CHANGE DETECTION IN HIGH RESOLUTION SAR IMAGES: AMPLITUDE BASED ACTIVITY MAP COMPARED WITH THE COVAMCOH ANALYSIS

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ABSTRACT

Change detection based on remote sensing data has become a highly frequented field of research with multiple applications for practical use. In this study, a fully-automatic change detection method based on SAR amplitude images is proposed. This method aims at the detection of small-scaled abrupt changes which are caused for example by different kinds of vehicles or building sites. As dataset, a time series (about half a year) of TerraSAR-X images covering the scene of Greding (Germany) and surroundings was used. From this dataset, an amplitude based activity map was calculated. For evaluation purpose, this method is compared with the CoVAmCoh analysis, which represents a complementary approach for SAR change detection. In a final step, first evaluations concerning the change categorization are considered.

Index Terms— Change detection, change categorization, activity monitoring, SAR, CoVAmCoh.

1. INTRODUCTION

In the last few years, change detection based on SAR remote sensing data has become a highly frequented field of research with multiple applications for practical use [1]. To detect changes between temporarily different satellite image data is of interest for example in terms of urban monitoring and disaster management [2]. In the latter case, accurate information about the dimension and the category of the detected change has to be available as fast as possible.

Change detection in general is not only the detection of changes between two temporally different images. Furthermore, categorization of the detected changes into classes representing the kind of change is an important step of change detection (e.g. post-processing classification, [1]). The change detection method described in this paper aims at the detection of small scaled, abrupt changes which are caused for example by different kinds of vehicles or building sites. With the proposed method, it is possible to detect area of changes between two SAR amplitude images automatically. To create a robust method which is simple to generalize, only a single parameter encoding the size of the detected changes has to be set by the operator. In this paper, changes between interferometric TerraSAR-X image pairs (11 day repeat pass cycle) were detected over a time period of almost half a year. By this, temporarily stable (> 11 days) and unstable changes (11 days) could be classified. For evaluation purposes, one area of stable changes and one area of no changes are analyzed by the CoVAmCoh method [3]. Two change detection methods are introduced. In general, both methods are able to detect changes, but they partially provide complementary information. The change detection method represented by the CoVAmCoh analysis considers phase information visualized as coherence image. Therefore, this method is sensitive to even very small areas of changes.

2. DATASET

For this study, TerraSAR-X image data acquired in ascending orbit and HS300 mode covering Greding (Germany) and surroundings over a time period of almost half a year (2008/08/08 to 2008/12/07) were used. The time lag between two SAR images composing one interferometric image pair was 11 days. The pixel spacing in range direction is about 0.45 m and in azimuth direction about 0.87 m, the scene center incidence angle is about 48.5°.

3. CHANGE DETECTION

The proposed method for change detection is based on two co-registered SAR amplitude images and requires no further input information.

In a first step, two ratio images are calculated (Figure 1). From these ratios, one image is calculated containing the pixelwise maximum (maxratio1) which is the input for a morphological filter, the so called alternating sequential filter. With this filter, the maximum ratio image is despeckled by applying the morphological methods of erosion and dilatation for a chosen area size parameter [4].

This parameter, which directly affects the size of the detected changes, is set by the operator. The morphological filter is essential due to the speckle noise in the maximum ratio image. The speckle noise could cause incorrect change detection results.
Also, the use of the morphological filter allows controlling the geometrical size of the changes which depends on the change detection task at hand.

From the morphologically filtered maximum ratio image (maxratio2), a threshold to convert the image into a binary image containing the detected changes on the foreground, is calculated using the Renyi's entropy [5]. This entropy criterion is based on a two-dimensional histogram derived from the filtered maximum ratio image and the filtered maximum ratio image preprocessed by a 3x3 mean filter (maxratio2*). The optimal threshold pair maximizes the sum of the Renyi's entropies for the foreground and the background. From this pair, only the first threshold value is applied to the morphologically filtered maximum ratio image.

![Figure 1](image1.png)

Figure 1: Workflow of proposed change detection method.

The thresholded binary image contains the detected changes as object pixels on the foreground. These object pixels are marked in red in the matching amplitude image. In Figure 1, the change detection workflow proposed in this paper is shown.

4. AMPLITUDE BASED ACTIVITY MAP

If more than two amplitude images of one scene are available, a time series analysis by evaluating the several resulting change maps can be performed (Figure 1). Then, the change maps are added building one index map which contains information on the change activity in the scene. This is why we name this final resulting image “activity map”.

5. COVAMCOH

The CoVAmCoh method enables the categorization of objects in the scene into several classes by analyzing physical aspects of SAR backscattering and coherence phenomena. Initial point of this analysis is the use of an interferometric SAR image pair. In terms of using TerraSAR-X image data, this pair covers a time interval of 11 days (see above). From this image pair, one Coefficient of Variation image (CoV, window size 5x5), one calibrated mean amplitude (Am) and one coherence image (Coh, window size 5x5) are processed. These three input layers are stacked together in a RGB arrangement as follows: R = CoV, G = Am, B = Coh [3], [6]. With these three layers, a simple classification statement could be established for scene analysis: Local heterogeneity (CoV), backscatter intensity (Am) and local stability (Coh).

6. ACTIVITY MAP VS. COVAMCOH

For each adjacent interferometric SAR image pair along the time series, one CoVAmCoh image was calculated. The changes in the summarized activity map were color coded, so that temporarily stable areas of changes appear orange to red (> 11 days). Temporarily unstable areas of changes (11 days) are colored yellow (Figure 2).

Comparing one stable area of changes and one area of no changes (Figure 2) by the CoVAmCoh method, it can be seen that the stable area of changes causes relatively high CoV and small Coh values (Figure 2). In CoVAmCoh terminology: the high variation in this area over the period of time caused by the temporarily parked vehicles results in relative high local heterogeneity (CoV) and low local stability (Coh) for each interferometric image pair. Focusing on the amplitude values, the curve represents relatively high backscatter (vehicles) and variation over time (present and non-present vehicles). In contrast, the area with no changes shows relatively small CoV values (Figure 2). The higher Coh values are caused by the absence of changes.

7. CHANGE CATEGORIZATION

The aim of this step was to establish a method for the evaluation of the change category based on one feature vector characterizing each detected change segment. Several features were chosen: Area (no. of segment pixels), compactness (relation of length and width of segment dependent on the area), orientation of the detected segment relative to the x-direction in the image, backscatter
intensities ($\sigma^0$ [dB]) in the region of the segment, CoV and coherence values in the detected change segment.

As a training dataset, the first image pair of the time series was taken. From this pair, the change map was evaluated and one representative change segment was selected in the stable change area presented in section 6 (Figure 3).

With the characterizing feature values for this selected change segment in Figure 3, it can be seen that this segment has an area of 140 pixels. Taking into account that a trailer truck could have measures of ca. 17 m x 2.6 m (44.2 m²), this change segment (ca. 97.5 m² on ground) represents nearly the doubled value. Taking a view on an optical image of this region, it was observed that there are often two trailer trucks placed side by side.

The compactness of a segment is calculated as following: ($\text{length}_{\text{Bounding Box}} \times \text{width}_{\text{Bounding Box}}$)/area. So, possible values reach from zero to infinity; an ideal compact segment is given by a value of 1. With a compactness value of ca. 2, the selected segment can be examined as nearly ideal compact.

The orientation value of ca. 77 degrees shows that the selected segment is nearly perpendicular oriented relative to the x-direction in the image.

By comparing the mean backscatter intensities in this selected segment in both images (t1 and t2), it can be seen that this change segment must be present in t1 and disappeared in t2 (decreasing $\sigma^0$ values) which could be confirmed by a visual verification (Figure 3).

A CoV value of ca. 1 shows that this segment area is nearly homogeneous concerning the locality, which is caused by the lack of structuring objects (e.g. lines etc.) in this area.

As expected, the selected segment contains a small coherence value (0.4) which is caused by the change in this area.

With these features, it can be assumed that the change segment could represent two trailer trucks placed side by side disappearing in the time interval between t1 and t2.

8. CONCLUSIONS AND OUTLOOK

An automatic change detection method based on high resolution TerraSAR-X image data was introduced. As results of the change detection using amplitude image data, a map of activity areas containing color coded temporarily stable and unstable changes was calculated. This map was compared with the CoVAmCoh analysis, a change detection method based on phase information that can be used in a complementary way. Between the CoVAmCoh theory and the measured values in the two areas visualized in Figure 2, no discrepancies occurred.

As a final step, a first approach to change categorization was presented. It was shown that shape parameters combined with CoVAmCoh values could permit promising conclusions about the possible change category.

As one outlook, the robustness of the proposed method will be verified by the evaluation of the time series dataset acquired in descending orbit.

Future steps concerning the change categorization will contain the extension of the proposed method on the time series dataset. By this, seasonal effects could be detected by the CoVAmCoh analysis. Furthermore, additional features characterizing the change segments will be investigated. For example, the well-known method named “differential morphological profiles DMP” ([7]) could contain potentials for a more precisely categorization task.

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REFERENCES


Figure 2: Above left: Mean $\sigma^0$ image overlaid with activity map containing temporarily stable (orange to red) and unstable (yellow) changes. Above right: CoVAmCoh image of the same area. Area 1: Parking slots beside the highway (cyan marked). Area 2: Area of no changes (red marked). Below: CoVAmCoh values of area 1 and area 2.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Value</th>
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<tbody>
<tr>
<td>Area</td>
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<td>Orientation</td>
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<tr>
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<tr>
<td>mean $\sigma^0$ (image t2)</td>
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<td>mean CoV ((t1+t2)/2)</td>
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<tr>
<td>mean Coherence (t1, t2)</td>
<td>0.40809</td>
</tr>
</tbody>
</table>

Figure 3: Left: Subsets of change map (above left), CoVAmCoh (above right), $\sigma^0$ image of t1 (below left) and $\sigma^0$ image of t2 (below right). Right: Values of feature vector for selected segment (marked by cyan colored box).