COMPARISON OF ALTERNATIVE IMAGE REPRESENTATIONS IN THE CONTEXT OF SAR CHANGE DETECTION

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ABSTRACT

This article compares four different alternative image representations in the context of a structure-based change detection. The framework is taken from the already published Curvelet-based change detection approach. Only the transform step is modified by inserting three additional transforms: the Laplacian pyramid, the Wavelet and the Surfacelet transform. The results of the change detection are compared to the single pixel difference image in order to find the representation that best illustrates the underlying structures. The Curvelet transform again turns out to be very powerful in describing man-made objects and landscapes.

1. INTRODUCTION

It is well-known that SAR change detection is not an easy task at all. Due to the geometric and radiometric characteristics of SAR images most of the standard change detection algorithms for optical remote sensing data fail. Some basic SAR change detection techniques, advantages and constraints can be found in [1], which reviews the fundamental approaches. [2] distinguishes two different types of change detection: amplitude change detection and coherent change detection, exploiting the phase information. The latter type has been examined by [3]. This method presumes a stable phase measurement, so that each incoherent region can be classified as changed. Regarding shorter wave lengths, even a repeat pass acquisition with a very short repetition time (11 days in the case of TerraSAR-X) cannot assure coherence over natural cover. In the case of natural disaster monitoring where reference images often are several years old coherence-based methods are not applicable because too much disturbing incoherence is caused by natural surfaces.

The amplitude-based change detection method is better suited for the monitoring of diverse landscapes over a long period of time. The only drawback to overcome is the influence of deterministic speckle noise. An idea starting with the fusion of several SAR images of different incidence angles and a coarse digital elevation model to a ”super-resolution” image is presented by [4]. Man-made objects, i.e. geometrical particularities that are not captured by the digital terrain model used for orthorectification, are classified by their diverse appearance in single orthorectified images due to the differing acquisition geometries. So, seasonal changes in natural surroundings can easily be distinguished from changes in built-up areas. One disadvantage is the large number of different SAR images of the same area needed to generate the ”superresolution” image. In contrast, [5] needs a high resolution elevation model (e.g. acquired by airborne laser scanning) to simulate a SAR image using the geometric appearance of the illuminated area. This simulated SAR image is subsequently compared to the real SAR data. The quality of the results is naturally highly dependent on the resolution of the digital elevation model and its co-registration to the SAR image. The influence of different surface materials is ignored so far. Although this method seems to be very promising, its application is still restricted to small-sized sample data.

First attempts using the Curvelet transform have been reported by [6]. The core of this method is a structure-based image comparison and subsequent image enhancement that is applied on the Curvelet coefficients of an image [7]. First experiences with polarimetric data sets in combination with this change detection approach on TerraSAR-X dual-polarized high resolution spotlight data have been presented [8]. However, it has not been demonstrated whether the Curvelet transform really is the best suited alternative image representation. In this paper three other representations, namely the Laplacian pyramid, the Wavelet transform and the Surfacelet transform are introduced. The results are compared to each other in order to find an optimal representation for the amplitude-based change detection in man-made areas.

2. ALTERNATIVE IMAGE REPRESENTATIONS

Before the alternative image representations are utilized in the change detection algorithm, the particularities of the transforms are briefly presented. The main differences between the representations are the location, the scale, the orientation and the form of the geometric primitive used for the image reconstruction. All given computation times are approximate and refer to a MATLAB implementation on a Solaris workstation, when transforming the sample image of 1024 x 1024 pixels.

2.1. Pixel

This is the most common image representation. The image is saved as a raster of same-sized "‘picture elements"’ (pixels). The pixel value refers to the image value at that corresponding position. We can call it multi-located, because every location can hold another image value (with respect to the image resolution). The geometric form of the pixel is not predefined [9], but naturally, for display reasons it is widely seen as a uniform rectangle or even square. Although it is easy to understand and easy to compute, there is a drawback to this method: As all pixels are captured as individuals, no neighboring relations can be described, even if the neighbored pixels share the same pixel value.

2.2. Laplacian pyramid

The Laplacian pyramid is also a multi-located representation, but it adds another type of information: the scale [10]. The original image – composed of many individual pixels – is subsampled, so that coarser images that hold fewer pixels, and therefore have a lower resolution, are produced. For this representation – called a Gaussian pyramid – the difference between two neighboring scales is calculated to form the Laplacian pyramid, which is in turn composed out of a coarse image and particular difference layers leading to the next finer image scale. Thus, it is able to describe relations between neighbored pixel values. As the original definition uses quadratic images with a size of $2^n x 2^n$ pixels ($n \in 2, 3, 4...$), the form of the features that can be delineated is also expected to be quadratic. One advantage of this representation is its simple implementation and the short computation time of only 3 seconds.

2.3. Wavelets

The Wavelet transform contributes another aspect: the directionality. Having been developed for the analysis of one-dimensional signals, it is adapted for image description by applying it both in the vertical and horizontal directions [11]. There is a variety of mother wavelets (special wave forms, mainly named after their inventor) that can be scaled and transported to different positions in a row or column, so that the input signal is best approximated. In the case of SAR data, if all features are oriented parallel or perpendicular to the flight direction, this is an ideal examination tool, e.g. for side-lobes near very strong backscatterers. For the exploration of man-made objects, e.g. cities, or for use on geocoded data sets, where the inlying features can hold an arbitrary orientation, it is not very suitable. The computation time is 6 seconds and is only double the computation time of the Laplacian pyramid.

2.4. Curvelets

The Curvelet transform – designed to represent images by their edges – extends the bi-directionality of wavelets to a multi-directionality. The basic element – called the Ridgelet – is a linear feature [12] that appears in different lengths (according to the scale), in different positions and in as many orientations as can be determined from the original image. Thus, in a $3x3$ neighborhood only horizontal, vertical and diagonal structures are distinguishable while in larger surroundings a finer angular resolution can be obtained. The computation of this transform is very expensive (12 seconds), although it has been optimized several times [13]. The result of this transform is a large number of complex coefficients, whose amplitudes refer to the strength of the corresponding linear structure in the original image. For urban areas imaged by SAR sensors, where buildings show up in bright lines, this representation is especially useful.

2.5. Surfacelets

The Surfacelet transform shares similar properties with Curvelets, but it uses a different element: the ellipse (in 2D) and the ellipsoid (in 3D). Originally, it was developed for denoising and feature extraction from 3D tomographic acquisitions [14], e.g. in the medical context. Therefore, applied to two-dimensional data it can been called a laminar image description. The transform produces a large amount of coefficients referring to the strength of the single ellipses in the image, that also appear in different scales, orientations and positions in the original image. We can conclude that this transform is mainly suited for the description of rounded laminar features apparent in the SAR image, e.g. ships or cars. The computation of Surfacelets is very expensive, and at 30 seconds it is nearly three times the Curvelet transform and ten times the Laplacian pyramid.

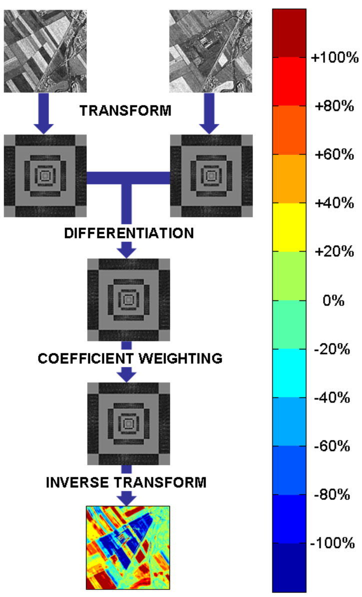
3. METHOD

As input we use geocoded TerraSAR-X amplitude images. They have been acquired in the *High Resolution Spotlight* mode using the HH polarization, and they are delivered as *Enhanced Ellipsoid Corrected (EEC)* and *Radiometrically Enhanced (RE)* products with a uniform pixel spacing of 1.25 m on ground (Fig. 1). Thanks to the high accuracy of the orbit information of TerraSAR-X the images coincide automatically without further coregistration. In order to model speckle noise with the help of an alternative image representation, the amplitude images are logarithmically scaled. After the input images have been transformed to the particular coefficient domain, the coefficient

(a) 2008-05-09 (b) 2010-04-02

Fig. 1. Original TerraSAR-X amplitude images (*EEC/RE*)

difference is calculated (Fig. 2(a)). This difference image is subsequently enhanced by weighting the coefficients. A special adaptive gain function estimates the threshold between structure and noise, i.e. between high and low coefficients. In a second step, the lower coefficients are removed completely while higher coefficients are decreased or kept without change according to their strength. This enhanced difference image is finally transformed back and scaled exponentially. For visual interpretation different colors mark the amount of change in the amplitude relative to the lower amplitude value of both images, see color bar in Fig.2(b).



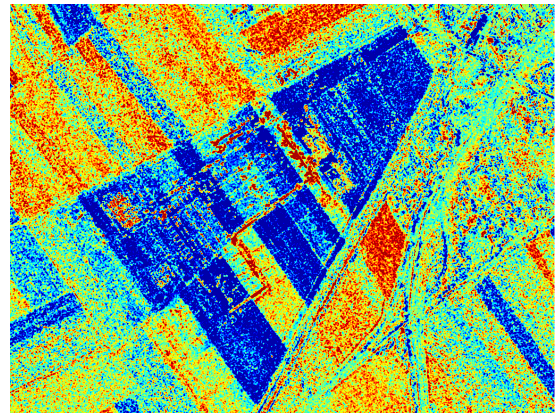
(a) (b)

Fig. 2. Flowchart and color bar

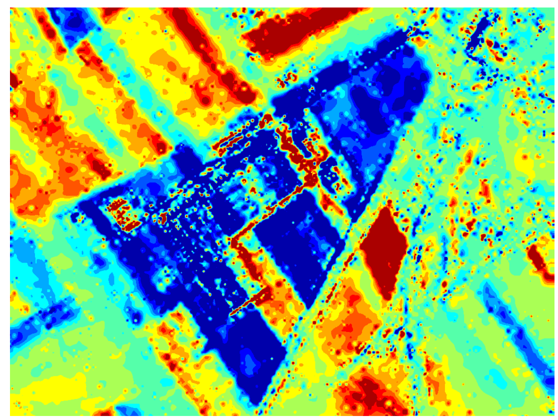
4. RESULTS

The results of running the change detection algorithm with different image representations are presented in this section. As expected, the pixel-based image comparison (Fig. 3(a)) is highly affected by speckle noise. In contrast, the Laplacian pyramid (Fig. 3(b)) delivers explicitly smoother results. However, there are many small and nearly circular disturbances visible that are probably caused by high (single) pixel differences. If the change in a single pixel value is much higher than in the surrounding area, it is conceivable that this change is transported even to coarser scales, and hence it is enlarged. As the Laplacian pyramid does not distinguish between different directions, the circular form might indicate the square as a basic element.

The difference image calculated by the Wavelet transform



(a) Pixel

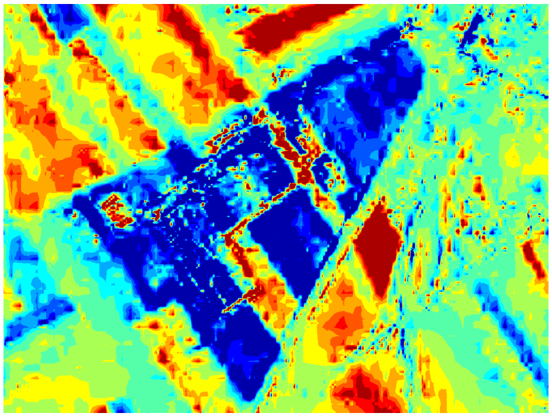


(b) Laplace pyramid

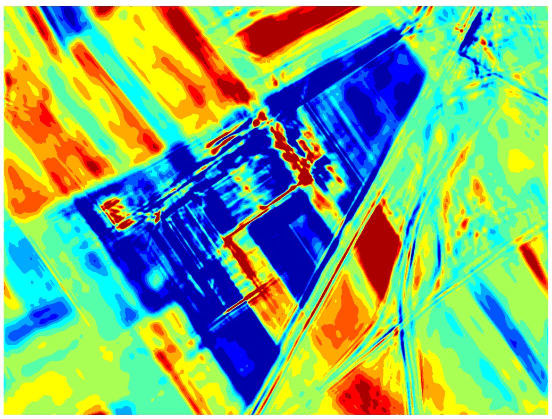
Fig. 3. Detected changes I

affirms the assumption that the basic element is somehow transferred to the resulting image. In Fig. 4(a) the large-scale changes are smoothed as well, but the inclined edges appear very rough. If we look closer on these we perceive a certain displacement in the horizontal and vertical direction, whereas the few structures along rows or columns are well approximated. The reason for this effect is the bi-directionality of the Wavelet transform. This problem should be solved by using the Curvelet transform. And indeed, Fig. 4(b) depicts completely smooth edges. Homogeneous regions as well as linear structures – independent of their orientation – are clearly delineated. Only some linear artifacts arising near strong structures might disturb surrounding smooth regions. Introducing laminar basic elements such as the ellipse-like Surfacelets brings no further improvement (Fig. 4(c)). The form of the geometric primitive can easily be recognized from the results because all changes are described by ellipse-like features. Straight lines appear bumpy being composed of a large number of rounded elements. Even presumably homogeneous regions show several ellipse-like features that stand out from the surrounding area.

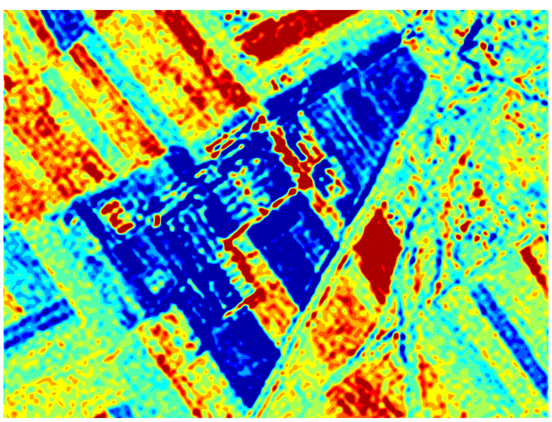
In summary, the large-scale changes are captured by all



(a) Wavelets



(b) Curvelets



(c) Surfacelets

Fig. 4. Detected changes II

image representations. The main difference is visible in the description of small-scale changes. There, the geometric form of the utilized basic element becomes inevitably apparent in the resulting difference image. Although this might help to identify objects, it can also complicate the recognition of objects that do not match with the chosen basic element.

5. CONCLUSION

The comparison of different image representations in the context of SAR change detection proved that all representations guarantee analogous results. As the description of the changes is carried out with the help of different geometric primitives, the degree of approximation depends on the similarity between the changes to be mapped and the form of the basic element. Unfortunately the increase of complexity in the image transform also entails an increase in computation time. Thus, we recommend using the simplest possible image representation with respect to the size and the form of the objects of interest. For our focal point – change detection on man-made structures – the Curvelet transform turns out to be the right choice because of the optimal approximation of linear structures.

6. REFERENCES

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