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Road Network Extraction from Satellite Images By Active Contour (Snake) Model And Fuzzy C-Means

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Abstract— ***In this paper automatic and semi automatic road detection algorithms are introduced. Semi automatic road extraction comprises of pre-processing the image via a gauss filter and reducing the yielding data into a single image which is of the same size as the original optical gray scale satellite image, then find the image gradient in x and y direction. After that image potential is calculated. After that the users specify some initial conditions in form of seed points. The seed points are entered by a human operator to specify initial and ending point of road network. In automatic road extraction unsupervised classification FUZZY C-MEANS algorithm is implemented. In fuzzy c-means there is no need of human operator because it's an automatic process. In this pixels identified as road are shown in white, whereas non road pixels are shown in black. Basically fuzzy logic is based on statistical information and geometry is used to extract the road pixels.***

Keywords— ***Road extraction, FUZZY C-MEANS, Active snake contour-model (Snake), satellite images.***

I. INTRODUCTION

This paper deals with a automatic and semi automatic road extraction algorithm. Road detection algorithms can be classified into two major groups; semi-automatic and automatic. The first approach necessitates that the user specify some initial conditions usually in the form of seed points entered manually by a human operator through some graphical user interface (GUI). Examples of these include and are not limited to differential snakes, graph connection etc. The other approach which is fully automatic on the other hand does not require input from an operator and works on its own. In this paper both semi automatic and fully automatic approach is presented. In semi automatic road detection active contour model and for fully automatic FUZZY C-MEANS algorithm is presented to carry out the road detection whose output can then be used as an input to a geographical information system (GIS) for cartographic or other purposes for that matter.

II. SEMI AUTOMATIC ROAD DETECTION METHOD

Deformable contour models (snakes) is an approach analysed in , which have lately been used extensively for detection and localization of boundaries for facilitating the image segmentation problem, and also for the extraction of manmade structures such as roads and buildings from gray level imagery. Snakes are utilized where semi-automatic methods on linear object extraction and road extraction are, respectively, This method deals with the extraction of road network from aerial (digital) images, using a semi-automatic method based in the Active Contour model algorithm first introduced by Kass et al in 1988, and which have been widely used by the computer vision community for different applications. Such algorithm deforms a contour toward features of interest within in an image. Usually that features are lines, edges, and/or object boundaries. Kass et al. named their algorithm, ``Snakes" because the deformable contours resemble snakes as they move. In a semi-automatic method on road extraction using dynamic programming is presented. Basically, a generic road model is formulated, which is solved sequentially by a dynamic programming algorithm in order to GIS update starting from aerial and satellite images. In this work a few seed points describing coarsely the road need to be provided by the operator. Likewise, this job proposes a solution for the optimization problem which consists in the search of the most short path between two points of an object.

(A) Road Extraction by Active contour (Snake) model.

Deformable models are used commonly for edge detection. They can be formulated within an :
(a)Energy minimizing formulation or
(b) Dynamic force formulation
Snake is one kind of parametric energy minimizing formulation.
To find the best fit between a snake and an object's shape, we minimize the function energy.

$$E_{snake} = \int_0^1 E_{internal}\, v(s) + E_{image}\, v(s) + E_{constraint}\, v(s).ds \quad (1)$$

Where the snake is parametrically defined as
For 3D

$$v(s) = (x(s), y(s), z(s))$$

For 2D

$$v(s) = (x(s), y(s))$$

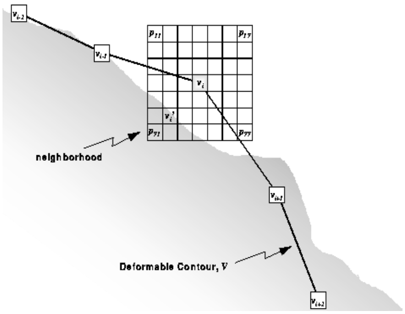


Fig 1 An example of the movement of a point, v_i, in an active contour. The point, v_i', is the location of minimum energy due to a large gradient at that point.

(1) The Internal Energy Term

$E_{internal}$ term concerned to the internal curve energy caused by stretching and bending.

The internal energy provides a smoothness constraint that can be defined as:

$$E_{internal} = \alpha(s)\left|\frac{dv}{ds}\right|^2 + \beta(s)\left|\frac{dv^2}{ds^2}\right|^2 \qquad (2)$$

Where,

α(s) is a measure of the elasticity of the snake, controlling the continuity(string forces).

β(s) is a measure of the stiffness of the snake, to control smoothness (rod forces)

Both parameters assume an arc length parameterization of the curve.The first order term makes the snake act like a membrane; the constant α(s) controls the tension along the curve (stretching a balloon or elastic band). The second order term makes the snake act like a thin plate; the constant β controls the rigidity of the spine (bending a thin plate or wire). If β(s)=0 ,then the function is discontinuous in its tangent, i.e. it may develop a corner at that point. If α(s)=β(s)=0 then this also allows a break in the contour, a positional discontinuity.

(2) The External Energy

E_{image} is measure of the attraction of image features such as contours.

The image energy is derived from the image data.

Considering a two dimensional image, the snake may be attracted to lines, edges or terminations.

$$E_{image} = w_{line} E_{line} + w_{edge} E_{edge} + w_{term} E_{term} \qquad (3)$$

Where w_i is an appropriate weighting function.

Commonly, the line functional is defined simply by the image function,

$$E_{line} = f(x,y)$$

So that if w_{line} is large positive the snake is attracted to light lines (or areas) and if large negative then it is attracted to dark lines (or areas). The use of the terminology ``line" is probably misleading.

The edge functional is defined by

$$E_{edge} = |\nabla f(x,y)|^2 \qquad (4)$$

Hence, the snake is attracted to large image gradients. i.e. parts of the image with strong edges.

Finally, the termination functional allows terminations (i.e. free ends of lines) or corners to attract the snake.

III. AUTOMATIC ROAD DETECTION ALGORITHM

Pattern recognition techniques can be classified into two broad categories: Unsupervised techniques and supervised techniques. An unsupervised technique does not use a given set of unclassified data points, whereas a supervised technique uses a dataset with known classifications. These two types of techniques are complementary. For example, unsupervised clustering can be used to produce classification information needed by a supervised pattern recognition technique. In this section, we first introduce the basics of unsupervised clustering. The fuzzy C-Means algorithm (FCM), which is the best known unsupervised fuzzy clustering algorithm is then described in detail. In road extraction first the Fuzzy C Means (FCM) algorithm is used to classify the satellite image. And Hough Transform is applied in windows to get segment candidates, which increases the robust of the method. Then a fitness function is used to group the segments. The membership values of the connection lines are used to connect the grouped segments. Finally the false road is removed and the main axes of roads are extracted. The result of road detection by this method is used for GIS updation .

(A) FUZZY C-MEANS ALGORITHM

This unsupervised clustering is motivated by the need to find interesting patterns or groupings in a given set of data. In the area of pattern recognition an image processing, unsupervised clustering is often used to perform the task of "segmenting" the images (i.e., partitioning pixel on an image into regions that correspond to different objects or different faces of objects in the images). This is because image segmentation can be viewed as kind of data clustering problem where each datum is described by a set of image features (e.g., intensity, color, texture, etc) of each pixel. It allow a point to partially belong to multiple clusters. Therefore, it produces a soft partition for a given dataset. In fact, it produces a constrained soft partition. To do this, the objective function J1 of hard c-means has been extended in two ways:

The fuzzy membership degrees in clusters were incorporated into the formula, and an additional parameter m was ntroduced as a weight exponent in the fuzzy membership.

The extended objective function, denoted J_m, is:

$$J_m(P,V) = \sum_{j=1}^{c} \sum_{x_i \in c_j} (\mu_{c_i}(x_k))^m |x_k - v_i|^2 \quad (5)$$

Where P is fuzzy partition of the dataset X formed by C1, C2,.., Ck. The parameter m is a weight that determines the degree to which partial members of clusters affect the clustering result.

IV. RESULTS AND DISCUSSIONS

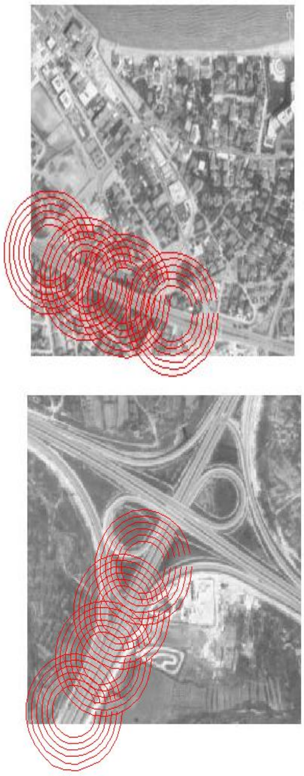
Results of the semi and automatic road detection algorithm have been shown for both urban and non-urban areas in Figure 2. In automatic road extraction pixels identified as “road” are shown in white, whereas the “non-road” pixels are shown in black. As it can be seen from these images fully automatic classification process outlined in this paper performs with a high degree of accuracy in both urban and non-urban areas. However, there are some very important concerns particularly regarding the urban area classification which presents a more challenging classification problem than its suburban counterpart. As it can be seen from Figure 2(a) only roads with rather large pixel widths such as the main highway are recovered well. Main roads and intersections are also recovered with good accuracy but inner city roads which are narrow have not been recovered. In addition, some pixels belonging to rooftops of buildings were falsely identified as roads.

(a) **(b)**

Fig 2 (a).Road Network in an Urban Environment
(b). Road Network in a Non-Urban Environment

(a) (b)

Fig 3 Results of the Fuzzy Classification (a). Urban Image (b). Suburban Image



(a) (b)

Fig 4 Results of active contour model (a) Urban Image (b) Suburban image

V. CONCLUSIONS

In semi automatic detection ,Using the seeds points from the user, it was possible interpolate new points, to generate a group of independent snakes, initialized as circle, then evolving them in such a sequence that could define the borders of the road, based in the energy minimization method. The results are highly depending on the resolution of the image used and the parameters of the snake. In our implementation of the snakes, we could solve the problem of disturbed areas by initializing more snake points, and smoothing, to let the snake pass over the non-road objects, during its evolution. One weak point of our implementation is that in areas with trees (dark areas) covering a part of the road, we got a non straight road side (border); this is because we are not feeding the program by information about the width of the road. An automated method for extracting road networks from satellite images is presented. It is observed that the image classification is carried out to a high degree of accuracy especially for the non-urban areas. In the urban areas however, only major roads with larger pixel widths have been recovered. Moreover, the presence of buildings and other objects that have linear features made the road extraction somewhat more difficult compared with the non-urban case. In this case some pixels belonging to rooftops of buildings were wrongly identified as road pixels. For urban road extraction with high fidelity this method seems to require higher resolution at which the narrow and small roads shall appear with larger pixel areas. The automatic approach introduced is structured such that it is quite possible to introduce very efficient parallelization in order to do the processing in real-time for other practical purposes such as target recognition. As fully automatic methods from mapping are still out of reach, due to the increasing complexity of objects within a diversity of contexts, semi-automatic methods for feature extraction are the most common implemented methods, which most of the time focus in the edge feature characteristics, since it is that what mainly help to distinguish one feature from another one.

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