P7

A comparison of change features from multi-temporal SAR images for monitoring the built-environment in disaster situations

○Marc Wieland[1,2], Wen Liu[2], Fumio Yamazaki[2] and Takashi Sasagawa[3]

Abstract **:** This study compares five change features (log-ratio per-pixel and per-window, correlation, change index, curvelet difference) derived from multi-temporal Synthetic Aperture Radar (SAR) images. The performance of these change features with respect to quantifying changes between SAR images is evaluated against an image-dependent manually derived reference dataset and an image-independent reference from ground-surveys. Two TerraSAR-X images over Sendai harbor acquired before and after the 2011 Tohoku earthquake and tsunami are used to detect changes to the built-environment caused by the disaster. The study concludes that the simple log-ratio computed over a moving window shows the best and most robust overall performance for the given experimental setup.

Keywords **:** SAR, change detection, performance evaluation, earthquake, Tohoku

1. Introduction

With the rapidly growing supply of multi-temporal satellite imagery and the demand for up-to-date situation awareness in disaster situations, the need for robust change detection methods is constantly increasing. Synthetic Aperture Radar (SAR) provides clear advantages over optical satellite imagery as its acquisition is largely illumination and weather independent. Direct image comparison shows large potentials for change detection in SAR images. However, the mixture of additive and multiplicative noise contributions may cause high false alarm rates, and the choice of robust change features becomes essential to reduce the effects of noise and improve the detection rates for any application. A widely used change feature is the logarithmic intensity difference (or log-ratio). To reduce the effect of noise, it is often used on speckle filtered images, as part of a window function that considers neighboring pixels, or in combination with additional features such as correlation [1]. A more recently proposed change feature uses a curvelet transformation to effectively deal with the image noise [2]. The objective of this study is to compare the performance of different change features for the task of detecting changes between SAR images in a natural disaster case.

2. Study area and data

The study focuses on the Sendai harbor area, Japan, which was most severely affected by the 2011 Tohoku earthquake and tsunami. Two TerraSAR-X (TSX) images taken before (t1: 21 Oct. 2010, 37.3° incident angle) and after (t2: 04 Sept. 2011, 38.6° incidence angle) the earthquake were used to detect changes (Fig. 1). The images were captured in StripMap mode with HH polarization in a descending path and delivered at orthorectified multi-look corrected product level with a square pixel size of 1.25 m. Image pre-processing included conversion of intensity values to radar backscatter coefficient, speckle filtering with an enhanced Lee filter (window size: 5 x 5 px) and co-registration.

[1] GFZ German Research Centre for Geosciences
(Address: Helmholtzstr. 7, 14467 Potsdam, Germany.)
(Contact: mwieland@gfz-potsdam.de)
[2] Department of Urban Environment Systems, Chiba University
(Address: 1-33 Yayoi-cho, Inage-ku, Chiba, Japan)
(Contact: wen.liu@chiba-u.jp, fumio.yamazaki@faculty.chiba-u.jp)
[3] PASCO Corporation
(Address: 4-10-1 Nakano, Nakano-ku, Tokyo, Japan)
(Contact: taawda5004@pasco.co.jp)

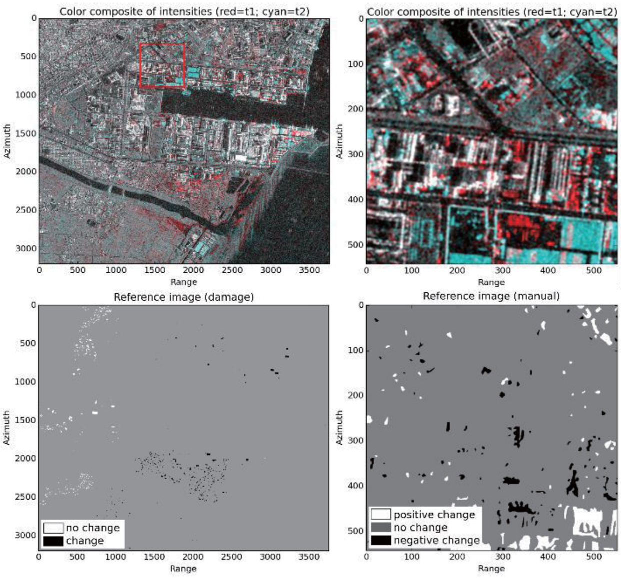

Fig.1. False-color composite of pre- (t1) and post-event (t2) TSX images, and damage reference data over the study area of Sendai harbor (left). Subset with manual reference data (right).

Two reference datasets were acquired over the study area. First, “image-dependent” reference data for a subset of the study area were derived from a visual interpretation of the color-composite image by a SAR expert. Positive, negative and no change classes were manually outlined based on expert judgment. Second, “image-independent” reference data were acquired from a database of building damages [3]. These building footprint data, which include seven types of building damage, were reclassified into two classes: “Change” refers to buildings that were originally classified as “washed away” and “collapsed”, whereas “no change” refers to buildings of class “no damage” in the original data. A stratified random sample of 1,000 buildings was taken to derive the actual reference dataset for this study.

3. Method

The change features that are being compared in this study include the difference computed per pixel, and computed as average over a window, the correlation coefficient, the change index as a combination of log-ratio and correlation, and the curvelet difference. The difference (d) is calculated by equation 1 and the correlation coefficient (r) is calculated by equation 2

$$d = \overline{Ib} - \overline{Ia} \quad (1)$$

$$r = \frac{N\sum_{i=1}^{N} Ia_i Ib_i - \sum_{i=1}^{N} Ia_i \sum_{i=1}^{N} Ib_i}{\sqrt{(N\sum_{i=1}^{N} Ia_i^2 - (\sum_{i=1}^{N} Ia_i)^2)\cdot(N\sum_{i=1}^{N} Ib_i^2 - (\sum_{i=1}^{N} Ib_i)^2)}} \quad (2)$$

where i is the pixel number, Ia_i and Ib_i are the backscattering coefficients of the second (post) and first (pre) images, and $\overline{Ia}_i$ and $\overline{Ib}_i$ are the corresponding averaged values over the N window (5 x 5 px) surrounding the pixel i.

Difference and correlation are combined into a change index as introduced by [1] and described by equation 3

$$z = \frac{|d|}{\max(|d|)} - c \cdot r \quad (3)$$

where $max(|d|)$ is the maximum absolute value in difference and c is the weight between the difference and the correlation coefficient.

The curvelet change feature (c) is derived by transforming the logarithmic intensity values into curvelet coefficients and differentiating them (equation 4).

$$c = T^{-1}\left[(\mu_b - \mu_a) + \sum_S \sum_D \sum_L G\,(dk_{S,D,L}, a, b) \cdot f_{S,D,L}\right] \quad (4)$$

The intensity values in curvelet domain are represented by the sum of the contributions of structure functions $f_{S,D,L}$ (Scales, Directions and Locations) and the mean value μ. The appearance of the single structures is controlled by the corresponding curvelet coefficients $k_{S,D,L}$ and a hyperbolic tangent function G is used to weight the coefficients. Coefficients that are not considered distinct structural information are being removed. After transforming the coefficients back to the spatial domain, the change feature is directly generated as log-ratio of the input images [2].

A typical change detection method is to threshold the change feature and different approaches exist for threshold optimization. In this study, we iteratively change the threshold over the whole range of feature values, where for each iteration the predicted changes are compared to the changes identified by the respective reference dataset. The comparison is done on a per-pixel basis for the manual reference, and on a per-building basis for the damage reference. In case of the damage reference, a building is identified as being changed if it intersects with pixels predicted as being changed.

4. Results

Fig. 2 shows the comparison of change feature performance over all thresholds on a speckle filtered (left) and unfiltered (right) image pair for the image dependent manual reference.

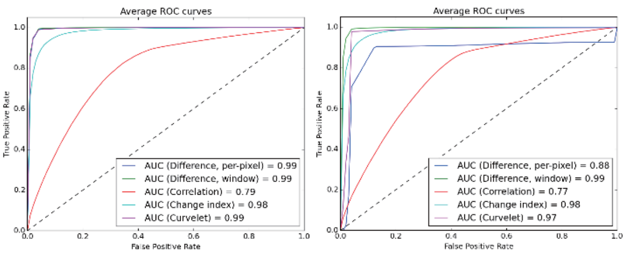

Fig. 2. Comparison of change feature performance on a speckle filtered (left) and unfiltered (right) image pair for the image dependent manual reference.

The simple difference computed over a window provides the most robust change feature with respect to speckle noise and changes in threshold. Also the change index and curvelet features show very good performance over all thresholds with only minor performance decrease on the not filtered image pair for the curvelet feature. Correlation performs worst, but is also hardly affected by noise since it is computed over a window. The difference computed at per-pixel level provides very good results for speckle filtered image pairs, but shows the strongest performance decrease on unfiltered image data.

Fig. 3 shows the comparison of change feature performance over all thresholds on a speckle filtered (left) and unfiltered (right) image pair for the image independent damage reference.

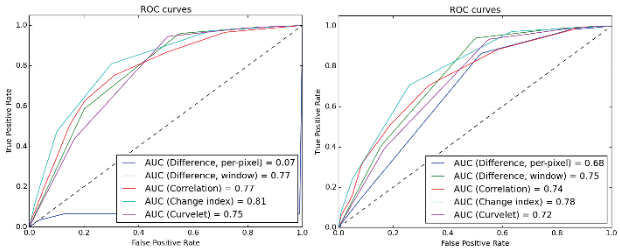

Fig. 3. Comparison of change feature performance on a speckle filtered (left) and unfiltered (right) image pair for the image independent damage reference.

The best performance can be observed for the change index, followed by per-window difference, curvelet difference and correlation. Per-pixel difference shows the worst performance on unfiltered images and performs even worse than random in the speckle-filtered case. For all other change features, speckle filtering improves the performance.

5. Discussion and conclusions

This study compared five change features on speckle-filtered and unfiltered TSX data in a unified framework against a manual reference and an independent damage reference. In this experimental setup the difference of logarithmic intensity values computed over a moving window appeared to be the most robust and simple feature of all the tested change features. Correlation showed only average performance. Change index and curvelet difference proved to be promising and can be applied with good results even without speckle filtering. Changes induced by tsunami and earthquake disasters could be sufficiently detected by all change features except the per-pixel difference, which showed a strong performance decrease after speckle filtering for the damage reference. This point will be further elaborated upon in future work along with a more extensive change feature testing.

Acknowledgements

The TerraSAR-X images used in this study are property of DLR, distributed by Airbus DS / Infoterra GmbH, and provided through PASCO Corporation.

References

1) W. Liu, F. Yamazaki, H. Gokon, and S. Koshimura, "Extraction of tsunami-flooded areas and damaged buildings in the 2011 Tohoku-oki earthquake from TerraSAR-X intensity images," Earthquake Spectra, 29 (1), 2013.

2) A. Schmitt, B. Wessel, and A. Roth, "An innovative curvelet-only-based approach for automated change detection in multi-temporal SAR images," Remote Sensing, 6 (3), 2014.

3) H. Gokon and S. Koshimura, "Mapping of building damage of the 2011 Tohoku earthquake and tsunami in Miyagi prefecture," Coastal Engineering Journal, 54 (1), 2012.