OBJECT BASED CHANGE DETECTION USING TEMPORAL LINKAGES

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ABSTRACT:

Change detection plays an important role in GIScience. Using appropriate methods of change detection allows us to observe, detect and analyse spatial processes which took place in the past. Furthermore, it enables us to understand processes in more detail, develop models and predict potential future situations. Remote sensing data as data source for change detection has the advantage of imaging the earth's surface as is just using electromagnetic radiation. However, using remote sensing data as the basis for change detection has always been difficult since a lot of knowledge from image processing and remote sensing is necessary in order to detect and outline relevant changes. Space-temporal knowledge about the object categories to observe is necessary in order to determine which changes are the result of the natural space temporal behaviour and which are a relevant change. By linking image objects of images taken at different dates via the time axis it is possible in principle to observe and assess their space-temporal behaviour and to decide whether this behaviour is natural or relevant in terms of a change or not.

1. INDRODUCTION

1.1 Change detection

Change detection based on geo-data is certainly one of the most important and challenging tasks in the GIScience domain. Focusing on multi-temporal remote sensing data, change detection methods are used in order to point out and document changes relevant for diverse application domains. Typical examples of such applications are: mapping processes as like urban sprawl, desertification or dry-out of lakes (Jat et al, 2008; TRIPATHY et al., 1996; Collado et al. 2002; Diouf et al., 2001). That is, when doing change detection with multi-temporal remote sensing data at least two images of a given region taken at different dates (t0 and t1) are compared and differences relevant for the application domain are mapped. For detecting changes over longer periods and with data measured at more than two dates (t0 … tn) the term *monitoring* is commonly used. In this context, a critical point for change detection using remote sensing data is to detect only the relevant changes.

1.2 Object based change detection

A rather simpler approach is to independently segment all images taken at t0, t1 or tn, virtually overlay them and identify corresponding image objects. However, this method presumes a spatial overlap of the temporal corresponding objects in order to establish a respective connection between them. Nevertheless, this way it is possible to observe and document the objects' courses and to decide whether the observed behaviour is normal or a change.

2. METHODOLOGY

2.1 Image segmentation and object linkage

In order to perform an object based image analysis using linked objects it is necessary to generate image objects which are timely independent. That is, each image of t0, t1 and tn needs to be segmented independently. For this purpose we have been using the software eCognition 8.7 by Trimble Germany, which allows to segment images on several scale levels and additionally to link spatially coherent objects using so-called maps. Each map in this particular case represents a single date and image, respectively. The software even allows loading image sequences. It automatically generates for each time frame a respective map. The map concept can also be used to independently segment images of different sensors and link corresponding objects (fig. 1).

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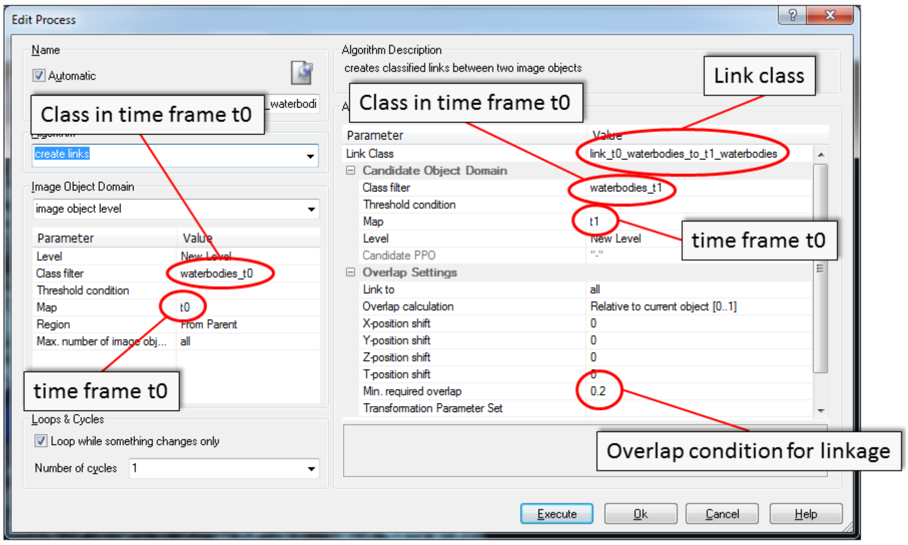

Figure 1: eCognition dialog for creating links between images of different time frames.

When linking objects of two different time frames the following principle relationships have to be considered:

(1) each object of time frame t0 can be linked to one or more objects of time frame t1 (1:n relationship).
(2) several objects of time frame t0 can be linked to one object of time frame t1 (n:1 relationship).
(3) objects of time frame t0 and t1 can be linked pairwise (1:1 relationship).
(4) objects of time frame t0 and t1 can have no object linked in either t1 or t0 respectively (1:0 and 0:1) relationship.

2.2 Multi-temporal image data

For our research we decided to investigate two different scenarios:

a) Detect changes in a pair of cohesive images of date t0 and t1.
b) Monitor the behaviour of objects in a series of images t0 … tn.

For case a) we selected two small subsets of two LANDSAT scenes in the north-western part of Kyrgyzstan both depicting the Orto-Tokoy reservoir southwest of the lake Yssykol (Fig. 2) From 5th of July in 1993 and 20th of August 2001. For case b) we resort to a sequence of microscope images showing golgi organelles with a temporal resolution of 4s per frame (see fig. 3).

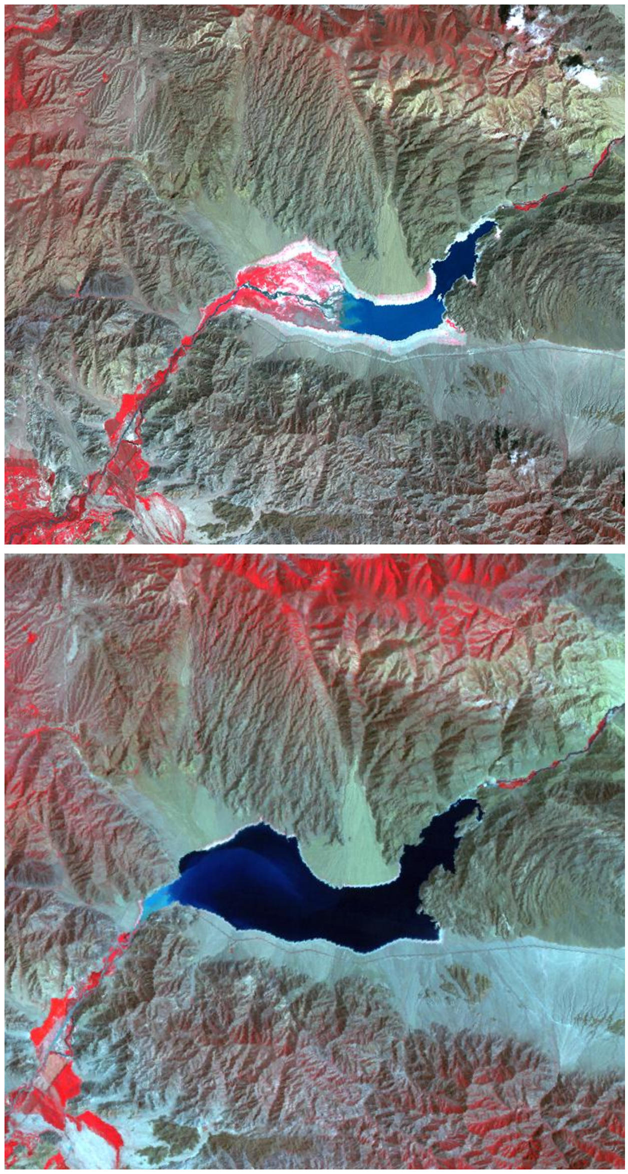

Figure 2: Subsets of LANDSAT scenes. Top 1993, bottom 2001. RGB = TM4, TM3, TM2.

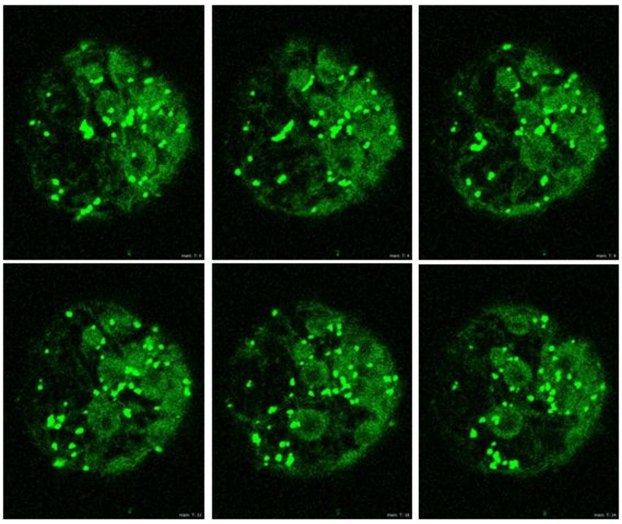

Figure 3: Sequence of microscope images from golgi organelles from. Top-left to bottom-right: t0, t4, t8, t12, t18 and t24 of 24 frames.

2.3 Linking objects in an image pair

To investigate object based change detection with image pairs (case a), we were loading the images as an image stack into the software and create respective maps representing the images of t0 and t1. We then segmented both maps independently using the multi resolution segmentation as described by Baatz & Schäpe, 2000). Each image then has undergone an object classification, whereas the classes *waterbodies*, *vegetation* and *other non-waterbodies* were created. We have then defined different linkage classes indicating the change on a class-level. Each linkage-class connects overlapping objects of the selected classes in the t0- and t1-image via the time axis. The degree of spatial overlap can be adjusted. This way, all dried out areas and all vegetated areas that have been waterbodies formerly can be identified (fig. 5).

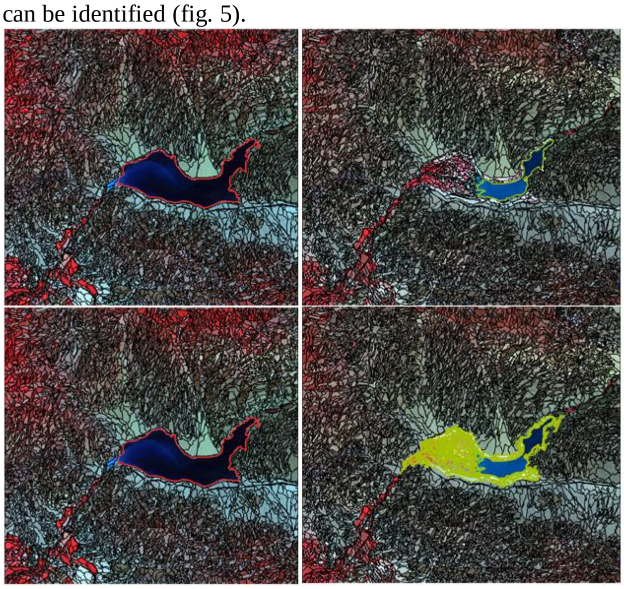

Figure 4: Linked objects in LANDSAT scenes. Left t0, red waterbodies. Right t1, green (top) waterbodies, green (bottom) non-waterbodies.

This way, it is possible to identify corresponding image objects in t0 and t1 and to assess the amount of changing area per object by analysing the underlying pixels. Additionally, by linking corresponding image objects it is possible to analyse their changing shape. For example an object that has been classified as *vegetation* in t1 has been by one part *waterbody* and by another part *vegetation* in t0. Analysing the underlying pixels, we can determine the respective area ratios (**Table 1**).

id	Class	Area at t0 [ha]	area of *unclassified* at t1 [ha]	area of *waterbodies* at t1 [ha]	area of *vegetation* at t1 [ha]
0	waterbodies_t0	2046,14	1088,17	666,29	291,68
1	waterbodies_t0	0,73	0,73	0,00	0,00

Table 1: Example for change of area amounts per t0-object calculated on per-pixel basis.

By analysing the t1-objects we can determine the change of shape and position, although the outer border of the t1-objects are not coherent with the linked t0-object(s) (see Fig.5).

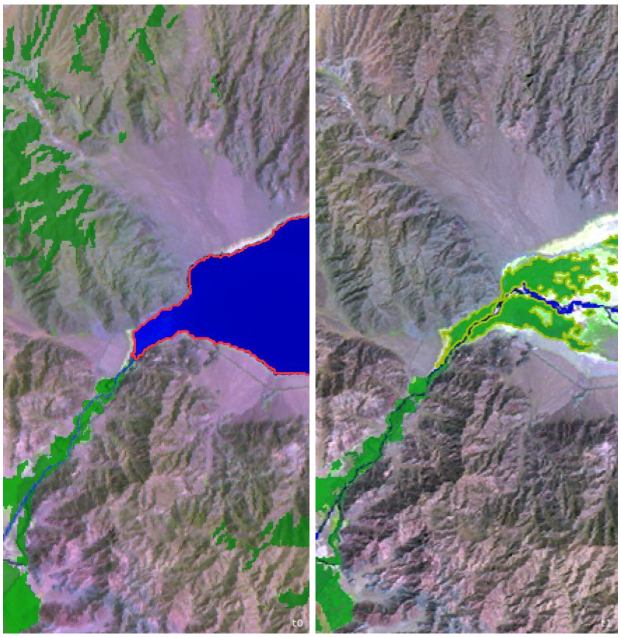

Figure 5: Waterbody (left with red outline) at t0 and linked vegetation objects at t1 (right, green outlines). The outer borders are not coherent.

2.4 Linking objects in an image sequence

In order to process the microscope image sequence we were loading the sequence as a time series. This allows performing each image processing step equally on each frame. We firstly eliminated background and separated noisy areas from those which might be of interest (organelle *candidates*). In order to document the space-temporal behaviour of the organelles, they were sequentially linked. This means, only successional organelles classified in each frame were linked (Fig. 6).

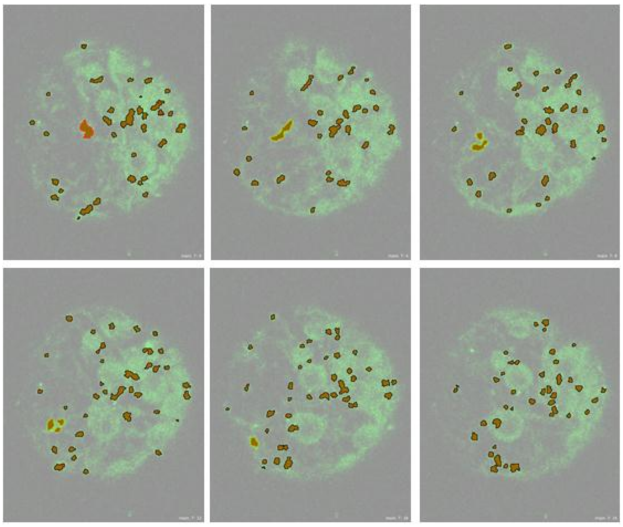

Figure 6: Linked objects in microscope image (same sequence as fig 3). Top-left in red selected object. Object can be tracked until frame 22. During its travel it splits and merges.

3. RESULTS AND DISCUSSION

We were linking corresponding image objects in an image pair of different dates t0 and t1 in order to detect changes of properties (size and shape) and simultaneously spatially document the observed changes. Further, we took an example from biology for practical reasons to demonstrate the potential for calculating space-temporal features. For this example, we were calculating the mean speed (in pixels per second) for each organelle and the distance travelled in the sequence (Tab. 2).

Table

ObjectShapes

FID	Shape	D	DX	DY	heading	i	NoOfLinkedObj	Mean v	Mean D	t0_Obj	t0_Obj_ID	v	XPos_t0	YPos_t0
0	Polygon	0	0	0	0	34	24	0	0	0	0	0	3,5	256
1	Polygon	0	0	0	0	34	0	0	0	1	1	0	250,791667	335,875
2	Polygon	1,341233	1,0375	-0,85	320,673022	34	15	0,310893	19,897142	2	2	0,335308	209,1	279,9
3	Polygon	4,422487	0,056096	4,422131	89,273222	34	22	0,74854	68,865683	3	3	1,105622	266,359375	296,25
4	Polygon	3,458043	-1,935829	2,865419	304,0423	34	6	0,543793	15,226218	4	4	0,864511	282,681818	260,924242
5	Polygon	0,339243	-0,094697	-0,325758	73,790975	34	5	0,412355	9,896509	5	5	0,084811	305,363636	296,590909
6	Polygon	0	0	0	0	34	0	0	0	6	6	0	317,5	276,75
7	Polygon	5,738742	-1,679048	5,487619	287,012547	34	120	0,852332	402,3008	22	22	1,434686	303,368571	250,654286
8	Polygon	1,338645	-0,9625	0,930357	315,972854	34	119	0,864123	400,953088	7	7	0,334661	316,4375	260,6875
9	Polygon	6,087994	5,127451	-3,282213	327,37565	34	6	0,922127	25,819567	8	8	1,521999	326,333333	295,761905
10	Polygon	0,299241	-0,112857	0,277143	292,156964	34	12	0,251168	13,060751	9	9	0,07481	348,78	283,42
11	Polygon	4,068722	3,385764	2,256346	33,680347	34	27	0,423733	45,763151	10	10	1,01718	336,987805	266,695122
12	Polygon	1,598891	1,084848	-1,174545	312,726576	34	13	0,312171	17,481603	11	11	0,399723	340,984848	258,045455
13	Polygon	4,162397	-1,122153	4,008282	285,640051	34	27	0,358901	40,196864	13	13	1,040599	190,282609	246,413043
14	Polygon	2,463889	-0,114943	2,461207	272,673867	34	1	0,307986	2,463889	14	14	0,615972	206,833333	233,375
15	Polygon	1,016535	0,951944	0,356576	20,534765	34	26	1,373099	148,29473	19	19	0,254134	254,048718	237,797436
16	Polygon	0,69091	-0,415584	0,551948	306,977596	34	2	0,17677	2,121234	15	15	0,172728	217,357143	176,809524
17	Polygon	0	0	0	0	34	0	0	0	17	17	0	216,642857	158,380952
18	Polygon	5,381502	-4,296296	-3,240741	37,027628	34	24	0,651265	65,126504	16	16	1,345375	223,888889	166,222222
19	Polygon	0	0	0	0	34	0	0	0	18	18	0	244,666667	134,5
20	Polygon	1,79689	-0,190732	1,786738	276,093182	34	25	0,579311	60,248311	20	20	0,449222	278,325397	248,722222
21	Polygon	0,83749	-0,083333	0,833333	275,710593	34	25	0,579311	60,248311	21	21	0,209372	286,041667	232,041667
22	Polygon	1,079978	0,52381	0,944444	60,986292	34	3	0,331745	5,307924	24	24	0,269994	309,357143	208,5
23	Polygon	8,564312	-7,828485	-3,473079	23,924293	34	2	1,361796	16,341556	26	26	2,141078	254,202128	143,659574
24	Polygon	7,777244	4,277898	6,495007	56,629333	34	2	1,361796	16,341556	25	25	1,944311	266,308511	153,62766
25	Polygon	1,768541	-0,278322	1,746503	279,054484	34	1	0,221068	1,768541	27	27	0,442135	306,990909	180,227273
26	Polygon	0	0	0	0	34	0	0	0	28	28	0	316,880952	175,595238
27	Polygon	7,112876	4,658824	-5,37479	310,918475	34	119	0,864123	400,953088	23	23	1,778219	322,058824	254,382353
28	Polygon	2,701038	0,831008	-2,570026	287,91841	34	97	0,773895	300,271257	29	29	0,67526	321,197674	240,174419

0 (0 out of 883 Selected)

ObjectShapes

Table 2: Results of analysing temporally inked image objects (microscope images). Each object with FID (unique ID for the whole sequence) belongs to a starting object in the first frame (t0_Obj_ID). The velocity is indicated by "v" and calculated in pixels per second.

4. CONCLUSION

Our results demonstrate the potential of multi-temporal object based image analysis using object links. We have demonstrated that it is necessary to consider four principal potential situations for temporally linked objects. Referring to the LANDSAT example in order to identify changes in many cases it might be necessary to have a clear space-temporal model of the desired object classes. In the case present it is not clear, whether the observed change is due to some natural behaviour or a true change in terms of a to-be-mapped change. The second example has demonstrated, that it is even possible to analyse complex dynamic processes using methods of object based image analysis. In order to separate different types of changes more accurately the temporal resolution of the image data used must be adequate. Especially for space-time modelling of object classes typical for Land Use and Land Cover (LULC) classifications and a reliable identification of changes temporal high resolution image data will be necessary.

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