A COMBINED ESTIMATION-DEFORMATION MODEL FOR AREA DETECTION: APPLICATION TO TOPOGRAPHIC AREA FEATURE UPDATE

KEY WORDS: active contour, multispectral boundary finding, region-based segmentation, MAP, change detection, topographic databases update, Raster and vector information, integration.

ABSTRACT:

This paper presents a fully automated approach for area detection based on multi-spectral images and features from a topographic database. The vectors residing in the database are refined using active contours (snakes) according to updated information provided by the multi-spectral images. The conventional methods of defining the external energy of the snake based on statistical measures or gradient-based boundary finding are often corrupted by poor image quality. Here a method to integrate the two approaches is proposed using an estimation of the maximum a posteriori (MAP) segmentation in an effort to form a unified approach that is robust to noise and poor edges. We further propose to improve the accuracy of the resulting boundary location an update of the snake topology. A number of experiments are performed on both synthetic and LANDSAT 7 images to evaluate the approach.

1. INTRODUCTION

Topographic databases are gaining popularity as a reference tool in many fields of application. The providers of topographic information are currently concerned with how to maintain data updated and also how to increase its accuracy with limited resources. Moreover, the evolving needs for current basic spatial data requires reliable and fast processing methods to address these concerns. This problem could be overcome through image processing techniques, which allow increasing accuracy of both geometric and temporal features. An increasing number of methods for updating spatial information based on image processing began to appear in the latest years. From the proposed methods, we are mostly interested with those based on the snakes. The proposed approaches deal with different type of images, mainly with single band satellite (Bentabet et al, 2001; Horritt, 1999) or airborne (Auclair-Fortier et al., 2001) images and from different type of sensors such as radar or optical. The snake model is defined according to the geometry of the target feature. Some works present linear snakes to search linear features such as road (Bentabet et al, 2001; Auclair-Fortier et al., 2001). Others present closed snakes to obtain a description of area features such as water regions (Horritt, 1999).

In this paper, we propose a method to update existing area features from a given topographic database using of multi-spectral images. The available database vectors provide an interesting initialization for the area localization process. In this context, the closed snake approach was presented as a natural solution. The main contribution of this work is the formulation of the external forces, which deform the snake by combining both statistical and boundaries information.

The region-based and the boundary finding measures provide us with complementary information. By reviewing the existing works focusing on the integration of region-based information with boundary information, we conclude that they are mainly made within image segmentation framework (Chakraborty and Duncan, 1999). The boundary-based methods have superior localization properties. Also, they are robust to changes in the gray-level distribution since they look at the derivative information. However, they often give high rate of false edges due to textured regions. In addition, a weak response is produced when far from the boundaries of the area. The region-based and especially statistical methods supply a good model for textured regions and good response when far from the edges. Furthermore, region-based methods have the advantage of being less susceptible to noise than other methods that involves derivative information. Unfortunately, these methods suffer from the problems of poor localization and over-segmentation.

As pointed out in the above discussion, the region and boundary based methods have their different advantages and disadvantages. This brings us to the fact that integration methods are likely to perform better than either of the methods alone. An integration method will combine the complementary strength of these individual methods and decrease their drawbacks, as pointed out in (Chakraborty and Duncan, 1999; Pavlidis and Liow, 1990; Tek and Kimia, 1995). Many works have addressed the problem of combination of region-based and boundary-based methods. Some studies focus on the AI techniques, which define a set of rules in order to deal with conflicting situations (Pavlidis and Liow, 1990). Another way of achieving combination is the reaction-diffusion method (Tek and Kima, 1995). However, the problem is that if any one of the processes makes error (e.g., a false edge), it is propagated to the final solution. Chakraborty et al. propose to use the game

theoretic method. The game theory as a concept has its roots in decision making under a conflicting and often hostile environment. This method processes by maintaining the modularity of the system involved and by allowing the modules (i.e., region-based and boundary-based modules) to interact by a decentralized mode of decision making. The contribution of each module is determined by achieving the Nash equilibrium (Chakraborty and Duncan, 1999). This method allows high performance when applied to noisy images, especially when applied to deformable models. However, the existence of the Nash equilibrium depends on weighting parameters of the goal function. While for simple problems it might be simple to mathematically choose right values for the weights, often, for complicated problems, it is almost impossible.

Our goal here is to develop a fully automated formalism for integrating boundary finding and region-based methods. This formalism will be used to model the external force acting on the deformable model. The region-based modeling is achieved at a global level by a statistical characterization. Thus, the cluster of interest could be considered as being a mixture of distributions. The boundary finding part is handled by the gradient information. Since the gradient defines a measure of non-homogeneity in the pixel neighborhood, its response is modeled as a potential function, that generates a Gibbs distribution of a Markov random field (MRF). The combination relies on an approximate maximum a posteriori (MAP) estimate that gives the likely segmentation according to the observed data. In order, to resolve the conflicting situation that could appear, each part of the MAP is weighted by a measure that ensures the selection of the suitable MAP configuration. The paper is organized as follows. Section 2 gives a brief overview of the deformable model approach as introduced by Kass et al., 1988 and the snake discretization using finite element used in this framework. Section 3 details the methods for both region-based and multi-spectral boundary finding formulation respectively. In section 4, we introduce the MAP combination and conflict resolving formulation for the external forces calculation purpose. In section 5, we resume the final algorithm. Finally, in the rest of the paper, we show and discuss the results obtained on both synthetic and LANDSAT7 images. A conclusion is given with the possible extensions of our work.

2. DEFORMABLE MODELS APPROACH

Active contours models or snakes were introduced by Kass et al., 1988 as a novel solution to the low-level imaging task of finding step edges. A snake is defined, in the image plane (n,m), as a parametric curve of the curvilinear abscise, r, by $v(n,m)=v(n(r,t),m(r,t))$. The snake is allowed to deform from some arbitrary initial location within an image towards the desired final location. Thus, the use of snakes involves a two steps process being an initialization and the iterative minimizing process. To initialize the snake, we first perform the discretization of the database vectors. The final snake location is obtained through minimization process acting upon the global energy of the snake defined as follows (Kass et al., 1988):

$$E_{tot}(t) = E_{int}(t) + E_{ext}(t) \qquad (1)$$

where $E_{ext}(t)$ is the external energy, $E_{int}(t)$ the internal energy. As described in classical snake modeling approach (Kass et al.,

1988), the internal energy acts as a stabilizer to the external data irregularities. The standard internal formulation is given as follow:

$$E_{int}(t) = \oint \left(\alpha \left| v'(r,t) \right|^2 + \beta \left| v''(r,t) \right|^2 \right) ds \qquad (2)$$

where α and β are Tikhonov stabilizers which controls respectively the elasticity and rigidity of the snake. In active contours framework, the external energy, $E_{ext}(t)$, is used to derive the external forces, $F_{ext}(t)$, which act on the snake to deform its shape and location. The relationship between external energy and forces is given by the following equation:

$$E_{ext}(t) = \oint F_{ext}(v(r,t)) ds \qquad (3)$$

As mentioned earlier, the initial location of the snake is provided by the database vectors. In the next step, the initial vectors are approximated by parametric curves. This task is undergone by the use of the finite elements method (FEM). The FEM enables accurate discretization of derivatives and smooth shape representation for the snake. The interested reader will find all details in (Bentabet et al., 2001). To summarize, the discretizing of the parametric curve $v(r)$ by FEM leads to an expression for each element given by:

$$v^e(r) = (N_1(r), N_2(r), ..., N_n(r)) \cdot \begin{pmatrix} X_1^e & Y_1^e \\ X_2^e & Y_2^e \\ \vdots & \vdots \\ X_n^e & Y_n^e \end{pmatrix} \qquad (4)$$

where, $N_i(r)$ define a vector of interpolation polynomials. In our case, the interpolation is carried out using a Hermite basis function. The two-columns matrix $V^e = \left(X^e, Y^e \right)$ contains the coordinates of the control nodes which are inserted at regular intervals of the initial curve issued from the database. Consequently, both snake topology and location will be entirely defined by the knowledge of the control nodes. Therefore, the segmentation purpose can be described as being a process of estimating the suitable values for the control nodes coordinates that minimize the global energy of the snake energy defined in equation (1). The estimation of these parameters to find the boundary is posed as an optimization process, where a MAP-based objective function measures the strength of the boundary given the set of control nodes. The snake evolution is governed by a partial derivative equation of motion obtained by resolving the Euler Lagrange equation ($\nabla E_{tot}=0$) which can be expressed as follows (Bentabet, 2001):

$$\gamma \frac{\partial v(r,t)}{\partial t} - \alpha \frac{\partial^2 v(r,t)}{\partial r^2} + \beta \frac{\partial^4 v(r,t)}{\partial r^4} = -\frac{\partial F_{ext}(v(r,t))}{\partial v} \qquad (5)$$

where γ controls the speed of evolution of the snake. A discretized form of Equation (5) can be derived using the finite elements formalism, which yields the following iterative process:

$$V^e_{(n+1)T} = \left(I + \frac{T}{\gamma}K\right)^{-1}\left(V^e_{nT} - \frac{\gamma}{T}F^e_{nT}\right) \qquad (6)$$

where I is the $N{\times}N$ identity matrix. *K is an $N{\times}N$ matrix which depends on α, β and the shape of the interpolating curves.* V^e_{nT} gives the location of the element nodes at iteration n.

3. EXTERNAL FORCES CALCULATION

The calculated external force is defined as a function of the region and the boundary information. We assume that the image can be modelled as a collection of homogeneous regions of uniform or slowly varying intensities. Let the image data be described by a random field Y defined on a rectangular grid, S, of N points, and the value of Y at a point $s \in S$ will be written as Y_s. When necessary the points in S will be explicitly written as integer pairs (n,m). X will denote the random field of a given segmentation of Y into uniform regions. Lowercase x and y will be realizations of the X and Y respectively. The probability $P(Z{=}z)$ is written as $p(z)$.

3.1 Statistical Measure

By definition, topographic features could be described by more than one texture. Indeed, for example, both hardwood and coniferous trees are included in a vegetation region definition. Also, these two types of forest can appear separately or in mixed areas. Thus, the statistical properties of the targeted area are computed assuming the region of interest is described by a number of textures being normally distributed. We propose a mixture estimation process independent but necessary for the region localization. Indeed, the definition of the mixture parameters for different type of topographic feature in an image can be recorded in a database and used as a prior knowledge. This information is essential to the snake process but can be defined in an earlier step.

The statistical information is described trough a number k of Gaussian distributions with the mixture proportion, p_j, the expected value of the argument, μ_j, and the covariance matrix, Σ_j with $j \in [1, k]$. The dimension of μ_j and Σ_j are related to the number of bands available in the multi-spectral imagery. Indeed, the definition of these parameters through n bands provides μ_j vectors of dimension n and Σ_j matrix of size $n{\times}n$.

3.1.1 Statistical prior knowledge

The goal is to define the ideal number of textures contained in a sample region witch describes the data. Recent studies (Olivier et al., 1999) propose an iterative algorithm for normal mixture definition. This operation is a two steps iterative process. It is done using the Expectation – Maximization (EM) algorithm assuming an adequate initialization of the parameters values for a given number of distributions. The objective of the EM algorithm is to maximize the log-likelihood in an iterative manner. The second step consists of evaluating the balance between the accuracy of the model and the number of components. Evaluating the Minimum Description Length (MDL) of the model provides this measure as described by Olivier et al., 1999.

The mixture model that minimizes the MDL criterion corresponds to the appropriate mixture model for the region of interest.

Since the statistical characteristics of the area are estimated, a goodness function based on these statistical features can be derived. Indeed, this function will define the region probability measure part of the external energy.

3.1.2 Region Probability Measure

Considering a realization of the field Y noted, y, the aim here is to evaluate $p(y|x)$. The statistical goodness measure is based on the calculation of a distance, $\psi(y)$, that evaluates the proximity of a pixel to the statistical properties of the region. This value can be defined using the Mahalanobis distance.

Having k textures for a given region, we associate to the sample y the smallest distance from all k distributions defined within the region. In order to consider this value in a generic way, one must take into consideration the number of bands from the multi-spectral image involved. Since we assume that y follows a Gaussian distribution, we know that the Mahalanobis distance follows a χ^2 distribution (Saporta, 1990) with n degrees of freedom (n being the number of bands for the multi-spectral image). Thus, we can set a threshold value based on some confidence value (0.005% for instance). This threshold value will serve to normalize the calculated distance for tested samples and also to identify outliers. Thus, the goodness function, $\psi(y)$, can be defined as follow:

$$\psi(y) = \frac{\sqrt{\min_{i\in[1,k]}\left((y-\mu_i)^T \Sigma_{i_i}^{-1}(y-\mu_{i_i})\right)}}{\psi_t} \qquad (7)$$

where ψ_t is a threshold given by the χ^2 table value according to the dimension of the data and the desired confidence value. From Baysian inference, the joint probability distribution, $p(y,\theta)$, comprises two parts, a prior distribution $p(\theta)$ and a likelihood $p(y|\theta)$. In this framework, we do not consider the prior distribution of θ, $p(\theta)$ in the evaluation of the closest distribution nor for the goodness function. The idea is to consider the closest texture according to the Mahalanobis measure for a candidate as the unique potential.

By observing the distance defined by equation (7), we find that when it is greater than 1, odds are that this pixel is outside the region. On the opposite, as the value decreases near zero, the indication of being inside the region increases. This information allows the definition of the direction of growth.

Finally, the likelihood $p(y|x)$ when the snake evolves inside the considered region (i.e., $\psi(y){<}1$), is given by a Gaussian distribution as follows:

$$p(y|x) \propto \frac{1}{(2\pi)^{\frac{n}{2}}\sqrt{|\Sigma|}}exp-(\psi(y)^2) \qquad (8)$$

For cases, where the snake is outside the considered region (i.e. $\psi(y){>}1$), the likelihood is described by a translated form of the Gaussian given in equation (8). The general case is defined as follows:

$$p_i(y|x) \propto \frac{1}{(2\pi)^{\frac{n}{2}}\sqrt{|\Sigma|}} exp-\left((\psi(y)-2i)^2\right) \qquad (9)$$

where $2i$ is the translation applied and for a given integer, i, $\psi(y) \in [2i-1, 2i+1]$.

3.2 Boundary Probability

The aim here is to provide a single gradient image given as input a multi-dimensional set of images. In order to integrate the contrast information contained in the various channels into one meaningful result, Drewniok, 1994 extended in a formal way a gray-level edge detector to multidimensional image data. The integrating approach combines the contrast information coming from the different spectral channels in a well-founded way. The resulting gradient image gives a suitable description of area boundaries well adapted to the purpose of our framework. Assuming that the ith channel produces an image $I_i(n,m)$:

$$I_i(n,m) = R_i(n,m) + N_i(n,m) \qquad (10)$$

where $R_i(n,m)$ is the ground truth and $N_i(n,m)$ is an additive Gausssian noise. The produced gradient image, $G(n,m)$, is corrupted by false-edges due to noise. The plausibility of false edges follows a Rayleigh distribution (Voorhees and Poggio, 1987). In order to distinguish real edges from false ones, Voorhees proposed to estimate statistically a threshold that separate these two populations. The threshold is calculated according to the estimation of the peak of the Rayleigh distribution. The threshold, κ, required to remove noise with a confidence value of 99% is defined as follows:

$$\kappa \approx 3\sqrt{\frac{2}{\pi}}\mu \qquad (11)$$

where μ is the mean of the Rayleigh distribution. We assume the plausibility of the true edges being described by a single distribution. Let μ_g be its expected mean value. As for the Mahalanobis distance discussed in Section (3.1.2), one need to normalize the gradient values in order to keep both measures (gradient and statistics) in the same numerical range. Therefore, we define the normalized gradient at a given position y_s as follows:

$$\tilde{G}(y_s) = \frac{G(y_s)}{\mu_g} \qquad (12)$$

The segmentation field, x, has an isotropic nature and its distribution is strictly defined in a local neighborhood. Thereafter, we use an MRF to model it (Bouman and Sauer, 1993). Using the Hammersley-Clifford theorem, the density of x is given by a Gibbs density on the form:

$$p(x) = \frac{1}{Z}e^{-\left(\sum_C V_C(x)\right)} \qquad (13)$$

Here, Z is a normalizing constant and the summation is over all cliques C. A clique is a set of points that are neighbors of each other. The clique potentials V_C depend only on the pixels that belong to clique C. They are inversely proportional to the homogeneity of the contour plausibility in the immediate neighborhood of the considered pixel, x_s, (Bouman and Sauer, 1993).

Since the gradient defines a measure of non-homogeneity and is evaluated in the immediate neighborhood of y_s, its response could be handled as being a transformation that maps the gray-level of y_s to the potential function $V_c(x_s)$. This relation is carried out in a proportional manner as follows:

$$V_C(x_s) \propto \tilde{G}(y_s) \qquad (14)$$

In view of this, the MRF field will henceforth be written in the following, simplified form (where the constant of proportionality in (14) is dropped for the sake of computational ease):

$$p(x_s) = \frac{1}{Z}e^{-\tilde{G}(y_s)} \qquad (15)$$

4. COMBINATION

As mentioned earlier, the segmentation purpose can be described as being a the estimation of the suitable values for the control nodes coordinates that minimize the global energy of the snake. The estimation of these parameters to find the boundary is posed as an optimization process, where a MAP-based objective function measures the strength of the boundary given the set of control nodes. The maximization of $p(x|y)$ given the control nodes could be written as follows:

$$\hat{x} = \arg\max_{V^e}\left(\prod_{s \in S} p(x_s / y_s)\right) \qquad (16)$$

By applying the Bayesian formulation, the combined probability $p(x|y)$ in equation (16) can be expressed as follows:

$$p(x|y) = \frac{p(x)p(y|x)}{p(y)} \qquad (17)$$

In the following, we ignore the term $p(y)$ because it is supposed to be a prior knowledge and it does not modify the MAP estimation. Thus:

$$\hat{x} = \arg\max_{V^e}\left(\prod_{s \in S} p(x_s)p(y_s|x_s)\right) \qquad (18)$$

By replacing $p(x_s)$ and $p(y_s|x_s)$ by their respective expressions, $\hat{x}$ could be evaluated in terms of the snake curvilinear abscise, r, as follows:

$$\hat{x} = \arg\max_{V^e}\left(\prod_{v(r) \in S} \frac{1}{Z}e^{-G(v(r))}e^{-\psi^2(v(r))}\right) \qquad (19)$$

It is clear that equation (19) combines the statistical and the gradient-based measures in order to find the optimal segmentation. The main question is to know if the formulation given below allows a constructive integration of both provided measures. In other words, we intend to investigate the behavior

of the MAP and determine if the two parts acts in such a manner to preserve the same objective everywhere in the image. This could be carried out by a qualitative analysis of the MAP. Indeed, when inside a textured region but far from the area boundaries, the statistical part may indicate that a pixel under investigation have a high confidence to belong to the region of interest. However, the gradient value can indicate that the pixel belongs to the area boundaries. This means that the gradient do not distinguish between the right area edges and those generated by the texture or the noise. In such situation, the gradient and the statistics are in conflict. Since, the MAP estimation is obtained by the product of these two parts, the decision made will be altered. Otherwise, when the pixel under investigation belongs to the area boundaries, its membership given by both gradient and statistics will be low. The two parts behave simultaneously to exclude this pixel from the segmented area. Knowing that the statistics suffers from a poor edges localization, the joint decision made could be affected.

To resolve this conflict, we propose the use of a weight to set the contribution of each part into the MAP estimation. The weight will act as a smooth switch, which gives priority to statistics when the pixel is far from the area boundaries. Also, when the pixel is closer to the edge, the priority will be transferred to the gradient. The modified MAP is given as follows:

$$\hat{x} = \underset{V^e}{arg\,max}\left(\prod_{v(r)\in S} \frac{1}{Z} e^{-\tau \tilde{G}(v(r))} e^{-(1-\tau)\psi^2(v(r))} \right) \quad (20)$$

where τ is a weight parameter resolving the conflict as described above. In the experimental results section, we propose a formulation to set this parameter.

The MAP estimation will be maximized during the evolution of the snake. This is performed by setting the external force proportionally to the combined probability $p(x_s|y_s)$. The final expression of the external forces will be:

$$F_{ext}(v(r)) \propto \frac{1}{Z} e^{-\tau \tilde{G}(v(r))} e^{-(1-\tau)\psi^2(v(r))} \quad (21)$$

Finally, the partial derivative equation that govern the snake motion given by equation (5) can be rewritten as:

$$\gamma \frac{\partial v(r,t)}{\partial t} - \alpha v''(r,t) + \beta v''''(r,t) =$$
$$-\frac{\partial}{\partial v}\left(\frac{1}{Z} e^{-\tau \tilde{G}(v(r,t))} e^{-(1-\tau)\psi^2(v(r,t))} \right) \quad (22)$$

This is equivalent to say that the evolution of the snake is equivalent to the estimation of the control nodes that maximize the criterion given by equation (20). This estimation is constrained by the snake topology described by the terms in the left side of equation (22)

5. ALGORITHM

Assuming the evaluation of the statistical mixtures done, the localization step defines the new position of every existing area of the database on the image. The operations performed over each area vector can be summarized as follow:

- Set the initial snake parameters.
- Until the snake energy is not minimum:
  - Set the external force of the snake from equation (21);
  - Compute the new snake location using equation (22).

While the minimization process is running, the snake α and β parameters are decreased in parallel in order to enable the snake to fit accurately to the high curved parts of the area borders. This decrease of the snake parameters is done by multiplying them with a constant factor, Δ, smaller than one (0.75 for instance). Also, updating the control nodes of the snakes optimizes the iterative energy minimization process. Indeed, two principal operations are performed: addition of new control points as the snake expands and deletion of control points whenever parts of the snake shrink at a point where control points overlap. Finally, the external energy factor is moderate considering the changes of direction for a node. The idea is to slow down when oscillations occur until it reaches its stable point.

6. EXPERIMENTAL RESULTS

From the experience of existing works, it has been established that it is difficult to set the rigidity and the elasticity parameters of the internal energy of the snake correctly (Horritt, 1999). In this work, we calculate the rigidity parameter β from the average curvature of the initial database vectors as proposed in (Bentabet, 2001):

$$\beta = \beta_{max}\left(1 - \overline{(curv)}^{\frac{1}{q}} \right) \quad (23)$$

where β_{max} is the maximum value assigned to the rigidity parameter, $\overline{curv}$ is a measure of the average curvature of the snake initialization using the segment of the database. The parameter q defines the degree of relationship between the curvature and the rigidity parameter. The elasticity parameter α is set to a value near zero in order to allow the snake to stretch according to the external energy only.

We propose a formulation for the τ parameter based on the idea of giving priority to statistics when the snake evolves far from the boundaries and transfer this priority to the gradient when near the area boundaries. In this context, , the τ parameter is set by an estimation of the proximity to the area boundaries that could be deduced from the normalized Mahalanobis, ψ, as follows:

$$\tau = \begin{cases} 1, & \psi(v(r)) \in [0.95, 1.05] \\ 0, & \psi(v(r)) \notin [0.95, 1.05] \end{cases} \quad (24)$$

The proposed approach was first tested on synthetic images presented in figure 1. The first result presents a region defined by 2 textures on 3 different layers. The initial vector that served to initialize the snake is shown in white on image (a). An intermediate image of the iteration process shows the snake on images (b) and the final result is presented in image (c). Specific parameters values for this result were 0.85 as the decreasing factor, Δ, the Mahalanobis threshold value was based on a confidence value of 0.0005, internal parameters α at 0.05 and β at 30.
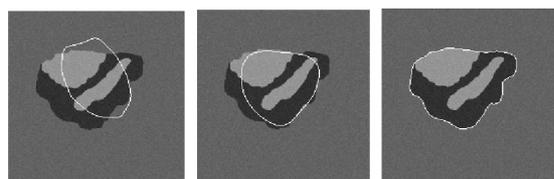
(a) Initial vector   (b) After 35 iterations   (c) Final result

Experimental results on synthetic images

The approach was then experimented on Landsat 7 images using 7 bands (30m resolution, we ignored band 6) to update features of the Canadian National Topographic Database (NTDB). The presented result in figure 2 show a homogeneous water region. The vector initializing the snake is shown in white on image (a) over enhanced band 2 of the Landsat7 image. Notice the lighter region inside the water area due to dense vegetation covering part of the lake and mostly obvious on this specific band. The mixture evaluation clearly defined two textures for this type of area that initially seems to be homogeneous on other bands. Over the enhanced image of band 4, an intermediate result of the snake process is presented on image (b) and the final result is presented on image (c). The specific parameters values for this result are the same as the previous example.
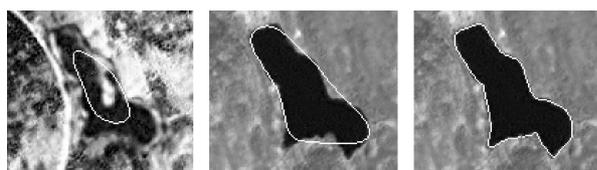
(a) Initial vector   (b) After 70 iterations   (c) Final result

Figure 2. Experimental results for water region on Landsat 7 images

Finally, results of the experiment on 7 bands of Landsat 7 images for textured regions like vegetation are shown in Figure 3. Notice that is difficult to visually delineate this kind of area on any of the bands. We present the result on an enhanced image of band 8 (15m resolution). The initial snake is presented in image (a), an intermediate image of the snake process is shown on image (b) and image (c) presents the final result. The only specific parameter different from the previous examples is the decreasing factor, Δ, that was set to 0.7.

(a) Initial vector   (b) After 40 iterations   (c) Final result

Figure 3. Experimental results for vegetation area on Landsat 7 images

7. CONCLUSION

Our work demonstrates the importance of using snakes and multi-spectral images for updating existing spatial area information. We propose a promising automatic approach for the update of existing vectors in topographic databases. The combined statistics and gradient information for the external

energy allows the snake to grow in both directions and provides complementary measures to precisely guide its deformation. Indeed, the proposed weighted MAP estimation strategically takes advantages of their respective strengths and overcomes their drawbacks. An efficient implementation using finite elements has been proposed for accurate localization. Finally, experimental results demonstrate the reliability of the approach.

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