Comparison of Automated Change Detection Methods

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This paper describes the results of a new combined method that consists of a cooperative approach of a number of different algorithms for automated change detection. These methods are based on isotropic frequency filtering, spectral and texture analysis, and segmentation. For the frequency analysis, different band pass filters are applied to identify the relevant frequency information for change detection. After transforming the multitemporal images using a fast Fourier transform and applying the most suitable band pass filter to extract changed structures, we apply an edge detection algorithm in the spatial domain. For the texture analysis, we calculate the parameters energy and homogeneity for the multitemporal datasets. Then a principal component analysis is applied to the new multispectral texture images and subtracted to get the texture change information. This method can be combined with spectral information and prior segmentation of the image data as well as with morphological operations for a final binary change result. A rule-based combination of the change algorithms is applied to calculate the probability of change for a particular location. The method was tested with high-resolution remote-sensing images of the crisis area in Darfur. Our results were compared with a number of standard algorithms for automated change detection, such as image differencing, image rationing, principal component analysis, Delta cue technique and post classification change detection. The new combined method showed superior results in accuracy compared to standard methods.

Keywords. Change detection, Fast Fourier Transform, accuracy assessment, isotropic filtering, texture, Principal Component Analysis, edge extraction, cooperative methods

1. Introduction

In the field of remote sensing many change detection methods have been designed and tested. An overview and comparison of different change detection methods can be found in [1], [2], [3], [4] or [5]. In generally, change detection methods are divided into three categories [4]: (i) Image enhancement-methods, (ii) multitemporal analysis, and (iii) post classification comparison. Other approaches combine several methods or consist of novel methodologies (an overview can be found in [5]). The large numbers of publications that deal with automated or semi-automated change detection methods prove that this field addresses an important research topic.

According to [6], these methods have different grades of flexibility, robustness, practicability, and significance. Most authors, however, agree that there exist no single best algorithm for change detection.

A fast detection and visualization of change in areas of crisis or catastrophes are important requirements for planning and coordination of help. As mentioned above, however, a ‘best algorithm’ for the automated detection of changes for all applications has yet to be developed if this is at all possible [6]. Therefore, new methods are still being developed and/or adapted, especially for the detection of damaged buildings and infrastructure in conflict or crisis areas. This paper is no exception to this, as it described the development of, and the results for, a set of new change detection algorithms. The objective of our research has been the development of reliable and accurate automated algorithms to detect changes on man-made objects. These algorithms should be used in catastrophic events or humanitarian crises to show the impact of this particular event.
2. Study area

Our study area is located in Sudan. This region has experienced dramatic changes during the Darfur conflict. This conflict is a dispute between different ethnic groups and the Sudanese government. Rebels from Sub-Saharan African tribes want a higher participation in the government and the development of their regions. The government has been fighting these rebels and has supported local militia consisting of Arabic rider-nomads (Janjawid). It is estimated that more than 300,000 people have already died in this conflict and more than 2 million people have been displaced.

The developed method for change detection was tested with very high resolution (VHR) satellite images of the Darfur conflict area in Sudan. Multitemporal images of the affected regions are recorded by satellites of very high geometric resolution such as Quickbird-2 and are displayed on a web site that is hosted by Amnesty International (http://www.eyesondarfur.org/villages.html). The destruction of villages in this region is clearly documented by these satellite images. With the permission of the satellite company Digital Globe, we were able to use georeferenced Quickbird data before and after an attack for our change analysis. Fig. 2 shows the study area and the manually digitized reference map for change analysis.
Figure 2: Study area of the panchromatic Quickbird-2 scene of Abu Suruj (280 x 350 pixel). T1 was recorded on March 2, 2006 (left) and T2 on February 28, 2008 (center). The manually digitized reference image of the town Abu Suruj is on the right. Black denotes no changes (background), white stands for new buildings (construction) and gray for changed buildings (destruction) (images © DigitalGlobe, 2006/2008).

A visual comparison and overlay of the existing man-made structures shows a high correspondence for both images, so that a new co-registration was not necessary and the problem of possible pseudo change was negligible.

3. Change detection methods

3.1. Standard change detection methods

For comparison of our new method it is necessary to test the performance of traditional change detection approaches. We selected those that are available in most proprietary image processing systems. These methods are image differencing [2], image rationing [7], PCA [8], delta cue [9] and post classification analysis [7].

Image differencing is an easily understandable and implementable method. It is based on calculating the gray value differences. The image ratio method is very similar to image differencing. For every pair of gray values at the same location at dates T1 and T2 the ratio of the two values is calculated. The PCA transform is a statistical method to calculate a new synthetic (uncorrelated) data space. With this approach, it is possible to strengthen wavelength dependent material specific differences. Detailed explanations of this method can be found, for example, in [10] or [8]. In this study, we employ a selective bitemporal PCA where unchanged areas are displayed in the first principal component whereas the changes are depicted in the second PC (for more information see [11]).

Post classification analysis is based on a comparison of two independent classification results for at least dates T1 and T2. For example, each input data set of T1 and T2 can be classified using an unsupervised isodata algorithm [7]. The Delta Cue software is a combination of different image processing techniques. These techniques are assembled into an integrated procedure. The following formula is used by all the presented change detection algorithms to compute the relative difference of the images T1 and T2:
Because the input data consist only of a single band, we use a single band difference algorithm. In the next step, a threshold is determined to differentiate between real change and pseudo change. New geometric properties are then used to identify the changed buildings. These geometric properties include area, elongation, and compactness of connected pixels. These connected pixels build a blob of which major and minor axis can also be determined.

3.2. Combined edge segment texture analysis

Based on the fact that simple methods such as image differencing or image rationing (see [12]) failed to reliably detect changes of buildings in the study images, we developed a different procedure for automated change detection. This procedure is based on a number of different principles, namely frequency based filtering, segmentation, and texture analysis. One of these methods is based on filtering in the frequency domain after a Fourier transform ([13], [14]), one on segmentation, and the others on texture features. More details about these algorithms can be found in [15]. The frequency domain is used because it allows the direct identification of relevant features such as edges of buildings. If no features are directly visible (such as partial destruction with walls that are still standing), texture parameters are used for debris identification. A segmentation algorithm is used to extract size and shape of buildings. These methods can be combined in a decision tree approach for accuracy improvement. The combination of these three processing steps is called Combined Edge Segment Texture (CEST) Analysis (see [12] for detailed description).

An overview of the CEST decision-tree approach is shown in Fig. 3. The basis for the classification is the result of the change detection algorithm using edge detection based on frequency filtering (see [15]).

![Decision tree diagram](image-url)

Figure 3: Decision tree for the combination of change detection methods. Edges = result of the Edge detection based on filtering in the Fourier domain. Segments = result of the change detection using segmentation. Homogeneity and Energy = results of the texture features. Numbers are related to the following classes: Class 1 = changed or destroyed buildings, class 2 = new buildings and class 0 = unchanged buildings.
If the pixel is classified as unchanged in this image it is also marked in the final image as unchanged. The first method that is checked is the edge detection after frequency based band pass filtering. If the edge parameter indicates ‘no change’, the pixel in the image is classified as ‘no change’. If the edge parameter indicates ‘new building’, the pixel is classified as new, if the texture feature ‘energy’ is an agreement. If energy indicates ‘change’ and one of the features ‘homogeneity’ or ‘segmentation’ indicate ‘change’, the result is ‘new’. Otherwise, it is classified as unchanged. If the edge parameter shows ‘change’, it is classified as ‘change’ if the texture feature ‘energy’ coincides. If energy indicates ‘no change’, the pixel will be classified as ‘no change’. If energy indicates ‘new’ but the segment and homogeneity parameters show ‘change’, the pixel is assigned to ‘change’. Otherwise it is classified as unchanged. The CEST procedures was tested against the standard change detection methods described in 3.1.

4. Results and accuracy assessment

4.1. Results of standard change detection methods

In the following section the results of the standard change detection methods are presented. Unchanged areas are marked in black, changed areas in white (new settlements) and gray (destroyed settlements). Fig. 4 shows the result of change detection using image differencing (left) and image rationing (right).

![Figure 4: Result of change detection using image differencing (left) and image rationing (right).](image)

By using different thresholds it is possible to detect the four different classes. It can be seen, however, that large areas of pseudo change are detected (Fig. 4, left). Due to brightness changes of the sediment, change is especially detected in the north of the image. Most of the new buildings which appear in the T2 image are detected. Buildings which are unchanged are often identified as destroyed or changed building.

For the image rationing, it is difficult to find a threshold between new and changed or destroyed buildings. Therefore most of the buildings are detected as new buildings (Fig. 4, right). As with im-
age differencing, buildings which are unchanged are often indicated as destroyed or changed. The amount of detected pseudo change is lower compared to image differencing.

Figure 5: Result of change detection using PCA (left) and post classification (right).

The image processed with the PCA change detection (Fig. 5, left) procedure shows a lot of detected pseudo change, especially in the south and west of the image. Similar to the image rationing, most of the buildings are detected as new buildings. For the post classification analysis (Fig. 5, right) pseudo change represents again a big problem.

4.2. Results of Combined Edge Segment Texture (CEST) Analysis

Superior results were obtained by the CEST procedure are. CEST combines the advantages of the different methods and generates the most accurate change image (Fig.s 6 and 7). Similar to the other figures three change classes can be identified: Black denotes no changes (background), white stands for new buildings and gray for changed buildings (Fig. 6).
Figure 6: Result of change detection using the CEST-method.

In comparison with the other results, this image is almost free of noise. Misclassification of vegetation as changed buildings is significantly less when compared to the other approaches. It also shows a better result when compared to each individual method that is integrated in CEST. By visual inspection, the combination of different methods generates the most reliable and accurate result for change detection.

4.3. Comparison and accuracy assessment

To assess the validity of the visual inspection, a quantitative accuracy check for the standard methods and the CEST procedure was performed. For the accuracy assessment, we added the class ‘changed and unchanged vegetation’ to the existing three classes:
- Class 0 = unchanged buildings
- Class 1 = changed or destroyed buildings
- Class 2 = new buildings
- Class 3 = changed and unchanged vegetation

The reference was the manually digitized map of buildings which was performed by an independent photointerpreter (see Fig. 2). Accuracy assessment of the first three classes is based on randomly chosen digitized objects. Only for class 0 all objects were used. If the majority of the pixels inside an object are the pixels of the correct class, the whole object was considered as correctly detected. For the third class, 404 randomly selected points are compared to the original image. This is done because this class covers a higher percentage in the study area than the object classes. Therefore a disproportionate sampling is used [16]. As result, Fig. 7 shows the calculated Kappa coefficients for all scenarios.
Figure 7: Kappa coefficients of the accuracy assessment in the area of Abu Suruj.

The accuracy assessment shows that the new combined CEST-method is far superior to the standard techniques for change detection. The combined method yields to the highest Kappa coefficient of 0.77 in comparison to the other methods. The Kappa value for image differencing is 0.59, for image rationing 0.50, for PCA 0.66 and for Delta cue 0.65. The Post Classification change analysis yields the lowest value of 0.33. The combined CEST-method shows the highest accuracies and produces also less pseudo change.

5. Summary and future work

In this paper, a new automated change detection method is presented. This method combines adaptive filtering in the frequency domain with edge detection in the spatial domain, calculation of the texture features with a PCA change detection approach and segment based correlation. This combined method is compared to five standard change detection algorithms (image differencing, image rationing, PCA, Delta cue, and post classification analysis). Results are visually and quantitatively analyzed. The accuracy assessment shows that the combined method is far superior to the standard techniques for change detection. The combined method yields a Kappa coefficient of 0.77 and especially a high number of unchanged buildings could be correctly identified.

To improve the results of our method other segmentation algorithm will be applied and tested for better object definition. Additionally, we will include the FLST (fast level set transform) into our decision tree [17]. The combined method will also be applied to other disaster areas such as the Japan earthquake images.

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References


