Automatic Change Detection and Updating of Topographic Database by Using Satellite Imagery: A Level Set Approach

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ABSTRACT:
In order to keep up-to-date geospatial data in topographic databases, automatic change detection and data updating is required. In the presented paper, we investigate the automatic change detection of geospatial data by using level set active contours. We propose an approach that is based on region comparison between two multi-temporal datasets. Firstly, the regions are extracted from two co-registered images taken apart in time by using level set based active contours segmentation. Then, the change detection is performed by comparing spatially the resulting region segments from the two images. The approach is validated by experiments relating to the change detection of lake surfaces by using Landsat7 multi-spectral imagery.

Keywords: Level set contours, features extraction, Landsat7 images, segments comparison, change detection.

1. Introduction
In recent years, Geographic Information System (GIS) technology has been gaining more and more popularity. The GIS are used by experts of many areas to analyze and query geographic databases. An important factor in the GIS, however, is to provide up-to-date spatial data that requires continuous updating of the database information. With the tremendous growing of the geographic databases and the rapid change of spatial data arises the necessity to develop automatic techniques to perform the change detection and update the datasets in shorter time, low cost and high degree of precision. This becomes possible by using the huge quantity of high-resolution satellite and airborne imagery that is available nowadays, where image processing techniques can be used to track the change of spatial data on multi-temporal images. Although, the research work for change detection is not a new topic, improving the accuracy of old techniques and introducing new ones is the focus of most current works (Li et al., 2002).

To date, various approaches have been investigated for automatic change detection. Most of them deal with the change detection between two multi-temporal images or consider the change between the database content and a recent image. In the former, the difference between the extracted features from the two images is calculated, followed by quantification and an identification of the change (Armenakis et al., 2002; Radke et al., 2005). In the latter, the content of database is compared to the extracted features from a recent image (Li et al., 2002). The technique of deformable contours has been widely investigated in this approach. After initializing a contour from a database polygon representing object, it is deformed spatially on a recent multi-
spectral image to track the new localization of the object (Agouris et al., 2001, Bentabet et al., 2002). The contours deforming is governed by an energy functional which has a minimum value when the contour is aligned with the tracked object boundaries. However, the Snake model has several shortcomings that limit its practical use. Due to the parameterization, the use of the Snakes is confined to the detection of deformed regions which has not undergone any modification of topology like splitting, or merging with other regions. The introduction of level set formalism for active contours has brought numerous advantages over the Snakes in several regards which make its use very promising (Osher et al., 1988). Firstly, the contours are no longer constrained to keep their initial topology; that is, they can split and merge automatically during their evolution (Osher et al., 1988). Secondly, the level set contours implementation has numerical stability that makes their use neither constrained by contours initialization, nor by the parameterization like the Snakes (Caselles et al., 1997).

In the present paper, we investigate the use of level set active contours for change detection between two multi-temporal datasets by using a two step algorithm. In the first step, region features are extracted from two co-registered images by using level set active contours segmentation. In this segmentation, the regions are identified by their color and texture signatures (homogeneity) as well as their boundaries (contrast) (Allili et al., 2004). In the second step, to detect regional changes a spatial comparison is operated between the polygons describing the region features in the two images. The use of level set active contours to implement the features extraction allows for tracking split and disappeared/appeared regions; then, updating the database content accordingly. The images taken apart in time are assumed to be co-registered before region extraction. Thus, the comparison of the features is performed by merely calculating the differences between the region localizations in the two datasets. To validate the approach, an application for lake surface change detection is proposed by using multi-spectral Landsat7 TM imagery.

This paper is organized as follows. In section (2), we give an insight on some recent works for change detection that used active contours approach. In section (3), we present the level set formalism for multiple regions tracking on an image. In section (4), an application for lake surface change detection is presented where the change detection is shown on real examples. We end the paper with a conclusion is presented and some future perspectives.

2. Related works

Automatic change detection by means of image comparison is not a new technique (Radke et al., 2005). Many works in the past investigated this technique by performing, most often, a comparison at pixel-level between two multi-temporal images (Li et al., 2002). However, the change detection based on pixel-level makes the approach very sensible to noise and variation of illumination. Besides, the approach depends on an empirical choice of a threshold to distinguish between significant and non-significant changes caused by noise for instance (Radke et al., 2005). Bringing the change detection to pixel-block or region level is a suitable approach to overcome the problem of noise. It remains, however, a major problem of how to extract automatically and accurately the blocks or regions to be matched from multi-temporal images (Armenakis et al., 2002). In the present approach, a framework is proposed to extract in a full automatic fashion the region features from multi-temporal images and to detect the change in the features by using their spatial comparison. The features extraction from the images is based on level-set active contours segmentation that we proposed recently in (Allili et al., 2004).

Note that active contours have been already used in the past for automatic change detection, where the Snake model was the mostly applied. To track the new localization of a modified object, a Snake contour is initialized from the database vector that represents the object. Then, the contour is deformed on a recent image where the deformation is constrained by the image content.
to be aligned with the new object boundaries (Agouris et al., 2001; Bentabet et al., 2002; Auclair-Fortier et al., 2000; Jodouin et al., 2002). However, due the physical properties of the Snake model, the approaches can only be used to track small deformations undergone by the objects being changed. That is, to guarantee the convergence, an initial Snake should be initialized near the new localization of the modified object. Besides, Snakes are unable to track objects that have undergone topology changes like splitting or merging with other regions. This constitutes for itself a major limitation since region changes involving modification of topology occur very often in nature (for water bodies, man-made objects...etc).

In the present work, the active contours implementation is based on level set formalism that has no constraint on topology changes. The proposed algorithm for change detection is composed of two phases. In the first phase, an extraction of homogeneous regions is performed on multi-temporal co-registered images by using level set active contours. The co-registration of the images can be performed by using image matching theory (Brown, 1992). In the second phase, the change detection is performed by comparing spatially the extracted region features from the images. Note that the approach could be also used to compare directly the database polygons and a recent image having regions extracted via the level set segmentation. In figure (1), an outline of the main steps of the algorithm for change detection between a pair of images acquired apart in time is shown.

3. Level set deformable curves for multiple regions tracking

3.1 Level set formalism for active contours

The Snake model was introduced by (Kass et al., 1988) and was designed to track a single connected region on the domain of an image $I(x,y)$ A Snake is defined as a parametric planar curve $\tilde{C}(s,t) = (x(s,t), y(s,t))$, where $s$ and $t$ are respectively the arc-length and the time parameters. To track a region boundary, the Snake is deformed from an initial localization by
minimizing a global energy functional. Then, the motion in time of the \textit{Snake} in the normal direction $\tilde{N}$ is given by the following equation:

$$\frac{\partial \tilde{C}(s,t)}{\partial t} = V\tilde{N} \quad (1)$$

Where $V$ represents the velocity of the curve. The \textit{Snake} $\tilde{C}$ shrinks or expands according to the sign of the velocity $V$. However, it is unable to change its topology due to the parameterization. Contrary to \textit{Snakes}, Level set representation for curves allows for automatic topology changes like splitting and merging (Malladi et al., 1995). In the level set formulation, the contour $\tilde{C}(s,t)$ is embedded as the zero level set of a 3-D distance function $\phi : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$ as shown in figure (2). This means that the curve $\tilde{C}(s,t)$ is given at any time by the zero level set of $\phi$, as represented by the following definition:

$$\tilde{C}(s,t) = \{(x(s,t), y(s,t)) / \phi(x, y) = 0 \} \quad (2)$$

The geometric definition of the \textit{Snake} based on the level set formulation was firstly proposed by (Caselles et al., 1997). Based on eq. (1), the zero level set is propagated in the normal direction by the following motion equation:

$$\frac{\partial \phi}{\partial t} = V |\nabla \phi| \quad (3)$$

Level set active contours have shown superiority over the \textit{Snakes} in many works. Firstly, the accuracy of tracking was significantly improved by the ability of the level sets to track region cusps. Secondly, the level sets are numerical stability since they have less parameter to control than the \textit{Snakes} (Caselles et al., 1997). In figure (2), we show a level set representation for a planar curve, where the zero level set representing a planar curve split during its evolution into two distinct parts.

![Figure 2: Level set representation of a planar curve. Figure (2.a) shows a deformed planar curve in the normal direction. Figure (2.b) shows a level set representation of a curve, where the curve was split by the deformation.](image)

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3.2 Extension of active contours to multiple region tracking

The extension of the method to multiple regions tracking requires that each region is distinguishable from the others by some specific criteria. In the present work, this is accomplished by using a characterization for the regions based on boundary and region information (Allili et al., 2004). We describe statistically the homogeneity of each region $\Omega_k$ by assuming the distribution of its color following a multivariate probability density function. The boundary information is extracted by using a filtering technique (Drewniok, 1994). Then, the tracking consists of deforming a level set contour for each region with respect to the extracted information. In our approach, a contour moves in the direction that maximizes the posterior probabilities of the pixel color inside the regions. Meanwhile, the boundary information put a constraint on the level set curves to stop motion at the region boundaries. To formalize this, consider an image composed of $M$ regions. The motion equation for each region contour is given by the following equation:

$$\frac{\partial \phi_k}{\partial t} = (\alpha \cdot V_b(x,y) + \beta \cdot V_r(x,y)) \left| \frac{\nabla \phi_k(x,y)}{\nabla \phi_k(x,y)} \right|$$ (4)

In the above equation, $V_b$ and $V_r$ represent respectively the boundary and the region information that is extracted from the image. The equation has the following property: In the interior of a region, the boundary term vanishes and only the region term drives the curve toward the region boundaries. In the vicinity of an edge, the boundary term forces the curve to stop its motion. In the equation, the coefficients $\alpha$ and $\beta$ represent the weights that control the contributions of the boundary and region terms respectively. The boundary and the region velocities are given respectively by the following equations:

$$V_b = g(|\nabla I(x,y)|) \kappa - \lambda g(|\nabla I(x,y)|) \frac{\nabla \phi_k(x,y)}{|\nabla \phi_k(x,y)|}$$

$$V_r = e_k(x,y) - e_h(x,y)$$ (5)

Here, the symbol $g$ represents a strictly decreasing function of the module of the image gradient $|\nabla I(C(s,t))|$ and $\kappa$ is the Euclidian curvature of the zero level set. The symbol $e_k$ (resp. $e_h$) represents the logarithm of the posterior probability function of the tracked region $\Omega_k$ (resp. $\Omega_h$). Here, $\Omega_h$ represents the region that has the maximum posterior probability for the pixel $(x,y)$. This signifies that the attribution of pixels for each region $\Omega_h$ results from the competition between the region $\Omega_k$ and the region $\Omega_h$.

In figure (3), we show an outline of the active contours segmentation. Here, four regions are tracked by using four level set contours initialized in the interior of the regions. The different forces acting on the contours are represented by the arrows. The blue arrows represent the region force that acts on the deformed contours, mainly in the interior of regions. The red arrows represent the boundary force that constrains a deformed contour to stop its motion in the vicinity of a region boundary. Remark that a region could be initialized by several contours since level set implementation permits the contours splitting and merging during their evolution.
3.3 Polygon comparison

Assume now the region features are extracted from two multi-temporal images. To detect the region changes, spatial comparisons are operated between the region segments (polygons). A segment is defined as a connected set of pixels enclosed by a contour. According to the above segmentation model, a region $\Omega_k$ can be constituted of several segments. However, before comparing any two segments, one has to ensure that they belong to the same region that has undergone some spatial change. A prior step is then needed to identify for each segment in the old image the segments in the new image to be compared with. To perform this identification, we use the region and boundary features of each segment as following:

Let us denote by $S^{(o)}$ and $S^{(n)}$ the set of segments in the old and new image respectively. Having a segment $S^{(o)}_k$ in the old image, we identify $S^{(n)}_h$ as a candidate segment in the new image to be compared with if satisfies the following conditions:

1. $S^{(o)}_k \cap S^{(n)}_h \geq \tau$.
2. $D(S^{(o)}_k(\mu_k, \sigma_k), S^{(n)}_h(\mu_h, \sigma_h)) \leq \xi$, where $\tau, \xi \in \mathbb{R}^+.$

In the first condition, the symbol $\cap$ designate the set intersection. This condition states that two segments have to be compared if they intersect. The threshold $\tau$ controls the significance of the intersection. The second condition is a distance between the region features of the two segments, which have to be small. This condition imposes for the two segments to share the same region properties; namely, the mean $\mu$ and the variance $\sigma$ vectors of their data. This ensures that the segments are originated from the same region, which has undergone some spatial change. In our case, we used the following statistical distance to measure the similarity between two segments content:

$$D(S^{(o)}_k, S^{(n)}_h) = 2 - \frac{2\mu_k \cdot \mu_h}{\|\mu_k\|^2 + \|\mu_h\|^2} - \frac{2\sigma_k \cdot \sigma_h}{\|\sigma_k\|^2 + \|\sigma_h\|^2}$$  \hspace{1cm} (6)
The value of the above distance is in the range $[0, 2]$, where values near zero correspond to the similarity of the statistical region information in the two segments $S_k^{(n)}$ and $S_h^{(n)}$. Once the set of new segments to be compared is established for each old segment, the quantification of the change is performed. In figure (4), we show the types of changes that can be detected by the algorithm. The green areas represent new added (appeared) parts to the segments and the blue ones represent the deleted (disappeared) parts.

Note that when an old segment has an empty set of new segments to be compared with signifies that the old region disappearance and, therefore, has to be removed from the dataset. Finally, to identify newly appeared regions in the recent image, the same process of comparison is performed, but now with reference to the new image segments. We consider a segment to be appeared if no segments in the old image constitute candidates to be compared with, according to conditions 1) and 2).

![Figure 4 An outline of the different types of change detection that can be detected by spatial comparison of the segments on multi-temporal images.](image)

### 4. Experimental results

The experimentation that we have conducted concerns the change detection of lake surfaces by using *landsat7* satellite imagery. The resolution of the images is of 30 meters. To obtain the best distinction of water bodies, we combined two bands in the color spectrum. The fourth and the fifth band, that constitute the infrared of the spectra, are used for their high absorption by water
bodies. Figure (5) shows an example of features extraction carried out on two multi-temporal images and the change detection after comparing the extracted features. Figure (5.a) and figure (5.b) represent respectively the original images and the obtained region polygons after features extraction. We refer the reader to (Allili et al., 2004) for further details concerning the automatic region initialization and the segmentation model implementation. Figure (5.c) shows the detected changes after comparing the extracted features. On the figure, the changes marked (1), (2) and (3) show respectively the disappearing of small lakes. The changes marked (4) and (5) show, rather, a modification of the boundaries of the lake surfaces.

Figure 5: An example of automatic features extraction by using level set active contours for region tracking and change detection. The rows (a) and (b) shows respectively two multi-temporal images and the resulted features extraction. The row (c) represents the detected changes after comparing the segments. In the experiments we put: $\tau = 20$ and $\xi = 0.3$. 

\[ \tau = 20 \text{ and } \xi = 0.3 \]
We should note finally that radiometric effects may influence the change detection since one cannot guarantee the same conditions of acquisition of the compared images. In this case a preprocessing step is required to eliminate this effects or use techniques based on histogram matching for segments comparison as suggested in (Radke et al., 2005). For computation time, the approach is not very consuming. It takes about 4 minutes to track all the regions of a 512x512 image when we run the program on a Pentium4, 2.5 GHz processor.

5. Conclusion

In the presented work, we proposed an automatic approach for change detection and updating of topographic databases based on level set active contours for region extraction and comparison. We showed the ability of the approach to detect changes that involve the modification of the topology of the regions. By this ability, the superiority of level set contours over the classical Snake model in change detection is demonstrated. We validated the approach by an application for lake surface change detection where the obtained results are very promising for application in other kind of area surfaces (urban, vegetation, ice bodies…etc). Besides, we propose in future researches to add to the model more characteristics (texture, shape) features to enhance the description of regions.

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7. References


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