DIFFERENTIAL OBJECT EXTRACTION METHODS FOR AUTOMATED GIS UPDATES

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ABSTRACT:

In modern geospatial applications object extraction becomes increasingly part of larger cycles of GIS updates. In such update cycles, the objective is to compare new information to older one, and to identify changes that occurred in the meantime. In this paper we present an image-based GIS updating framework and corresponding image analysis algorithms developed by our group to automate GIS updates. More specifically, we present an overview of our work on two different types of objects to be extracted and monitored, roads and buildings, and the corresponding algorithms, namely differential snakes and differential template matching. Our approach to both problems is characterized by the comparison of a new image to pre-existing information through an automated image analysis tool. This is equivalent to comparing an object as it is represented in an image to the same object represented in a GIS at a prior instance, setting up a novel matching problem, whereby an object is compared to itself to identify how it has changed. For both roads and buildings our algorithms make use of accuracy estimates accompanying the pre-existing information, to ensure the meaningful update of geospatial databases. Making use of these accuracy measures we differentiate change detection and versioning. In this paper we present an overview of theoretical issues behind our algorithms and experimental results from the developed software solutions.

1. INTRODUCTION

Object extraction from digital imagery is a key operation for modern geospatial applications. The evolution of the current state-of-the-art among digital image analysis and computer vision activities on the subject of automated object extraction from digital aerial and satellite imagery may be found in Suetens et al. (1992), Gruen et al. (1997), and Lukes (1998). Attempting to summarize the current state-of-the-art in this area we could point out that currently existing solutions are semi-automatic, with a human operator providing manually approximations of the location and shape of the object to be extracted. Then, an automated algorithm uses these approximations to precisely delineate the object's outline, or centerline as might be the case in roads.

In modern geospatial applications object extraction becomes increasingly part of larger cycles of GIS updates. In such update cycles, the objective is to compare new information to older one, and to identify changes that occurred in the meantime. In this paper we present an image-based GIS updating framework and corresponding image analysis algorithms developed by our group to automate GIS updates.

More specifically, we present an overview of our work on two different types of objects to be extracted and monitored: roads and buildings (and similar structures). Our approach to both problems is characterized by the comparison of a new image to pre-existing information through an automated image analysis tool. This is equivalent to comparing an object as it is represented in an image captured at instance *T* to the same object represented in a GIS at *T-dt*. This sets up an interesting matching problem, whereby an object is compared to itself, to identify how it has changed. The algorithms we developed to support this type of differential image analysis make use of accuracy estimates accompanying the pre-existing information, to ensure the meaningful update of geospatial databases. This allows the differentiation of change detection from versioning, an important distinction to improve information flow within modern geospatial databases.

In this paper we present an overview of the theoretical issues behind the algorithms we developed to monitor roads and buildings. Regarding *roads*, we have extended the model of deformable contour models (snakes) to function in a differential mode, producing the concept of differential snakes. Regarding *buildings*, we have developed differential application of template matching to compare the content of an image to the record of a building in an older GIS database and identify changes in it.

The paper is organized as follows. In Section 2 we present our view of image-based change detection and versioning. In Section 3 we present an overview of our work on differential snakes for the updating of road segments. In Section 4 we present an overview of our work on differential template matching to update building outlines. Experimental results form our algorithms are presented in Section 5, and concluding remarks are presented in Section 6.

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2. IMAGE-BASED CHANGE DETECTION

Image-based change detection processes typically proceed in two steps. First, a complex algorithm (e.g. snakes, template matching) is used to identify objects in a new image. Then, the GIS database is updated by comparing the newly extracted outline to the prior recorded information. If the new outline is different, we commonly proceed by using it to replace the older information and thus update the database. In this context, information is treated as deterministic in nature: any difference between the two outlines is considered as change. This often results in storing multiple slightly different representations of an object, even though this object has actually remained unchanged.

We aim to remedy this problem by integrating object extraction and change detection in a single process. It is meant to function within an integrated geospatial environment, whereby image analysis proceeds by having access to pre-existing information for the processed area. We assume a process where a new image is analyzed to determine changes in and update the existing GIS of a specific area. Within this environment pre-existing GIS information provides us with shape information for geospatial objects (e.g. roads, buildings) and accuracy estimates for this information. This prior information may have been produced by prior image analysis processes (exploiting older imagery), or by any of the other established methods to collect GIS information (e.g. traditional surveying processes).

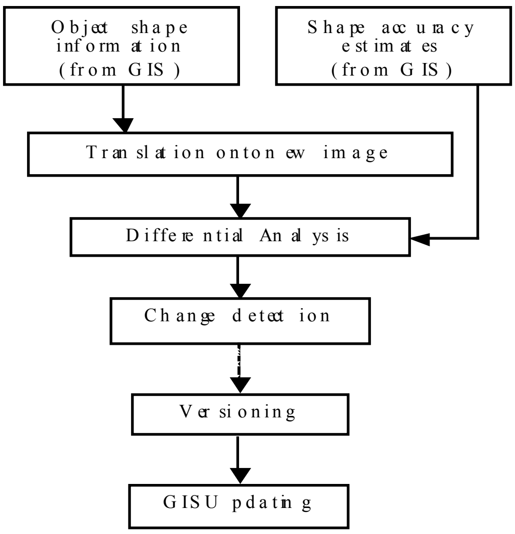

Figure 1: GIS updating process

A schematic overview of our process is described in Fig. 1. As mentioned above we make use of pre-existing object outline information. The older outline is projected onto the new image, using standard orientation parameters and relevant transformations. Once projected onto the new image, we proceed with *differential image analysis*, whereby the older outline together with its accuracy information becomes the input for a GIS update cycle. This update cycle comprises two processes:

- a mandatory *change detection* process, whereby we identify any parts of an object that have changed since its last record, and
- an optional *versioning* process, whereby we replace an otherwise unchanged object (or object segment) by a higher accuracy version of it, if the current imagery so permits.

The results are used to update the GIS information for this object by modifying its outline and/or updating its uncertainty estimates.

Following common practice in computer vision, we have developed two distinct differential analysis algorithms for smooth curvilinear (e.g. roads, rivers) and regularly shaped (e.g. buildings) objects. Details of these two algorithms are presented in the following two sections.

3. DIFFERENTIAL SNAKES FOR ROAD UPDATES

Deformable contour models (a.k.a. snakes) have been developed in the computer vision community as object extraction tools (Cass et al., 1987). In its numerical solution the snake is represented by a polygonal line, defined by nodes and segments connecting these nodes. The geometric and radiometric relations of these nodes are expressed as energy functions, and object extraction becomes an optimization problem (see e.g. (Williams & Shah, 1982) for an appropriate optimisation algorithm).

In a traditional snake model the total energy of each snake point is expressed as:

$$E_{snake} = \alpha \cdot E_{cont} + \beta \cdot E_{curv} + \gamma \cdot E_{edge} \tag{1}$$

where : E_{cont} , E_{curv} are energy terms expressing first and second order continuity constraints (internal forces); E_{edge} is an energy term expressing edge strength (external force); and α, β, γ are (relative) positive weights of each energy term. For brevity we avoid further analysis of the snakes model here. The reader is referred to (Cass et al., 1987) and sub-sequent publications of these researchers for further details on the formulation of these parameters.

To support change detection we expand the traditional snake model to perform a comparison of the current image content to the prior outline projected on it (and its uncertainty measures) instead of standard object extraction. We use the term *differential snakes model* to refer to this model, as it is used to identify differences. In this differential model, the snake solution is constrained not only by the radiometric and geometric terms of Eq. 1, but also by the pre-existing information. We accomplish that by expanding Eq. 1 to introduce an additional energy term E_{unc} and a corresponding (relative) weight δ:

$$E_{snake} = \alpha \cdot E_{cont} + \beta \cdot E_{curv} + \gamma \cdot E_{edge} + \gamma \cdot E_{edge} + \delta \cdot E_{unc} \tag{2}$$

The additional energy term E_{unc} describes the discrepancy between the current snake solution and the pre-existing information. It has an effect similar to that of a spring attracting the current snake solution towards its prior record. Change is detected if and only if the gray value content of the new image supports the notion that the object has moved beyond the range of attraction of its older record, breaking its spring-like effect. If the new image content is only suggesting a small move within the limits of the older information's attracting force we do not detect change. In this case, the spring-like force will keep the snake in its earlier location, avoiding the extraction of yet another version that does not differ statistically from its older version.

3.1 Modeling Uncertainty

The above presented differential snakes model is making use of expressions of the uncertainty with which information can be extracted from an image. To model this type of uncertainty we use a method based on fuzzy logic.

Uncertainty information resides implicitly in the values of snake energy E_t and the rate of energy change (DE_t) along a road segment. The analysis of these values at various locations along the snake contour describes how well the extracted contour approximates an ideal road model (as it is expressed by Eq. 1) at these points. More specifically, we use snake energy information to generate uncertainty values (U) using fuzzy linguistic rules. One can select various sets of linguistic values to express the range of energy, uncertainty, and energy rate values. In our approach we use: E_t={low, medium, high}, DE_t={low, medium, high}, and U={low, medium, high}, with each membership function following a Gaussian shape. A fuzzy rule base is the generated, expressing the interrelationship between energy, energy gradients and uncertainty. A sample from this fuzzy rule base is:

- *If E_t is LOW and DE_t is LOW, then U is LOW*

Through this analysis we can assign uncertainty estimates to all points along an extracted outline. The uncertainty coefficients (in the range 0-1) are saved together with the coordinates of the points. By multiplying an uncertainty coefficient by a global accuracy measure we obtain pixel accuracy measures for points along a snake. The global accuracy measures are expressions (in pixel units) of the expected accuracy in extracting a linear object from a specific image.

The additional energy term of Eq. 2, describing the effect of prior information (and its corresponding measures of uncertainty), is expressed conceptually as:

$$E_{unc} = f\,[Unc(v0_i),d] \qquad (3)$$

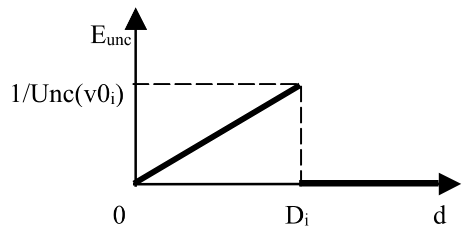

Figure 2: Uncertainty energy (E_{unc}) diagram

This additional energy term at a specific point is a function of the uncertainty with which we know the corresponding prior information ($Unc(v0_i)$), and the distance (d) of the current point from the older outline. Drawing from physics we define this energy term to be proportional to the distance between the current solution and the prior outline, inversely proportional to the corresponding uncertainty of the older outline, and acting within a threshold D_i. Beyond the threshold, this energy component is cancelled. In mathematical terms, this energy function is given by the set of equations:

$$E_{unc} = [1 / D_i \cdot Unc(vO_i)] \cdot d \quad (\text{if } d < D_i) \qquad (4)$$
$$E_{unc} = 0 \quad (\text{if } d > D_i)$$

where $Unc(v0_i)$ and D_i are as defined above, and d is the distance between current point (v_i) and original outline. The diagram of this function is shown in Fig. 2.
Based on this modeling of uncertainty energy, when prior information is known with high uncertainty (low accuracy), its equivalent force is small but operates over a rather large interval. When it is known with low uncertainty (high accuracy), its equivalent force is strong but operates over a short interval.

The threshold D_i is a parameter that defines the neighborhood over which the prior information is actively affecting the current object extraction process. Its statistical meaning is equivalent to the selection of confidence intervals in statistical analysis (e.g. selecting a global interval D_o for a complete curve to be equal to 3 times the standard deviation of our solution). Accordingly, the local evaluation D_i of this parameter can be defined at each location along an outline as:

$$D_i = D_o \cdot Unc(vO_i) \qquad (5)$$

where $Unc(v0_i)$ = local uncertainty value, in the range (0,1), and D_0 = global threshold. A more detailed description of the differential snakes model may be found in (Agouris et al., 2001b).

4. DIFFERENTIAL TEMPLATE MATCHING

While the differential snakes method presented in section 3 above is suitable for roads and other curvilinear smooth objects, it does not support operations on buildings and other similar objects. The outlines of such box-like objects violate the smoothness criteria of Eq. 1, forcing the extracted outlines to overshoot corners. Accordingly, we have developed a technique that makes use of least squares template matching to detect changes in buildings.

Our change detection method employs least squares matching for the detection and tracking of edges in digital images. Using prior information we generate a window depicting an edge pattern, and introduce it as a reference template. This reference template will be matched to digital image patches in the vicinity of actual edge segments. The concept behind the method is simple yet effective: by matching the edge template window to an image window, we can identify edge locations in the image as conjugate to the a priori known template edge positions [Gruen & Agouris, 1994].

Assuming *f(x,y)* to be the reference edge template and *g(x,y)* to be the actual image patch, a matching correspondence is established between through least squares matching, observation equations can be formed relating the gray values of corresponding pixels, and they are linearized as:

$$f(x,y)-e(x,y) = g^o(x,y)+[fg^o(x,y)/fx]dx+[fg^o(x,y)/fy]dy \qquad (6)$$

The derivatives of the image function in this equation express the rate of change of gray values along the *x* and *y* directions, evaluated at the pixels of the patch. Depending on the type of edge, the geometric relationship describing the two windows may be as complex as an affine transformation, or as simple as a simple shift and/or rotation. Regardless of the choice of geometric transformation, the resulting observation equations are grouped in matrix form as:

$$-e = AX - l\,; \quad P \tag{7}$$

In this system, l is the observation vector, containing gray value differences of conjugate pixels. The vector of unknowns x comprises the shift at the x direction, while A is the corresponding design matrix containing the derivatives of the observation equations with respect to the parameters, and P is the weight matrix. A standard east squares solution allows the determination of the unknown parameters as:

$$X = (A^T PA)^{-1} A^T Pl \tag{8}$$

While the above formulas reflect a standard template matching method, our problem introduces certain challenges. Indeed, comparing templates of the same object in various time instances and often captured by different cameras introduces large amounts of noise. In order to optimize the performance of our template matching method, we have to minimize the effect of radiometric variations among the two images (e.g. due to noise, differences in general histogram properties, or even different resolutions). Towards this goal we have developed a technique that analyses the content of matching windows to identify edges in them and assign higher weights to these locations (Agouris et al., 2000). This allows the solution of Eq. 8 to focus mostly on the information conveyed by outlines and thus be less susceptible to changes in common radiometric variations.

The variance-covariance matrix Σ_X of the solution of Eq. 8 expresses the error in locating the object's outline, and can be used to differentiate between change detection and versioning in a manner similar to the process outlined in the previous segment. A more detailed description of our differential template matching approach for change detection in buildings may be found in (Agouris et al., 2000).

5. EXPERIMENTS

The differential image analysis methods presented in this paper has been implemented in a PC, using Matlab. Fig. 3 and 4 present the application of our differential snakes technique to update road segments. In Fig. 3 we can see a prior record of a road's outline projected onto th enew image. In this specific application the outline was extracted from an older image using a snake solution, and points 1-5 are nodes from that snake solution. Of course, prior information may have been extracted with any of available techniques, and then points along the outline may be selected using any type of sampling technique. The circles around the nodes of Fig. 3 are a visualization of the corresponding accuracy measures. It is easy to see that nodes 1 and 2 are available with higher accuracy than nodes 3-5.

Fig. 4 shows the result of change detection (top) and versioning (bottom) for the data of Fig. 3. By comparing these figures it can be easily seen how the new road segment (as captured in the image) lies within the threshold of nodes 3-5, but clearly beyond the threshold of nodes 1 and 2. Accordingly, during change detection nodes 1 and 2 move to the correct location and this change is recorded (dashed line in Fig. 4 top). Subsequently, nodes 3-5 are moved during versioning, to improve the accuracy of the recorded outline. The result of versioning is marked as dashed line in Fig 4 bottom. Together, change detection and versioning comprise a complete updating process for this road segment.

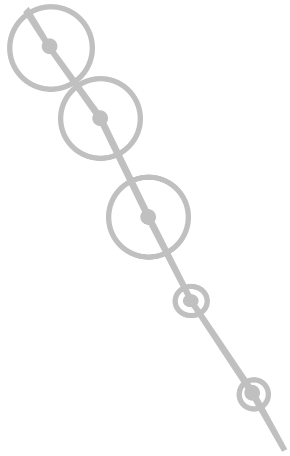

Figure 3: Pre-existing information (outline and accuracy information) projected onto a new image window.

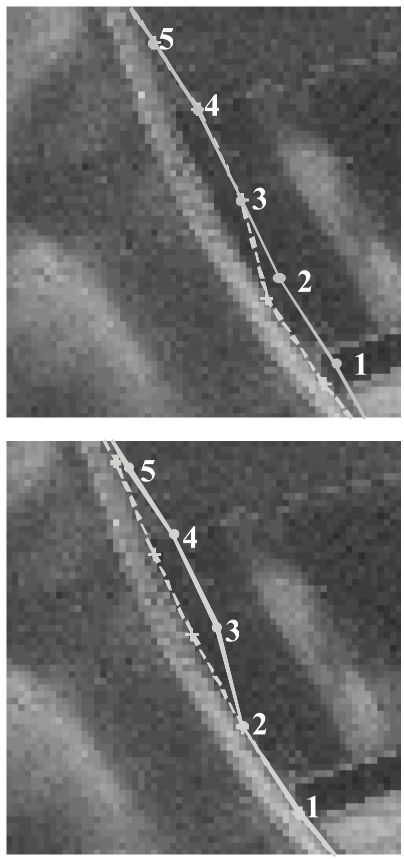

Figure 4: The results of change detection (top) and versioning (bottom).

In our applications, the average time required to perform change detection for a typical road segment was 2.1 sec, while versioning required 0.6 sec, for a complete cycle requirement of less than 3 sec per road segment (using a 1.1GHz processor). When proceeding with a node redistribution process to best describe the geometric complexity of the extracted outline

(Agouris et al., 2001a) we can expect an additional 0.4 sec in computational time per segment.

Fig. 5 shows an application of differential template matching to update a building outline. An older outline has been projected onto a new image. The lower part of the figure shows a zoomed window of the shaded area of the top. We can see that the older outline (thick black line) did not include the new addition (at the bottom left of the figure). Our algorithm proceeded by checking points along the outline as indicated by the check marks and crosses in Fig. 5. A check mark indicates a successful match (where established that nothing changed), while a cross indicates a failure (and therefore marks change). We can see crosses marking correctly the part of the older outline where the new wing was added. The spacing of the points to be checked along the outline depends on the resolution of change that we are after. It also affects in an obvious manner the time required to perform this differential analysis process. For the set-up of Fig.5 the time required to complete the process was approximately 1 minute.

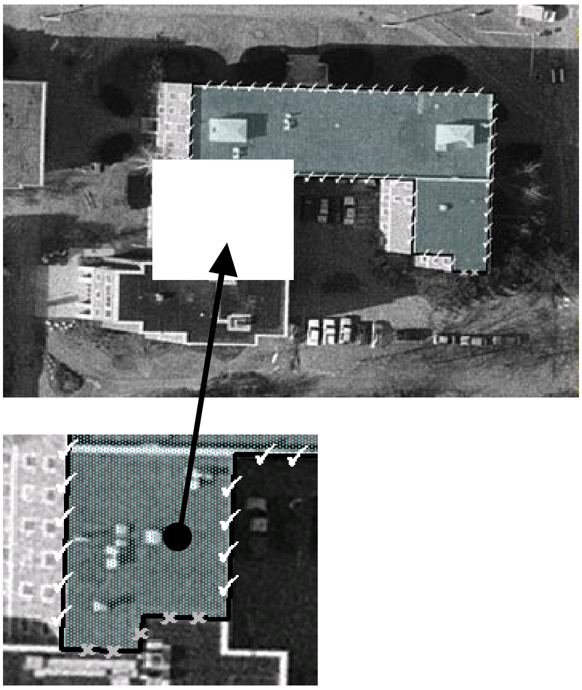

Figure 5: Application of differential template matching for building updating.

6. CONCLUSIONS

The accelerated rate of change of modern environments is bringing forward the need for frequent updates of GIS databases. Digital imagery is highly suitable for this task, as advances in sensors and platforms have expanded its availability to unprecedented levels of spatial and temporal coverage. In this paper we presented an image-based GIS updating framework and corresponding image analysis algorithms developed by our group to automate GIS updates. They can handle both smooth curvilinear features (like roads) and regularly-shaped ones (like buildings). Our approach is characterized by the comparison of a new image to pre-existing information through an automated image analysis tool.

By making use of pre-existing information in the form of outlines and accuracy estimates we establish a fully automated updating process. This allows us to update the record of a road segment in less than 5 seconds, and to examine a complete building outline in approximately 1 minute. We are also able to differentiate between change detection and versioning, eliminating the confusion caused by the recording of numerous slightly different records of an object that has actually remained unchanged. We are currently working on integrating our techniques with work on scene similarity metrics to support the updates of abstract GIS views, and on extending the application of the techniques presented here to handle moving objects.

7. ACKNOWLEDGMENTS

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