AUTOMATED CHANGE DETECTION FROM HIGH-RESOLUTION REMOTE SENSING IMAGES

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ABSTRACT:

A fast detection of change in areas of crises or catastrophes is an important condition for planning and coordination of help. This paper describes the results of a cooperative suite of algorithms for automated change detection based on the availability of new satellites with high temporal and/or spatial resolutions. The methods are based on frequency and texture analysis, and segmentation. For the frequency analysis, different band pass filters are applied to identify relevant frequency information for change detection. After transforming the multitemporal images via a fast Fourier transform and applying the most suitable band pass filter, four different methods are available to extract changed structures: differencing and correlation in the frequency domain and correlation and edge detection in the spatial domain. For the texture analysis, we calculate four different parameters (i.e. energy, correlation, contrast and inverse distance moment) for the multitemporal images. The next step is the application of several change detection methods (difference, ratio, regression and principal component analysis) to visualize the changes in the texture images. This method can be combined with a 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 methods were tested with high-resolution satellite images of the crisis areas of Darfour and Haiti. For the frequency based change detection, best results were obtained with adaptive band pass filtering and subsequent edge detection. For the texture based method, a bitemporal principal component analysis for the feature energy provided the best results for change visualization. The next steps will involve the extension of the developed algorithms to test their suitability for other applications such as environmental or phenological change.

1. INTRODUCTION

Over the last thirty years, many automated and semi-automated change detection techniques have been developed and tested. An overview and comparison of different approaches for change detection can be found in Singh (1989), Macleod & Congalton (1998), Mas (1999), Lu et al. (2003), Coppin et al. (2004), Jianyaa et al. (2008), or Tomowski et al. (2010a). Based on their findings and those of others, it is evident that there exists no 'best algorithm' that suffices for all applications. Performance and success of the methods differ widely based on the employed image data, the objectives of the analysis, and the geographic area with respect to landuse and landcover. Niemeyer & Nussbaum (2006) demonstrated that this wide range of different techniques shows different grades of flexibility, robustness, practicability and significance. In general, change detection approaches can be divided into three categories (Mas, 1999): Image enhancement methods, multitemporal analysis, and post classification comparison. These approaches can be combined with each other or with other techniques.

Image enhancement methods are based on unclassified image data which combine the data mathematically to enhance the image quality (Jensen, 2005). Examples are image-differencing, image-ratioing, principal component and regression analysis. Multitemporal analysis is based on an isochronic analysis of multitemporal image data. This means that n bands of an image at time t_1 and n bands of an image at time t_2 of the same area are merged to form a new image with 2n bands to extract the changed areas in this merged picture (Khorram et al., 1999). Post classification analysis is based on a comparison of independent classification results for at least two points of time t_1 und t_2. This method allows the determination of change from one class to another.

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The large number of published scientific results in the case of combined and novel change detection methods is multifarious which shows that change detection is indeed an important research topic. In this paper, we concentrate on change detection in areas where catastrophic events took place which resulted in rapid destruction especially of buildings and infrastructure. For this purpose, we developed an automated approach that is primarily based on texture and frequency analysis. Practical tests were performed for our study sites in Darfur and Haiti.

2. STUDY SITES

The first study area is located in Sudan. The village Shangil Tobay is located in North Darfur, and was one of seventeen villages in this region which were attacked and destroyed since 2004 in the Darfur conflict. The panchromatic images were taken by Quickbird with a ground sampling distance (GSD) of 0.6 m. They can be found at the web site which is maintained by Amnesty International (AI, 2010). Fig. 1 and 2 show the Quickbird images for the Darfur study site taken on March 3, 2003 and on December 18, 2006. Both images were provided courtesy of Digital Globe.

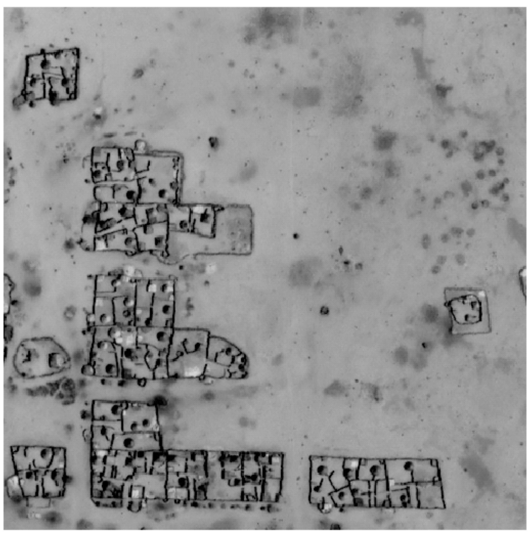

Figure 1. Subset of the Shangil village before destruction (©Digital Globe 2003)

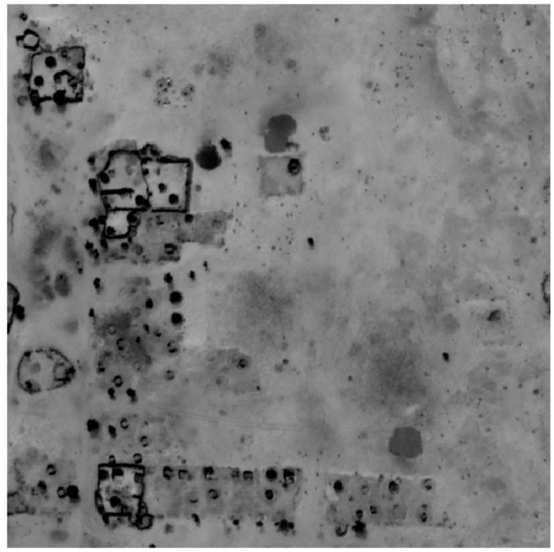

Figure 2. Subset of the Shangil village after destruction (©Digital Globe 2006)

On January 12, 2010 at 4:53 p.m. (local time) an earthquake took place in Haiti with its epicenter 25 kilometers southwest of Port-au-Prince. It is estimated that up to 300,000 people were killed in this event. For immediate help, Digital Globe and the Laboratory for Imaging Algorithms and Systems from the Rochester Institute of Technology (RIT) provided satellite and aerial imagery for the affected area. A subset of a satellite image recorded by WorldView 2 on January 7, 2010 is shown in Fig. 3. The aerial image (Fig. 4) was acquired a few days after the earthquake on January 22, 2010. The destruction of the red buildings near the bottom of the image and the partial demolition of the President's Palace (white building near the top) are clearly visible.

Figure 3. Satellite scene of Port-au-Prince from Worldview 2, recorded before the earthquake. (©Digital Globe 2010).

Figure 4. Aerial image of the same area recorded after the earthquake (image courtesy of RIT).

3. METHODOLOGY AND RESULTS

3.1 Texture Based Change Detection

For the texture analysis, four different texture parameters ('energy', 'correlation', 'contrast' and 'inverse distance moment') are calculated for the multitemporal images (for a detailed description, see Haralick et al., 1973; Haralick & Shapiro, 1992; Tomowski et al., 2010b). These texture values replace the images to form the basis for change analysis and are combined with several change detection methods (e.g., difference, ratio, regression and principal component analysis – see Fig.5).

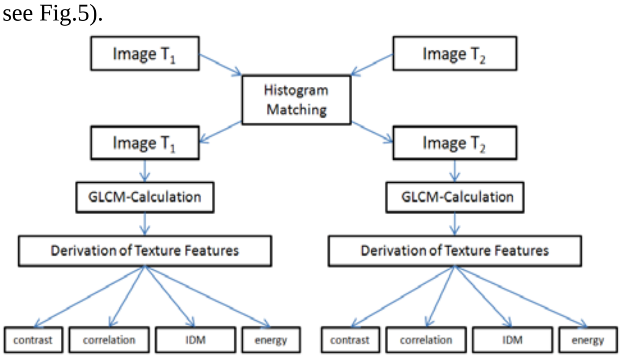

Figure 5. Steps for the derivation of texture image data for change detection

These techniques are used to visualize the changes in the texture images. For the study area of Darfur, a bitemporal principal component analysis (PCA) with the texture feature 'energy' provided the best result. In general, the PCA is a statistical method to calculate new synthetic data. With this approach, it is possible to intensify wavelength dependent material differences to expand the significance of image data (Schowengerdt, 2007). In the case of change detection, the PCA is used to highlight the differences between change and no-change in the image data (Nussbaum & Menz, 2008). By means of a bitemporal PCA we consider the fact that multitemporal image data in single spectral bands can be similar or not in the following way.

In a twodimensional feature space, a PC transform is performed for the two bitemporal spectral bands of the same location (see Fig. 6).

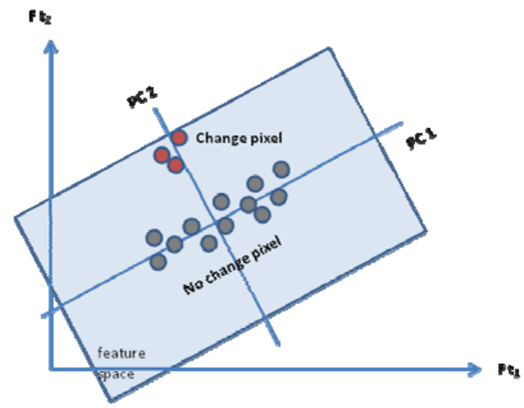

Figure 6. Change detection through bitemporal selective PCA.

Assuming that most pixels are unchanged, these pixels will have a high correlation with the first PC, whereas the pixels representing change will have values that are perpendicular to the first PC. As consequence, the first PC represents the unchanged information. The second component displays the change information which can also be differentiated in positive and negative change depending on the location along the second PC (Macleod & Congalton, 1998). For our test area, the PCA result for the Darfur Test site is shown in Fig. 7.

The changed pixels are dark (negative change for the texture 'energy') and bright (positive 'energy' change) whereas the unchanged areas are of a medium grey. Please note that the positive changes do not indicate new buildings but rather stronger contrast which is probably due to burning and thus making the features more prominent. White pixels show a complete disappearance of the original structure. For a final classification of the changed areas, we use an iterative self-organizing data analysis technique (ISODATA) within the Erdas software environment.

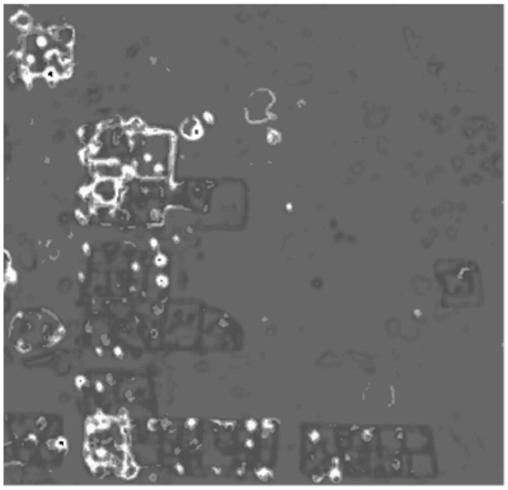

Figure 7. Texture based PCA with the feature ‘energy’. The bright and dark areas represent different levels of change

3.2 Frequency Analysis Based Change Detection

The second method that we developed makes use of Fourier transform techniques (Cooley & Tukey, 1965). The Fourier transform is an operation that divides a periodic signal in its basic frequency components. With this, it is possible to enhance selected spatial frequencies in the spectral (Fourier) domain that represent catastrophic changes in the images. Four different methods based on adaptive filtering in the spectral domain were developed to detect destroyed buildings in the images (see Klonus et al., 2010 for a detailed description). These methods are a) subtraction and b) correlation in the spectral domain, c) correlation and d) edge detection in the spatial domain. All these methods are based on filtering in the Fourier domain. The best results were produced by method d) (Klonus et al. 2010). Consequently, this method was used for further analysis.

To apply our change detection method, all bands from the images before (image T1) and after the destruction (image T2) were averaged to obtain a single band. A fast Fourier transform (FFT) was applied to the averaged image. The transformed images were filtered in the spectral domain using a band pass filter. To find the appropriate band pass filters, different narrow band pass filters were created. Using an inverse FFT, the resulting images were transformed back into the spatial domain to find the relevant information for change detection.

With this approach, we could design a band pass filter that enhanced the building edges. As anticipated, the highest frequencies contained only noise whereas the low frequencies provide only information about the background. Both components were suppressed by the band pass filter. To avoid the problem of the Gibbs phenomenon a wider band pass filter with an additional a Hanning filter window was used (Brigham, 1997). After transforming images T1 and T2 via FFT and applying a band pass filter, they were transformed back into the spatial domain using an inverse FFT. Thereafter, an edge detection operator was applied to both images. The best results were obtained by the Canny edge detector (Canny, 1986). The result of the Canny edge detector is a binary image. The edges are marked by one and the background by zero. The two images are then subtracted followed by a morphological dilation and closing. The basic effect of the dilation on a binary image is to gradually enlarge the boundaries of objects which have the value one. The dilation is defined as:

$$A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \varnothing\}$$

where A is the binary change image, B a structuring element, $(B)_z$ is the translation of B by the point z defined as:

$$(B)_z = \{c \mid c = b + z, \quad \text{for} \quad b \in B\}$$

$\hat{B}$ is the reflection of the structuring element B:

$$\hat{B} = \{c \mid c = -b, \quad \text{for} \quad b \in B\}$$

The basic effect of the erosion on a binary image is to erode the boundaries of regions that have the value one.

$$A \ominus B = \{z \mid (\hat{B})_z \subseteq A\}$$

The erosion of A by B is the set of all points z such that B, translated by z, is contained in A. Closing is also used to smooth sections of contours which is contrary to opening. Narrow breaks and long thin gulfs are fused, small holes are eliminated and gaps in the contours are filled. It is defined as:

$$A \bullet B = (A \oplus B) \ominus B$$

Therefore the closing of image A by a structure element B is the dilation of A by B, followed by the erosion of the result by B. The closing in this study is applied with a squared structuring element of 3 x 3 pixels (Gonzales & Woods, 2002). The result was stored in a binary image, where the number one represents change and the number zero no change or pseudo change. Fig. 8 shows that nearly all changed buildings could be identified.

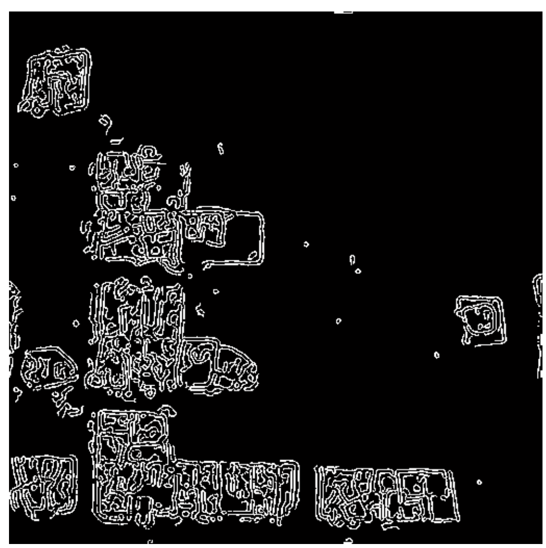

Figure 8. Change detection using frequency based analysis and Canny edge algorithm

3.3 Segmentation Based Change Detection

The third method that was used in this study is based on a pre-segmentation of the input data for dates T1 and T2. The segmentation approach is based on the Euclidean distance (Priddy & Keller, 2005). After segmentation of the scenes T1 and T2, the segments of T1 are selected and used also for the T2 image. For each segment, the T1-T2 correlation between its pixels is calculated. The result is assigned to each pixel in the segment. In the next step, the segments of T2 are selected and superimposed on the T1 image. Again, the correlation – this time between T2 and T1 - is calculated for all pixels in each segment. A new layer with the result of this segmentation is created. Segments with a high correlation represent no changes. Segments with a low correlation represent changes. A threshold based binary image is created using one for change and zero for no change.

If only one of the images were segmented, objects occurring only in one image cannot be recognized as a segment in the other image and therefore assigned to a bigger segment in this image. This segment will probably display a low correlation value. The change, however, is not related to the whole segment, but only to a part of it. Boundaries of the change areas would not be correct. To solve this problem, both images are individually segmented and the correlation is calculated for both directions. With conditional operations the small changed segments can be delineated.

The result of this segmentation approach for the scene of Darfur is shown in Fig. 9. The result contains still a few areas with pseudo change. The reason for this are changes in vegetation and soil surface in the vicinity of the buildings. The method, however, is faster than the FFT based analysis and allows future improvements.

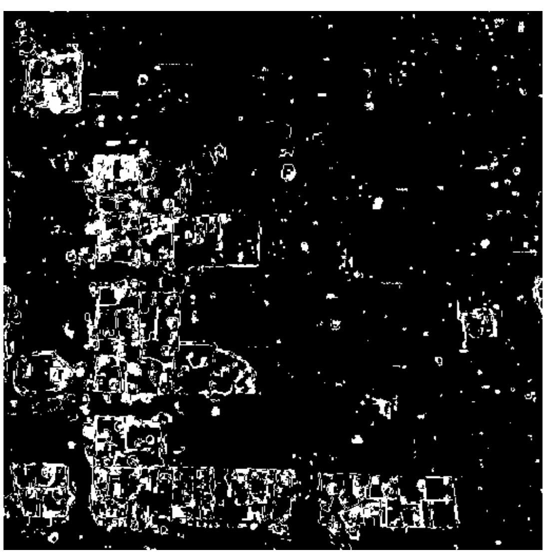

Figure 9. Change detection using a segmentation approach

4. COMBINED APPROACH FOR THE HAITI STUDY SITE

The Haiti test site is a lot more complex that the Darfur area. In addition, many buildings were only partially destroyed and the viewing angles of the recording cameras were different. It comes therefore as no surprise that the individual change detection methods do not show acceptable result. Consequently, we tested a new method that is essentially a combination of the three algorithms (Fig. 10).

For this approach, digitized polygons of the buildings before the event are used. Using these polygons the correlation coefficient of each building is calculated for the T1 and T2 images. All images locations with a correlation value below 0.4 are considered as changed. In a second step, the amount of changed texture and edges in a building (polygon) is determined and thresholds are generated to decide if the building is destroyed, partially damaged, or still unchanged.

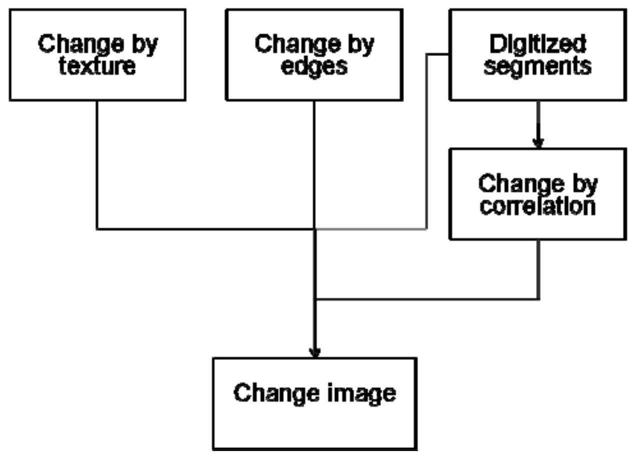

Figure 10. Combined approach for change detection

The result of this combined approach is shown in Fig. 11 (bottom); the digitized reference image in Fig. 11 (top). The polygons in green color represent the unchanged buildings, the red polygons are the damaged or destroyed buildings.

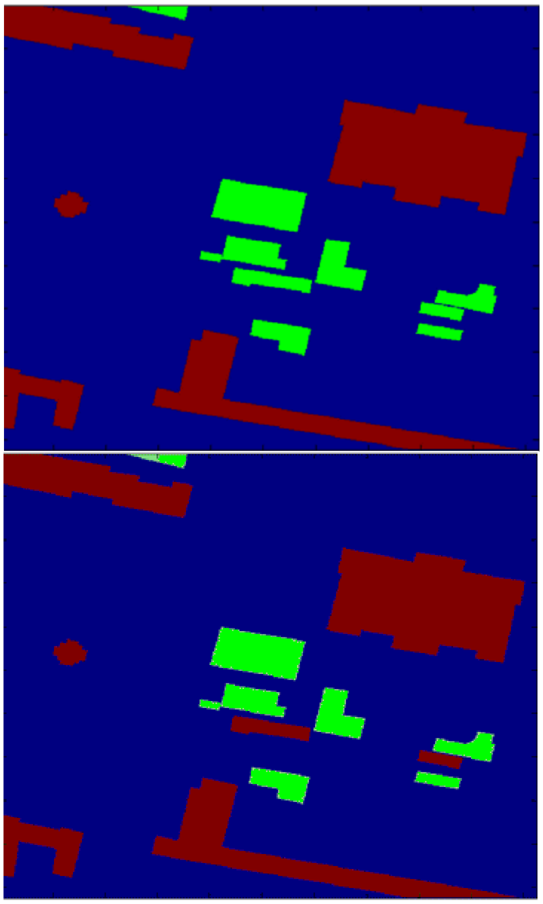

Figure 11. Digitized reference image (top) and the result of the combined change detection (bottom) of the Haiti test site.

In this subset, 14 different polygons were digitized with five objects being destroyed. The combined algorithm detected all changed buildings; however, it also showed two unchanged buildings as damaged. It is evident that this method shows potential but has to be further investigated.

5. SUMMARY AND FUTURE WORK

The presented method combines three different change detection approaches: A texture and segmentation based approach as well as an approach based on filtering in the spectral domain with subsequent edge detection. While the individual algorithms perform well in areas with little structure, they do not produce acceptable results for complex regions. Here, we combined all three techniques in a cooperative approach. This method could detect all changed buildings with only two buildings that were incorrectly classified as changed.

The next steps will involve the advanced combination of both methods to strengthen the change/no change decision and to test the algorithms for a broader application of change analysis (e.g. environmental, phenological change). It will also be applied to different test regions and data sets.

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