {}_{x}^{2} + {}_{y}^{2}) + |\nabla \quad f \quad v \quad f \quad dxdy$$

The parameter μ is the regularization parameter and this controls the quid pro quo between the first term and the second term. GVF can be found by using the Euler's equation by applying Laplacian operator the equations will be

$$\mu\nabla^2 u - (u - f_x)(f_x^{\ 2} + f_y^{\ 2}) = 0 \tag{11}$$

$$\mu\nabla^2 v - (v - f_x)(f_x^{\ 2} + f_y^{\ 2}) = 0 \tag{12}$$

Treating the variables u and v as functions of time and solving:

$$u_t(x, y, t) = \mu\nabla^2 u(x, y, t) - [u(x, y, t) - f_x(x, y)].$$
$$[f_x^{\ 2}(x, y) + f_y^{\ 2}(x, y)] \tag{13}$$

$$v^t(x, y, t) = \mu\nabla^2 v(x, y, t) - [v(x, y, t) - f_x(x, y)].$$
$$[f_x^{\ 2}(x, y) + f_y^{\ 2}(x, y)] \tag{14}$$

The steady state solution of these linear parabolic equations is the sought after solutions for equation (11) and (12) and when they are decoupled we will get from (13) and (14):

$$u_t(x, y, t) =$$
$$\mu\nabla^2 u(x, y, t) - [b(x, y)u(x, y, t) + c^1(x, y)] \tag{15}$$

$$v_t(x, y, t) =$$
$$\mu\nabla^2 v(x, y, t) - [b(x, y)v(x, y, t) + c^2(x, y)] \tag{16}$$

Where:

$$b(x,y) = f_x(x, y)^2 + f_y(x, y)^2$$

To set up the iterative solutions we are taking the indices i, j, n corresponding to x, y, t correspondingly and let the

spacing between the pixels of the image be Δx and Δy, let Δt be the time step. Then the required partial differential equations will be

$$u_t = \frac{1}{\Delta t}(u_{i,j}^{n+1} - u_{i,j}^{n})$$

$$v_t = \frac{1}{\Delta t}(v_{i,j}^{n+1} - v_{i,j}^{n})$$

Substituting this in equation 15 and 16 we can
The following approximation:

$$u_{i,j}^{n+1} = (1 - b_{i,j}\Delta t)u_{i,j}^{n} + u_{i,j+1}^{n} + u_{i-1,j}^{n} + u_{i-1,j}^{n} + u_{i,j-1}^{n} + u_{i-1,j}^{n} - 4u_{i,j}^{n}) + c_{i,j}^{1}\Delta t \tag{17}$$

$$v_{i,j}^{n+1} = (1 - b_{i,j}\Delta t)v_{i,j}^{n} + v_{i,j+1}^{n} + v_{i-1,j}^{n} + v_{i-1,j}^{n} + v_{i,j-1}^{n} + v_{i-1,j}^{n} - 4v_{i,j}^{n}) + c_{i,j}^{2}\Delta t \tag{18}$$

Where

$$\Gamma = \frac{\mu \Delta t}{\Delta x \Delta y} \leq 1/4$$

Courant –Friedrichs-Lewy restriction.

C. Limitations of Traditional approach.

This approach requires initialisation and doesn't give accurate results for boundary concavities.

III. OUR APPROACH.

Since the classical method had its own drawbacks, considering those drawbacks we are providing a method which we feel is enhanced ways of detecting the mountains and surface waters. [1] Previously it was suggested that when we are trying to capture the control points, we are getting superfluous points which are create an undesirable way of defining the control points and hence canny double thresolding is used. The performance of the canny algorithm hinges heavily on the variable parameters, σ, which is the standard deviation for the Gaussian filter, and the threshold values, σ also controls the size of the Gaussian filter. The bigger the value for σ, the larger the size of the Gaussian filter develops. This concludes more blurring, necessary for noisy images, as well as detecting larger edges. There are basically two threshold values T1 and T2 where T1>T2. For every control point chosen we have to check whether our gradient value is greater T1 if so then that’s the retained point. Now if the neighbourhood point is lesser than our T1 but greater than T2 condition then also it is used but we will check it with the third threshold, T3 and it should exceed that to be our next control point. If there is any sort of fragmentation or fuzziness in our edges, interpolation is an option but for highly noisy images it can be time taking and inaccurate. There is a way where we can commonly detect whether we are asking for the straight lines or edges which are curved by nature. Both curves and straight lines are detected during segmentation. However for better segmentation of the inconsistent structure in the topology we will be using a graph based deformable model.

1. Input an image
2. Convert that to grayscale
3. Define the number of contours used
4. Define the control points around the specific structure.
5. Calculate the constants (this will be the parameters which are contributing towards our total energy).
6. Initialise those parameters
7. Define the number of iterations
8. iterations)
9. If count<iterations then go to 21
10. Calculate average distance between the control points.
11. Initialise ptr=1.
12. Check ptr < number of control points else go to 19
13. Initialise vi, vin, vip
14. Calculate the curvature and elastic energy for flexibility and deformation.
15. Calculate the gradient vector energy as the external energy
16. Normalise the energy parameters
17. Check the point in the neighbourhood which gives us the minimum total energy
18. Move the control point to that particular position
19. Increment the ptr and repeat from 11
20. Capturing the process and use the canny detection here
21. Increment count and go to 8
22. Apply graph cut segmentation. [Gibbs model]
23. Output image is the final Icapture.

IV. EXPECTED RESULTS.

The detection of the topological structures by merging both the parametric and graph based segmentation is a huge process. So by applying both algorithms we are expecting that the surface water and mountain concavities can be detected.

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