RAPID CHANGE DETECTION ALGORITHM FOR DISASTER MANAGEMENT

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Kurzfassung:

1. INTRODUCTION

Change detection analyses are known as useful methods in a wide field of applications where two images of the same area taken at two or more different time steps were compared in order to identify changes (Radke et al., 2005). A main focus of these analyses is on ecosystems as they are in a permanent conversion (Coppin et al., 2004). Image differencing, post-classification comparison and principal component analysis are popular methods in change detection studies. During last decades artificial neural networks and spectral mixture analysis were carried out as feasible methods for change detection as well. An overview of the typical change detection methods could be found at Jianya et al. (2008) and Lu et al. (2004). In recent years change detection methods become applicable in particular to the field of disaster management (Günther et al., 2011; Al-Khudhairy, Caravaggi, 2005).

Rapid change detection is used particularly with regard to natural hazards and disasters. This analysis leads to rapid information on areas of damage. In certain cases the lack of information after catastrophe events is obstructing supporting measures within disaster management. Earthquakes, tsunamis, civil war, volcanic eruption, droughts and floods have much in common: people are directly affected, landscapes and buildings are destroyed. In any case, geospatial data is needed to gain knowledge as a basis for decision support. Where to go first? Which infrastructure is usable? How much area is affected? These are essential questions which need to be answered before appropriate, eligible help can be established. The main question after a catastrophe which has to be answered is where to help? In the context of this background, the paper represents a new way of analyzing remote sensing data with regard to rapid results. By using panchromatic datasets and simple, automated and transferable algorithms, comparable results for different case studies were carried out. The cognition net-
work language (CNL) which is implemented in Trimbles eCog-
ition Developer was used to design an easy to use algorithm
which rely on an Temporal Change Index (TCI).

2. INVESTIGATION AREAS AND DATA

For the development of an automated transferable algorithm for
rapid change purposes different investigation areas were used.
In the focus of interest were four villages in Darfur as part of
Western Sudan (see fig. 1) which were affected by civil war
actions in this African region. In addition there is a small area
of urban patterns in Zimbabwe (Porta Farm, a slum near
Zimbabwe's capital Harare) with different housing structures to
check transferability of the developed algorithms.

Figure 1. Investigation areas. Source: own representation based
on Bing Maps (Copyright © 2009 Microsoft Corporation).

Darfur is experiencing a complex structure of violence that led
to a civil war with a peak in the years 2004 to 2006 (Reyna
2011). The circumstances which lead to the disaster of more
than 200,000 persons killed and more than 2 million displaced
people are not completely clear today (Kevane; Gray, 2008).
The history of colonialism since the late 19th century to the
droughts in 2003 leads to damage in human settlements in great
parts of Darfur (Reyna 2011). This paper focuses on rapid
change detection which is useful for several applications like
monitoring of ongoing war actions, monitoring of new building
constructions and urban growth and detection of affected areas
for disaster management. A crucial factor for fast analysis and
processing is the use of remotely sensed data with sparse pre@
processing and low specific requirements to gain transferability.
In addition a farm with about 850 buildings, where
condemnation took place, will be investigated.

The remote sensing imagery used for the development of the
rapid change algorithms are very high resolution data sets with
a pixel size of 2.4 meter and below (see tab. 1). To gain
transferability only panchromatic datasets were used, this is a
crucial factor for the mentioned application as in case of
disasters quickly captured data can be treated similar because
panchromatic datasets are available from nearly every remote
sensing platform. Each of the datasets was available in two time
steps, before and after the disaster event. Those datasets which
are available only in multispectral layers were modified by
summating the channels to get a pseudo panchromatic image (in
this study for Shangil). A basic pre-processing was necessary to
get a coarse co-registration of the image pairs (Copin et al.,
2004). No further pre-processing was necessary.

<table>
<thead>
<tr>
<th>Study Site</th>
<th>Spatial Resolution</th>
<th>Radiometric Resolution</th>
<th>Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ligeibedia</td>
<td>0.6 m</td>
<td>8 bit</td>
<td>QuickBird 2</td>
</tr>
<tr>
<td>Abu Suruj</td>
<td>0.6 m</td>
<td>16 bit</td>
<td>QuickBird 2</td>
</tr>
<tr>
<td>Donkey</td>
<td>1 m</td>
<td>8 bit</td>
<td>Ikonos II</td>
</tr>
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<td>Shangil</td>
<td>2.4 m</td>
<td>8 bit</td>
<td>QuickBird 2</td>
</tr>
<tr>
<td>Zimbabwe</td>
<td>0.6 m</td>
<td>8 bit</td>
<td>QuickBird 2</td>
</tr>
</tbody>
</table>

Table 1. Remote Sensing Data Specifications of the Different
Investigation Areas

3. METHODOLOGY

The main goal of this study was to detect the changes in the
investigation areas in three categories: destroyed, preserved and
new constructed in a bi-temporal image change detection
framework. Jianya et al. (2008) identified three general ways for
change detection methods: direct comparison, post-analysis
comparison and uniform modeling. In the presented study direct
comparison was used in an object-oriented approach without
post classification. This kind of analysis can’t be defined as
belonging to any category described in the change detection
review studies in (Coppin et al., 2005; Blaschke, 2005; Radke
et al., 2005; Jianya et al., 2008).

Workflow

The general workflow (see fig. 1) consists of three steps. Due to
the fact that only manmade objects are of interest, the first
processing step is the semi-automatic definition of the area of
interest (AOI). In the presented framework the contrast split
segmentation (Trimble, 2011) is used to divide the datasets into
AOI and area of no interest (AONI). By definition of an upper
and a lower threshold for the brightness of objects, the
segmentation optimizes the contrast between neighboring
objects and a preferred object size. This segmentation is done
on the data before (T1) and after (T2) the disaster event
separately. If the resulting objects size is similar to the
given parameter during segmentation, those areas are
considered as area of no interest. This step is done three times
with decreasing object sizes and can be described as AOI
definition. This step is somehow a basic classification without
using feature space criteria. The result is thematic information
about areas which are homogeneous and which are not in the
focus of the change detection.

Figure 2. Schematic workflow of the analysis steps.

A standard change detection algorithm is not available within
the used software; therefore the two datasets (T1 and T2) are
treated like two spectral channels of one shot with two different
object levels. By using a Temporal Change Index (TCI) (see eq. 1)
objects of interest can be compared directly in the next step.

\[
TCI = \sqrt{(\sigma(T1) - \sigma(T2))^2}
\]

where  
\( \sigma = \) standard deviation  
T1 = dataset before disaster event  
T2 = dataset after disaster event

The TCI is included as a feature for the appraisal of change. For
the time step T1, every object of the AOI will be evaluated with
the TCI. The idea behind can be described as follows: If
something is damaged the structures will be smoother and sharp
edges appear less clear, hence the standard deviation will be
smaller. Vice versa it can be assumed that new objects, which
are only on the image object level derived from T2 will show a
higher standard deviation. These circumstances can be used for
dark and bright objects as well. By a logical linkage between
the object level T1 and T2 objects of the AOI can be classified
as ‘destroyed’, ‘new constructed’ and ‘preserved’. The
evaluation of the change is done by the use of a threshold for
the TCI; low values are indicating destruction while high values
are allusion to new constructed areas.

Results
In Figure 3 a false colour composite shows the investigation
area of Abu Suruj, where the red parts are indicating structures
which are only in T2 and greenish areas showing objects which
are only during time step T1.

Figure 3. Falsecolor composite for Abu Suruj. Green = T1, Red =
T2

The outcome of the transferable algorithm is shown in figure 4.
The classification result is distinguished in AONI (area of no
interest) and in different categories of change.

Figure 4. Results of the Change Detection Analysis for the
village Abu Suruj.
In the case of Abu Suruj (see figure 4) at time T1 little huts surrounded by fences are dominating the landscape. They are clearly visible with a darker shade when comparing to the environment. While the second image (figure 5) shows areas in south-east in detail where buildings are destroyed and in north-west some new constructions were already set up.

The rule set was applied to the other investigation areas and showed similar results with modified thresholds for the definition of the AOI and for the classification of damaged areas. Figure 6 gives an overview over the village Donkey where nearly all buildings were destroyed and now reconstruction took place.

The classification result (see figure 7) was retrieved with the same rule set and only slight modifications for the thresholds. Those parts in green which are marked as 'preserved' are infrastructural objects like trails.

**Accuracy Assessment**

The results were evaluated by pixel based accuracy assessment for each investigation area with Imagine ERDAS 2010 (see tab. 2). Per scene 200 points were randomly collected and compared visually to the classification. For the selection of samples, the points were determined by using stratified random distribution over the three classes. The confusion matrix shows some differences in classification quality where the overall accuracy remains comparable. Because of absence of ground truthing possibilities only visual check of accuracy could be done with the same datasets which were uses as input for the change detection. Without a reference dataset an overestimation of accuracy cannot be ruled out. Not every scene is presented by all three classes while in some cases reconstruction didn’t took place (Shangil and Zimbabwe) or buildings were not preserved (Zimbabwe and Ligeibedia).
<table>
<thead>
<tr>
<th>Class Name</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Prod. Accuracy</th>
<th>Users Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Donkey</td>
<td>74</td>
<td>72</td>
<td>69</td>
<td>97.29%</td>
<td>93.24%</td>
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<td>28</td>
<td>26</td>
<td>24</td>
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<td>92.31%</td>
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<td>97</td>
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<td>93.14%</td>
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<td>200</td>
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<td>64</td>
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<td>192</td>
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<td></td>
</tr>
<tr>
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<tr>
<td>Totals</td>
<td>200</td>
<td>200</td>
<td>190</td>
<td>95%</td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Results of the Accuracy Assessment Calculation

The accuracy values appear to be very high when comparing to other change detection studies, especially when using only 8-bit panchromatic data for the analysis. However the restriction into three classes minimizes misinterpretation.

4. CONCLUSION AND OUTLOOK

This paper presented a new rapid change detection method for disaster monitoring based on a semi-automated algorithm by means of an adapted segmentation approach and an elaborated Temporal Change Index. It shows also great promises in transferring this algorithm to different datasets and areas. Our future work will combine different algorithms which we had developed for rapid change analyses (Sofina et al. 2011, Demharter et al. 2011, Thunig et al. 2011, Klonus et al. 2011 and Ehlers et al. 2010).

REFERENCES


