Change Detection in Satellite Images

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ABSTRACT

Change detection plays an important role in different military areas as strategic reconnaissance, verification of armament and disarmament control and damage assessment. It is the process of identifying differences in the state of an object or phenomenon by observing it at different times. The availability of spaceborne reconnaissance systems with high spatial resolution, multi spectral capabilities, and short revisit times offer new perspectives for change detection. Before performing any kind of change detection it is necessary to separate changes of interest from changes caused by differences in data acquisition parameters. In these cases it is necessary to perform a pre-processing to correct the data or to normalize it. Image registration and, corresponding to this task, the ortho-rectification of the image data is a further prerequisite for change detection. If feasible, a 1-to-1 geometric correspondence should be aspired for. Change detection on an iconic level with a succeeding interpretation of the changes by the observer is often proposed; nevertheless an automatic knowledge-based analysis delivering the interpretation of the changes on a semantic level should be the aim of the future. We present first results of change detection on a structural level concerning urban areas. After pre-processing, the images are segmented in areas of interest and structural analysis is applied to these regions to extract descriptions of urban infrastructure like buildings, roads and tanks of refineries. These descriptions are matched to detect changes and similarities.

Keywords: Change detection, structural object description, assignment, registration, classification, segmentation

1. INTRODUCTION

The detection of changes in images taken from the same terrain at different times and the quantitative estimations of parameters describing objects of interest are often needed in military applications. The objective of the proposed change detection task is the detection of temporary significant infrastructural changes in two IKONOS image bundles depicting the same terrain (scene), generally taken from two different view points. Each image bundle consists of a panchromatic image with a spatial resolution of 1 m per pixel, RBG+NIR (near IR) image data with 4 m spatial resolution, and meta-data in ASCII format including flight and sensor parameters (sensor azimuth and elevation relative to the terrain, sun azimuth and elevation, etc.).

Before performing any kind of change detection, it is necessary to separate changes of interest from changes caused by differences in data acquisition parameters. The latter distortions are caused by different resolutions, displacements due to topography variations and different aspect angles, direction of illumination (shadow caused by active or passive illumination), atmosphere (e.g. clouds, fog, and dust), reflectivity (e.g. soil moisture), vegetation, and seasons (e.g. summer, winter). If possible, these effects should be excluded by a controlled data acquisition. But, in many cases the military operations can not respect these demands and the images contain changes caused by the effects mentioned before. Thus it is necessary to perform a pre-processing to correct the data. The images are normalized with respect to radiometric properties, and shadow areas are determined.

Segmentation was applied to the images for different purposes. One was the exclusion of regions of minor interest (e.g. vegetation areas, water areas) or to focus the detailed analysis to specific areas of interest like rivers if bridges are in the focus. The analysis can also be supported by GIS information (e.g. DTM, vector maps) to distinguish between rural areas and urban areas for further investigation or to focus the analysis to region of interest (e.g. vehicles on road). Another aspect of the investigations was the extraction of buildings, roads and tanks in refineries. These objects are represented in the images predominantly by geometrical shapes (e.g. straight lines, circular arcs, rectangular borders).

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For these objects structural descriptions were obtained. Image interpretation and object recognition make the analysis more robust against geometric and radiometric differences between the images being compared.

Image registration and sometimes ortho-rectification of the data is a necessary step before applying change detection. A 1-to-1 geometric correspondence should be aspired for. As we investigated images taken under comparable flight conditions and aspect angles a fine-registration of the images was possible in most cases. Linear structures of man made objects were used for the matching process. Especially in non-flat topography and under different aspect angles, a registration adapted to the height levels of the objects has to be performed. Differing projections of buildings or other elevated objects have to be compensated. Therefore it is necessary to register the surface level of the images and the elevated objects separately to bring them in corresponding positions.

Change detection can be done determining changes on an iconic level with a succeeding interpretation by the observer or by an automatic knowledge-based analysis delivering hints for changes on a semantic level. Dependent on abstraction level, different techniques can be applied, e.g. image differencing, image correlation, comparison of segmentation or classification results, and comparison of structural object analysis results. On a low level of abstraction the differencing or correlation methods can be used to acquire hints for any change in the data. For more stability this can be replaced by differencing on segmentation or classification results or structural descriptions. We have tested pre-classification results and different distance measures to match structural object descriptions on a higher level of abstraction.

In this paper we will present an approach for the detection of significant infrastructural changes in high-resolution satellite imagery. In section two we describe the pre-processing and methods dealing with radiometric and geometric distortions. Additionally pre-segmentation methods are addressed. In section three the registration of images is discussed. In section four we will explain methods for the recognition of interesting infrastructural objects, e.g. represented by rectangular, circular, and curvilinear structures. A discussion of different change detection approaches on iconic and symbolic level will be presented in section five. The comparison of corresponding structural descriptions follows. Finally, some conclusions are made in section six concerning the current state of the investigations and the continuation of the work.

2. DATA PRE-PROCESSING

Before applying change detection methods we recommend to correct distortions caused by radiometric or geometric effects, to focus the analysis to the most prominent parts of the image, and to describe the class of interesting objects on a higher level of abstraction. Some of these processing steps are addressed in the following.

2.1 Radiometric Corrections

Radiometric distortions can have different reasons: different intensity distribution in the images caused by the lighting situation, and atmospheric effects and processes (e.g. clouds, fog, and dust). Prior to employing an algorithm for detection of changes of the local areas of interest it is desirable to normalize them. Such normalization makes the comparison less sensitive to the possible differences of illumination. For this task we use a local linear histogram warping technique [Hayes, 2004]. To the IKONOS images a pan sharpening was applied to use the spectral information in an optimal way. Pan sharpening fuses the high resolution panchromatic channel with the low resolution spectral channels (RGB, NIR) to high resolution information. A severe problem is the distortion in the data by atmospheric effects. We have applied the commercial software ATCOR [www.atcor.de] to the data to reduce the effects of haze in the images. The approach is a combination of the algorithms described by [Richter, 1996] und [Zhang, 2002]. It only works on multispectral images and only eliminates translucent clouds (haze). At least 40% of the image have to be clear areas. Before applying the algorithm, water areas have to be determined and excluded using the NIR-channel of the data. The approach consists of the following steps:

- Masking all clear and hazy areas in the image using the Tasseled-Cap-Transformation TC [Crist, 1984]: TC = x_1 * BLUE + x_2 * RED, here BLUE and RED are the corresponding color channels, x_1 and x_2 are weighting coefficients. The clear areas are given by pixels lower than the mean of TC.
- Determination of regression between blue and red channel for clear areas („clear line“ and inclination angle α).

- Hazy areas are orthogonal to „clear line“, that means an optimized transformation HOT („haze optimized transform“) can be defined as: HOT = BLUE * sin(α) - RED * cos(α)
- Determination of HOT-Histograms for hazy areas.
- For each band below 800nm a number of grey level histograms for the pixel in the HOT intervals is generated. The intervals are defining HOT-levels. The height of HOT-Level is corresponding to the density of the haze. The value of correction Δ (subtraction of the additive component for haze in the radiometric signal) is determined by the grey value DN corresponding to the HOT-level j, with DN(new)=DN - Δ.

Examples of successful haze reduction are shown in Figure 1.

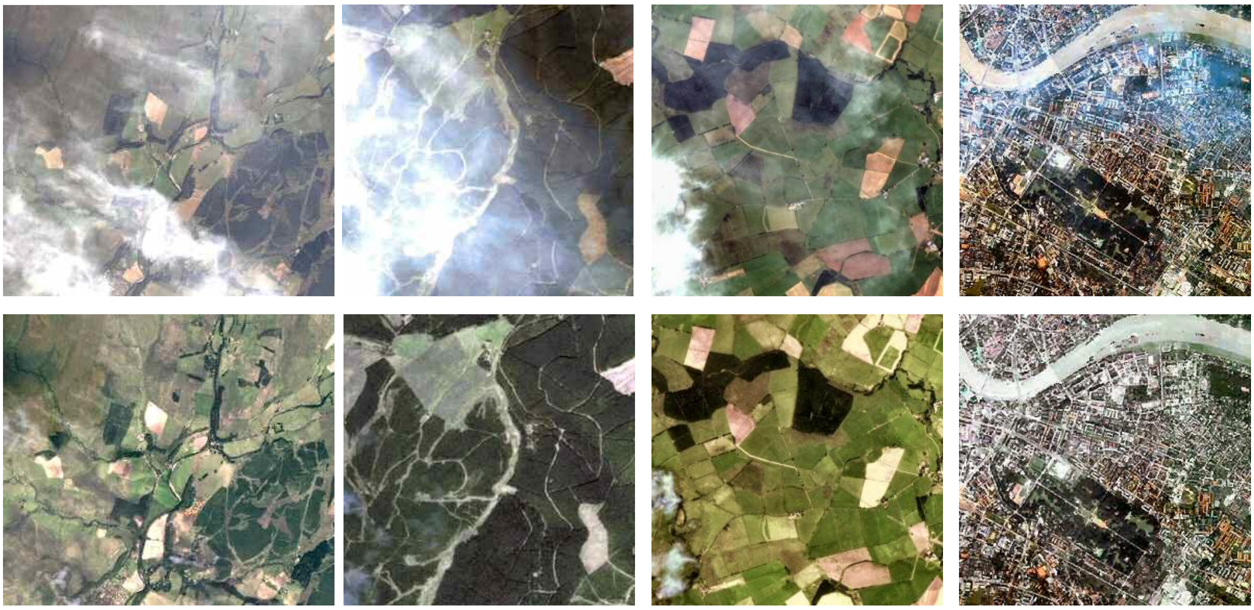


Figure 1: Example of a haze reduction in IKONOS-images (upper row: images with haze, lower row: corrected images); Source: www.atcor.de (IKONOS-Data: Courtesy of European Space Imaging / © European Space Imaging GmbH)

2.2 Shadow Extraction

Extraction of shadowed zones was carried out based on the analysis of the gray value intensity histogram of the image deriving a threshold. If the brightness value is less than the threshold, we mark the pixel in the image as belonging to shadows. To exclude the accidental extremes the histogram is smoothed by means of local averaging and median filtering. For images consisting of three spectral channels the thresholding algorithm is consistently applied to each of the three channels. We mark a point as a shadow in the resulting image if it is flagged in at least one channel.

2.3 Preliminary Segmentation of Images

A preliminary segmentation of the input images enables us to reduce the amount of data to be investigated. This segmentation was performed using the fused panchromatic, RGB and NIR images as sources. We investigated the Normalized Difference Vegetation Index (NDVI) and a statistical approach to segment the data. The vegetation index can discriminate between interesting and excludable areas, e.g. urban vs. rural area. Figure 2 shows an example. NDVI is calculated by the following formula:

$$NDVI = (NIR - RED) / (NIR + RED)$$

Land use classification as a statistical approach is another possibility for a preliminary segmentation. To overcome problems due to sufficient training areas, and robust reject criterions for multi-class problems we propose a kernel-based classification module. The kernel-machines, especially the SVM, are known as robust classifiers [Vapnik, 1974] [Vapnik, 1998] [Schölkopf, 1997] [Christianini, 2000] for two-class problems. Therefore an effective 1-to-1 heuristic has been chosen to handle operational classification problems of many classes. It uses classifiers for each pair of classes.

A two stage majority decision follows. The reject criterion is given in the high dimensional feature space of the kernel machine that is defined implicitly by the kernel – following [Byun, 2003] here we use the RBF kernel only. Classification in this feature space is done by simple linear discrimination. Using a 1-to-1 decision heuristic for multi-class problems each class has been trained against each other, i.e. hyperplanes define the classes' boundaries. The reject is done by thresholding with respect to the minimal distance to all related hyperplanes. Thus it is possible to optimize the classification result with respect to the reject threshold and the kernel parameter of the RBF. These methods were applied successfully to high-resolution SAR-data [Middelmann, 2004]. In the change detection framework it has been used for pixel-based classification employing four spectral channels. An improvement will be investigated by incorporating small neighborhoods to take textural information into consideration. Further investigations will utilize the NDVI or other features.

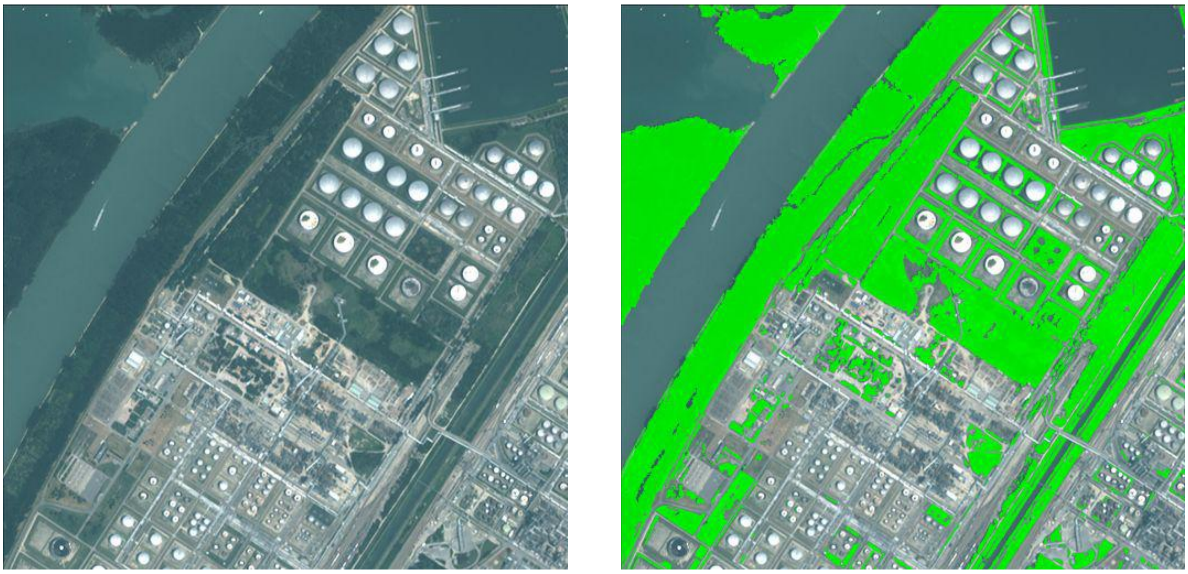


Figure 2: Result of applying vegetation index task to RGBNIR image (Original images: Courtesy of European Space Imaging / © European Space Imaging GmbH)

3. IMAGE REGISTRATION

Image registration is a prerequisite for change detection approaches. Especially if differencing on a pixel level is proposed, the registration has to be in a sub-pixel quality to avoid too many false alarms. But also if the comparison of the images is performed on a higher level of abstraction e.g. structural object description, the precision of the registration process has a strong influence on the result of change detection. Especially if the objects are small and located close to each other, confusion can be avoided only when the registration is precise e.g. cars on a parking area.

We use a multi-stage algorithm of image registration [Lutsiv, 2002], [Middelmann, 2003] composed of three separate matching algorithms. The first matching algorithm is based on juxtaposition of the pieces of straight lines detected using the contour information; it is intended for working with the narrow range of possible types of images but has the highest speed and good reliability. The second matching algorithm is based on juxtaposition of contour sequences i.e. curvilinear contours approximated by a set of consecutively connected straight-linear segments. It works slower but can deal with a wider range of images. The last matching algorithm is based on the Fourier-Mellin transform. All these algorithms are adapted for working with large images using a multi-resolution technique. Consecutive application of several matching algorithms with different characteristics allows a significant increase in reliability of image registration but the precision of registration cannot be sufficient, especially for the structural matching of contours. Therefore an additional step of improvement of the transformation parameters based on the calculation of local mutual shifts of local elements using the Fourier-Mellin transform was appended.

If the observed scene is flat enough, an image matching technique applying the same transformation model to the whole scene can be used. However, in many situations we are encountered with non-flat scenes e.g. urban landscapes. These images are mostly taken under different aspect angles with observation directions deviating from Nadir. Different mutual transformations are necessary for corresponding object surfaces. The bottom of elevated objects and the visible projections of their tops should be transformed separately. To determine regions related to ground level and to elevated objects several approaches were investigated using stereo matching and optical flow estimation. Because not only the region is identified, but also the orientation vector is obtained, the elevated objects could be registered. The robustness of the approach has to be evaluated with respect to its influence on the results of the change detection process.

4. RECOGNITION OF INFRASTRUCTURAL OBJECTS

The essential problem of pixel-based change detection are the different representations of an object in images taken at different times. Even if the content of the images is the same from the change detection point of view, in many cases differences on the pixel level will result in false alarms. Although differencing on the pixel level may show changes in the images (e.g. vegetation or illumination), the result of a focused analysis can provide both images to be equivalent. Often, the task of change detection is goal driven and addressed to specific changes e.g. changes in infrastructures. Therefore it seems to be more successful to perform change detection on a higher level of abstraction. Image interpretation and object recognition makes the analysis more robust against geometric and radiometric differences between the images being compared. For our investigations, the scene is separated in different infrastructural objects like tanks of a refinery, roads, and buildings. This was done by segmentation of homogenous regions and an extraction of linear or circular line segments with a succeeding structural analysis.

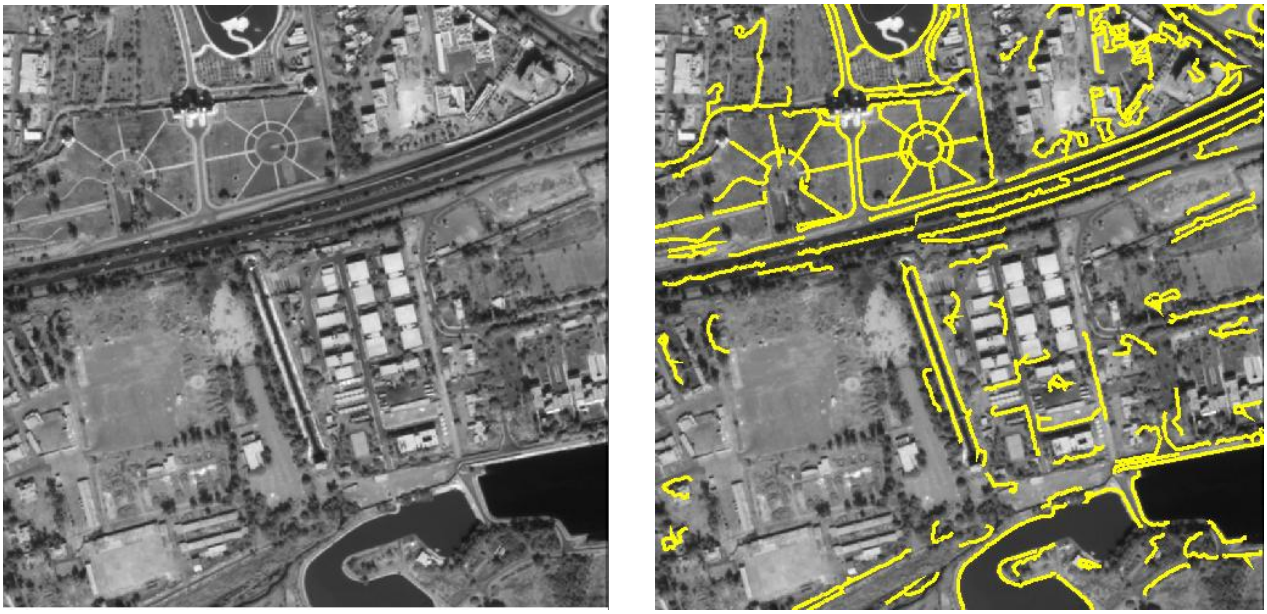


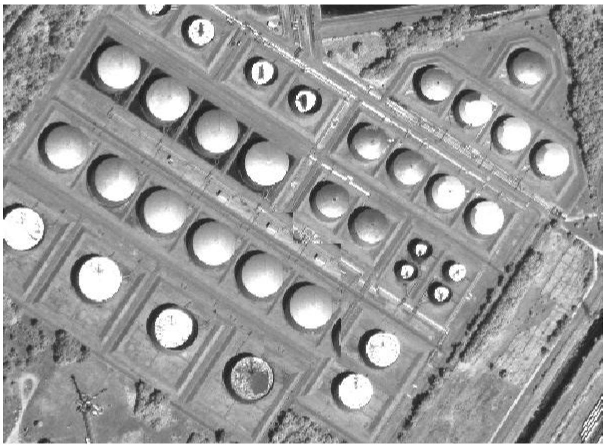
Figure 3: Curvilinear structures in an IKONOS image (Original images: Courtesy of European Space Imaging / © European Space Imaging GmbH)

One class of infrastructure objects are roads, railway tracks, and rivers, which are represented as curvilinear structures in the images. Most existing operators use a simple model for the line that is to be extracted, i.e., they do not take into account the surroundings of a line. This leads to the undesirable consequence that a wrong position is determined whenever a line with laterally variable contrast is extracted. In contrast, the algorithm used in this paper [Steger, 2000] utilizes an explicit model for lines and their surroundings. By analyzing the scale-space behaviors of a model line profile, the bias induced by asymmetrical lines can be removed. Furthermore, the algorithm not only returns the precise sub-pixel position, but also the width for each line point, also with sub-pixel accuracy. The algorithm can be adapted to bright and dark lines as well as to the width of the curvilinear structure. A result applying the algorithm to an image is shown in Figure 3.

Another object of military interest are tanks of refineries. An algorithm to detect these circular contours has been developed that consists of the following steps:

- Detection of contours in the image as described before [Steger, 2000].
- Linear approximation of the line segments
- Determination of a center point of point triples
- Clustering center hypotheses of arcs to form a circle [Takaiyama, 1989], [Thomas, 1989]
- Filtering of arcs over 180° and texture analysis in potential tank areas.

The different steps are illustrated in Figure 4 and Figure 5.



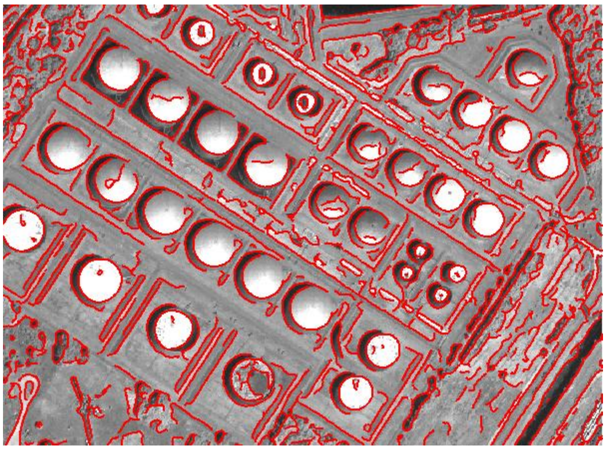
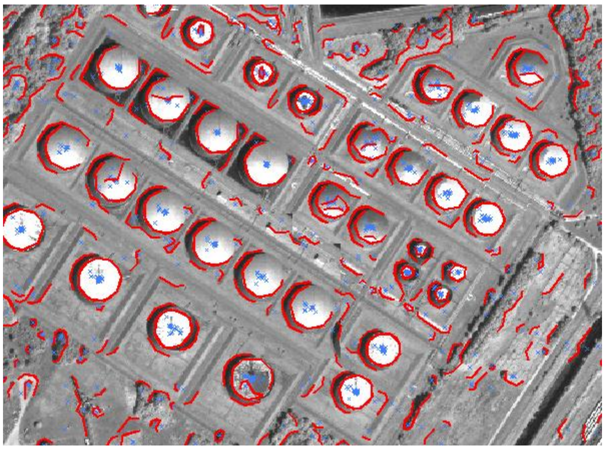


Figure 4: Segmentation of circular structures (Original images: Courtesy of European Space Imaging / © European Space Imaging GmbH), right) line structures segmented by Steger operator



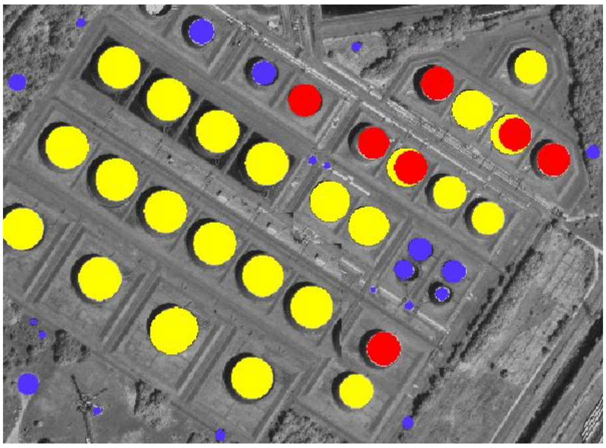


Figure 5: left) circle segments with center hypotheses, right) resulting circles from arcs bigger than 180°after circle segment clustering

Infrastructure objects like buildings are extracted by a multiscale gradient watershed segmentation process [Vanhamel, 2003]. The proposed scheme comprises a nonlinear scale-space with vector valued gradient watersheds. It is the aim to produce a meaningful hierarchy among the objects in the image using the three image components of distinct perceptual significance for a human observer, namely strong edges, smooth segments and detailed segments. The scale space is based on a vector valued diffusion that uses the numerical scheme of additive operator splitting. Furthermore the principle of dynamic of contours in scale space that combines scale and contrast information is used. Results of segmentation on different levels are shown in Figure 6. One of the main problems is the selection of the most representative segmentation result. A robust solution has to be developed for this problem.

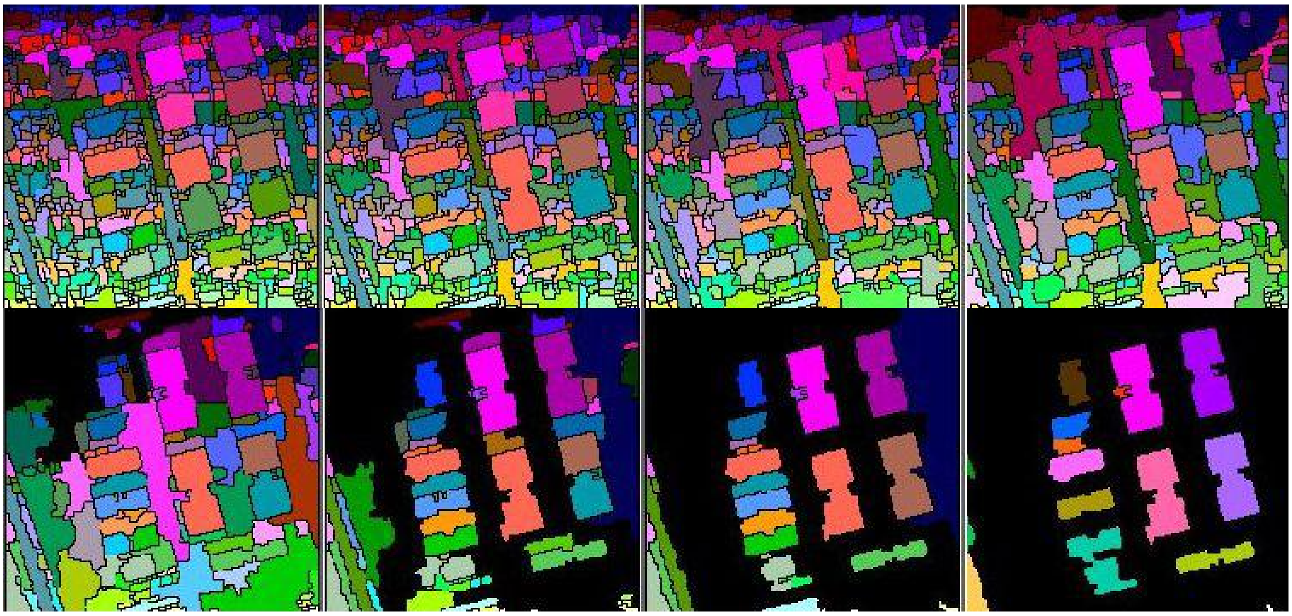
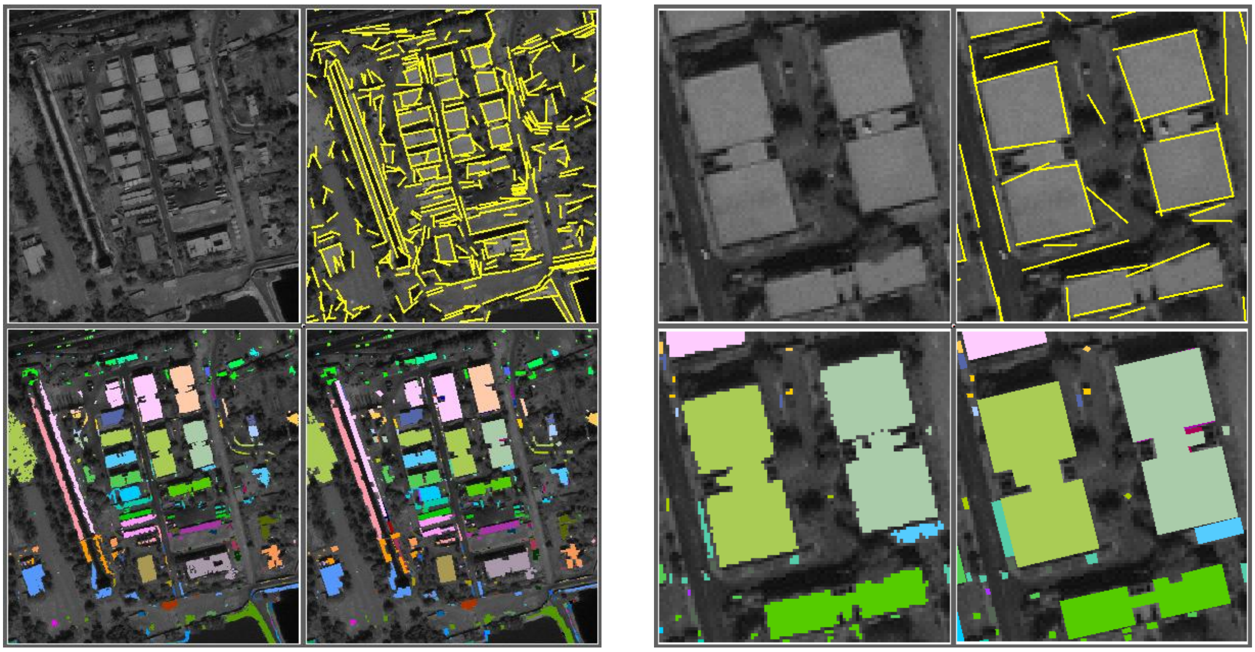


Figure 6: Different levels of segmentation by a vector valued diffusion process



a b

Figure 7: Results of segmentation a) original, edges, regions, generalized contours b) enlarged sub-window with original, edges, and different degrees of generalization (Original images: Courtesy of European Space Imaging / © European Space Imaging GmbH)

The extracted building hypotheses are described as rectangular structures. The segmented regions are generalized up to a predefined level of detail by a recursive process. Substructures of the polygon are eliminated if their area is smaller than a threshold or an edge of the polygon is shorter than a threshold. The resulting structures are used for the change detection process. Additionally edges were extracted by the Burns Line operator [Burns, 1986]. Especially edges in the neighborhood of shadow regions are of strong interest. Some results are presented in Figure 7.

5. CHANGE DETECTION BY STRUCTURAL MATCHING

Change detection has been defined as the process of identifying differences in the state of an object or phenomenon by observing it at different times. This can be done determining changes on an iconic level with a succeeding interpretation of the changes by the observer or an automatic knowledge based analysis delivering hints for changes on a semantic level. Many problems in change detection caused by differences in data acquisition parameters and small misregistrations can be avoided by structural object analysis. Structural methods are well suited for man made objects (e.g. linear structures, rectangles, cubes ...) and build hierarchies by composing less complex object structures into more complex object structures.

The comparison of the images starts with segmentation by a vector valued diffusion process. Due to the variance in the result of segmentation all segments were taken into account at the beginning. Because in many cases the objects are unchanged from level to level the first step is a reduction of the segmentation results given on different levels. To reduce the combinatory effect of the assignment process of the segments in both images, similar segments on succeeding segmentation levels in each image are fused to one representative. The stability over several levels can be used as an additional feature.

As mentioned before, the change detection task is usually focused to a specific ROI and a class of objects. We propose a feature based pre-classification of objects. So the change detection task has to start with a coarse description of the objects of interest. These features may be the estimated size and radiometry of the objects under consideration. By this step the combinatory effect of the following assignment process is also reduced essentially.

An important function of the assignment process is to determine the similarity of two objects. In our first investigations we applied the Haussdorff distance [Huttenlocher, 1992] as distance function between the obtained structural descriptions to match two contours (e.g. given by polygons). The Haussdorff distance measure may be useful to compare two sets of points. Nevertheless this measure overestimates modifications of few points of the objects (see Figure 8). Due to lightning effects or something else the segmentation process of the same object at different time delivers always different set of points. Furthermore any normalization of this Haussdorff distance measure may not self-evident. This is required for comparison with other measures.

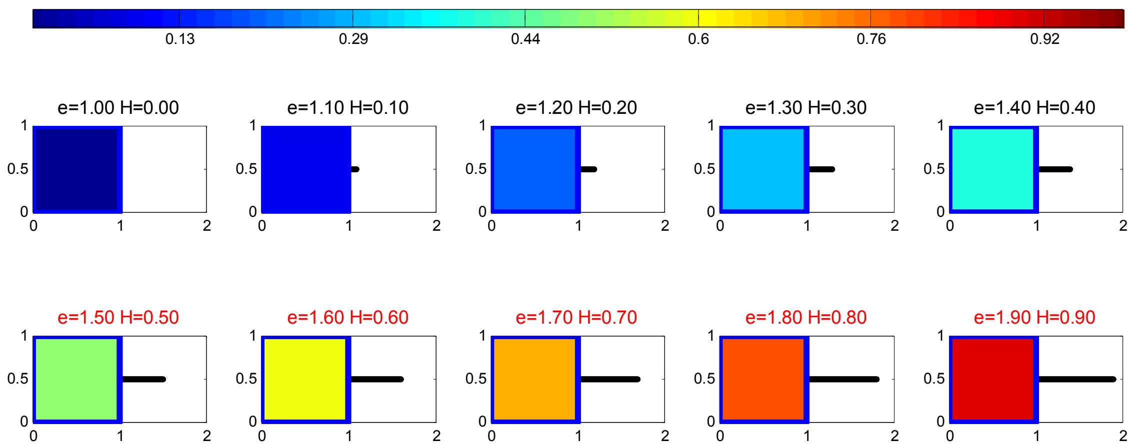


Figure 8: Haussdorff distances between a square and an identical object with a small additional extension

By this reason we prefer a combination of measures based on the iconic representation of the object (like the rate of union/intersection) and some symbolic features (area, perimeter, …). Additional features may be also included but are not tested yet. The normalization of all measures allows to consider and to handle the distance measures like Fuzzy sets. The weighting of the included distance measures is given by using fuzzy like logical operators (AND, OR, …).

Furthermore the area-based features may be more robust under small segmentation differences. A distance measure was defined incorporating the intersection of the areas and the similarity of the shape of both segments comparing the radii of inertia. Given shapes A and B, we calculate $x=D/U$ as the rate of the intersection $D=A\cap B$ and the union $U=A\cup B$. The sigmoid function $f(x)=1/(1+e^{a(b-x)})$ with constants $a=4$ and $b=0.25$ yields a congruence measure for this rate. Another feature usable to compare two objects is the rate of compactness. Let $a(A)$ be the area and $p(A)$ the perimeter of A. The compactness is defined by $c(A)=4\pi a(A)/p(A)^2$. The rate of compactness is $r_c=\min\{c(a)/c(B),\ c(B)/c(A)\}$. Combining both congruence measures the distance is defined by $S_{fc}=1-f(x)r_c$. Figure 9 shows the behavior of the distance measure of two objects. The reference object is the blue square. The test object is the cross shaped object with different position (left to right) and different size (top to bottom). The color of the test object corresponds with the distance measure also shown by the color bar on top of the figure. The best congruence for both objects is given in the lower left subplot. Further object features (e.g. radii of the inertia a. s. o.) may also be considered for calculation of the distance measure. Equal segments give a distance measure near 0.0. Segments with an empty intersection, particularly objects with no correspondence, result in a distance measure near 1.0.

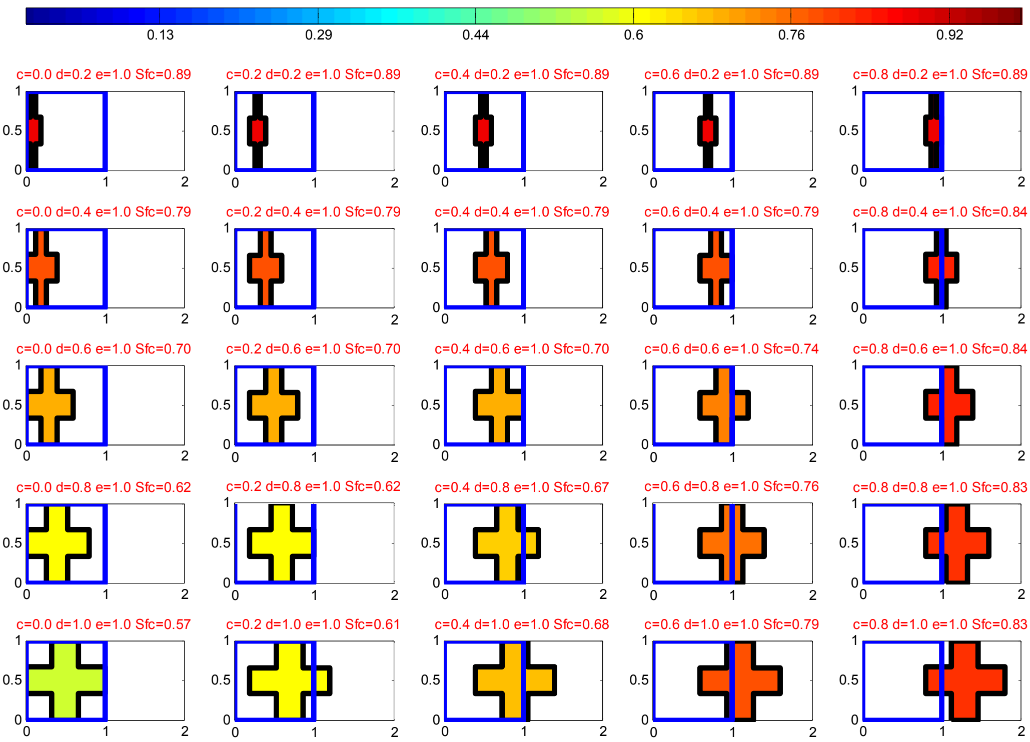


Figure 9: Distance measures between square and cross shaped object for different position and size

The next step is an assignment of possibly corresponding objects. There are three possible cases of correspondence: 1:1, 1:n, n:1. To avoid a multiple assignment of objects in the first image to one object in the second image the distance measure is determined for all segments of the reference image to all segments in the test image. By this a distance matrix is defined. The problem of selecting exactly one element in each row and column of the distance matrix so that the sum of distances becomes minimal is solved by the Hungarian method. A post-processing is done for objects composed of more than one segment in one of the images. If sub-segments are missing, but a comprising segment is found in the other image this case is not reported as a change.

The change detection task was applied to different regions of interest in IKONOS images taken at different times. The images are showing no changes as well as changes concerning specific object classes. An example is given in Figure 10. Here container like objects are in the focus classified by their geometrical features. The upper left image shows the classified segmentation result in image taken at time t_0. The upper right image shows the corresponding classified segmentation result in image time t_1. The images in the lower row show on the left side the segmentation result of image time t_0 overlaid image time t_1. The lower right image contains corresponding objects found in image time t_0 and image time t_1. An interesting effect can be seen for the object in the middle of the images. A coarse inspection would identify a correspondence. Due to the missing overlap of this object's segments (it was shifted to another position), a change has been identified.

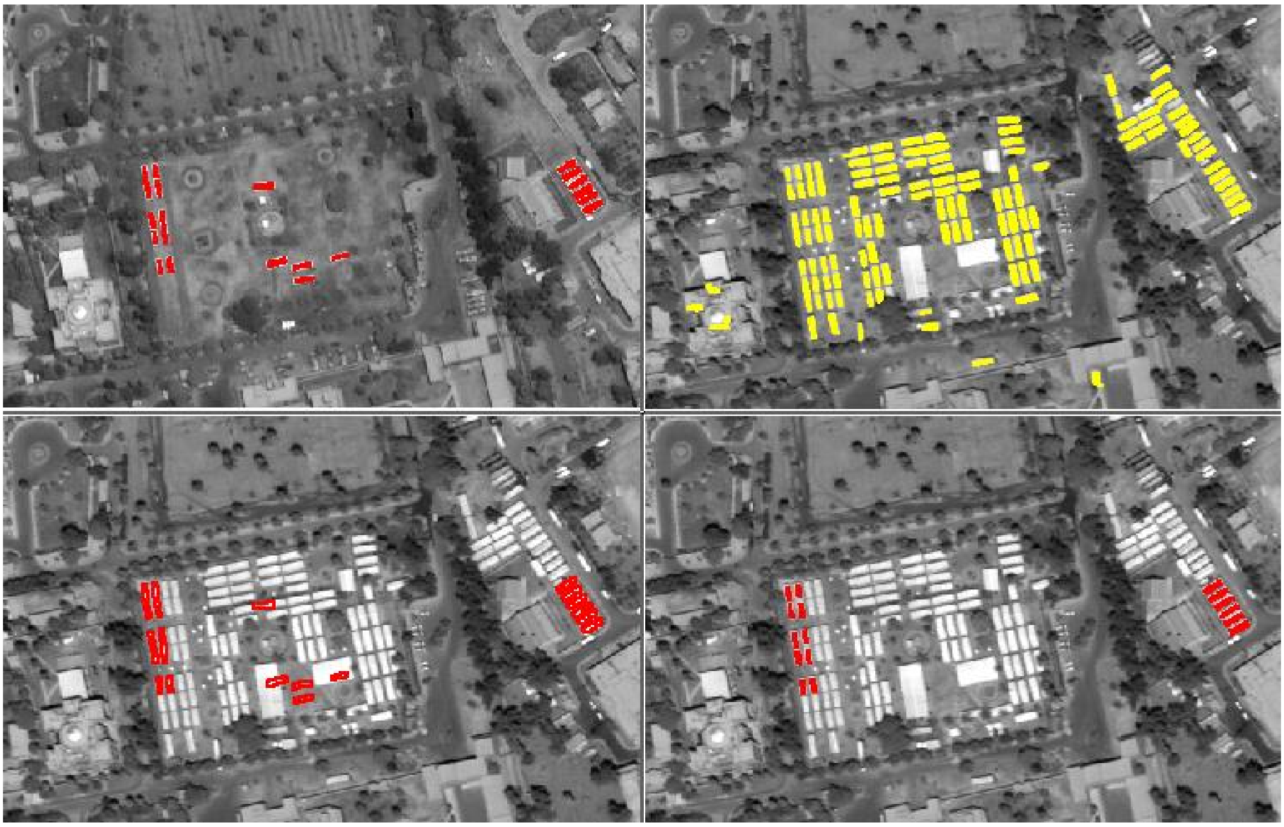


Figure 10: UL) Classified segmentation result in image time t_0, UR) Classified segmentation result in image time t_1, LL) segmentation result of image time t_0 overlaid image time t_1, LR) corresponding objects found in image time t_0 and image time t_1 (Original Quickbird images © 2003 DigitalGlobe Inc. ALL RIGHTS RESERVED, provided by the DLR in context of the NATO RTO SET045/TG26)

6. CONCLUSIONS

We presented and discussed different steps of a processing chain for change detection in IKONOS images. One main focus was on structural descriptions of image content and the comparison of descriptions generated from images taken at different times. First results of a comparison of these structural descriptions were presented. The main problem is the compensation of different parallax effects in the images due to different aspect angles. This leads to a lot of false alarms. In the future we will concentrate our effort on these phenomena.

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