SAR change detection techniques and applications

R.J. Dekker
TNO Defence, Security and Safety, The Hague, The Netherlands

Keywords: SAR, change detection, adaptive filtering, segmentation

ABSTRACT: Change detection, the comparison of remote sensing images from different moments in time, is an important technique in environmental earth observation and security. SAR change detection is useful when weather and light conditions are unfavourable. Five methods of SAR change detection are presented and evaluated. The performance of the first one, post-classification change detection, is strongly dependent on the accuracy of classification. Because the latter can be a problem in SAR images, this is not a proper method. The second one is CFAR detection. This method is only suitable when the changes are small compared to the resolution. The third method uses an adaptive filter and is able to deal with distributed changes as well. Besides, it can be more effective in case of small changes, but it lacks in reproducing the shape of changes. The fourth method makes use of multi-channel segmentation, a method that reproduces the shape of changes well for multi-look images, but lacks in the detection of small changes. The fifth method is a combination of CFAR detection, adaptive filtering and multi-channel segmentation. This method combines the appropriate detection of distributed and small changes, even for noisy SAR images. As a result there is a preference for the last three methods, but what method can best be used is dependent on the application too.

1 INTRODUCTION

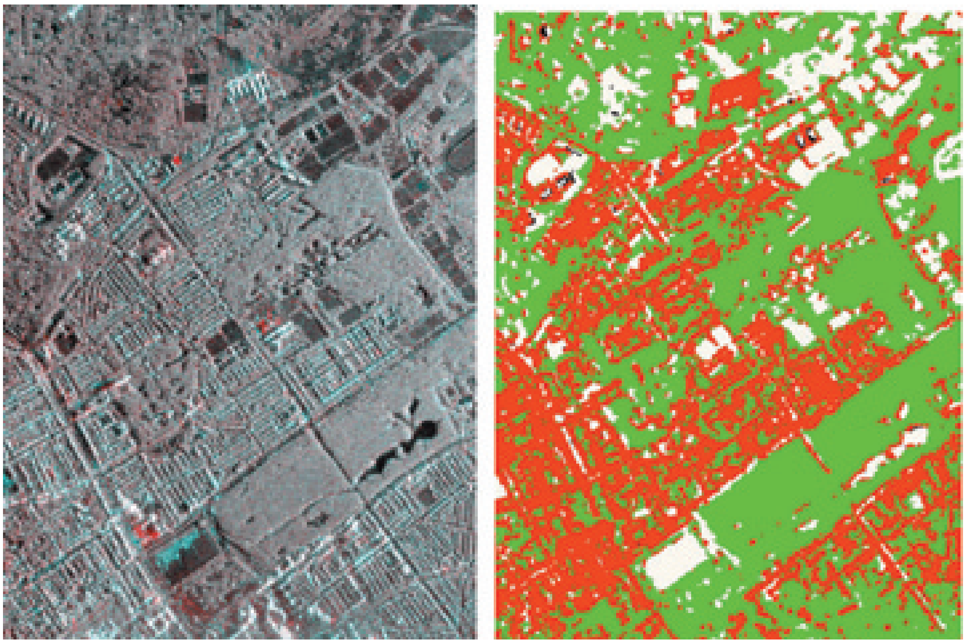
Change detection is an important technique in environmental earth observation and security, and implies the comparison of remote sensing images from different moments in time. Different sensors can be used for this purpose. SAR (Synthetic Aperture Radar) sensors become useful when weather and light conditions are unfavourable. SAR can operate under cloudy skies, day and night. Today the resolution of SAR satellites is not better than 10 m, but in the near future platforms will be launched carrying sensors with a resolution of 1-3 m (e.g. Radarsat-2, TerraSAR and Cosmo/SkyMed).

This paper will give an overview of SAR change detection methods and some examples of applications. Generally there are two basic methods: post-classification and pre-classification methods. Post-classification change detection takes place after classification into land cover or land use. Pre-classification techniques operate on the images and can be divided into CFAR detection, adaptive filtering, multi-channel segmentation and hybrid methods. The focus is on non-coherent change detection techniques.

2 POST-CLASSIFICATION CHANGE DETECTION

In post-classification change detection, the classification results of two images are compared. Therefore the accuracy of post-classification change detection is strongly dependent on the accuracy of classification.

To evaluate this method for SAR images it was applied to two co-registered PHARUS images of The Hague (Dekker 2003a). PHARUS is the airborne polarimetric C-band SAR of TNO, the Netherlands Organisation for Applied Scientific Research (Greidanus et al. 1996). The images were acquired on 26 April 1996 respectively 27 January 1998. The resolution is 4 m, the imaged area about 3×4 km. The equivalent number of looks is 5, which means that the speckle noise is reduced by averaging five independent looks (the bandwidth of one look corresponds to one-fifth of the antenna beam). The polarisation that is used is HH. Figure 1 (a) shows a false colour composite of both images. Changed land cover appears in red or cyan, non-changed land cover as a tone of grey.



(a) (b)

Figure 1. (a) False colour composite of two PHARUS SAR images of The Hague, The Netherlands (27 January 1998 = red; 26 April 1996 = cyan). (b) Classification of the PHARUS image of 27 January 1998 using mean intensity, variance, weighted-rank fill ratio and semivariogram (buildings = red; trees = green; smooth surfaces = light yellow; black = unclassified).

Both images were classified using an object-based approach (Benz et al. 2004). The number of classes (three: buildings, trees and smooth surfaces) is a result of the different physical properties of the existing land cover with respect to radar. Smooth surfaces are for instance roads, bare soils, low vegetation as grass and water. Basis for the classification were the following texture measures: mean intensity, variance, weighted-rank fill ratio and semivariogram (Dekker 2003b). The images were trained separately. Figure 1(b) shows the classification results of the PHARUS image of 27 January 1998. The results are compared with a 1:10.000 map in Table 1, which shows low accuracies for classification of the PHARUS images. An important reason for that is that the map shows much more smooth surfaces than the image. But even then, comparing both classified images results in a lot of false alarms, i.e. changes that are not really there. Classification of ERS SAR data shows similar accuracies (Dekker 2003a, 2003b). Therefore post-classification change detection is not a reliable method for SAR.

Table 1. User accuracies as a percentage of the classification results.

PHARUS image	Buildings	Trees	Smooth	Overall	Kappa
26 April 1996	40.6	44.4	89.7	48.3	29.4
27 January 1998	43.8	42.2	88.7	49.3	29.7

3 PRE-CLASSIFICATION CHANGE DETECTION

In pre-classification change detection, changes are detected before classification. Four methods were investigated:

1. CFAR detection
2. Adaptive filtering
3. Multi-channel segmentation
4. Hybrid methods

The first and the second method are based on the ratio image, which is obtained by dividing the after image by the before image. Dividing images is preferred above differencing, in which the images are subtracted (Rignot and van Zyl 1993). The third method is based on segmentation techniques. A disadvantage of pre-classification change detection is that the changes still have to be classified.

3.1 *CFAR detection*

The first method to detect changes is based on a two-dimensional Constant False Alarm Rate (CFAR) detector (Novak and Hesse 1991). A CFAR detector generally consist of a moving kernel such as in Figure 2 and compares the pixel-value of the central pixel with its background pixels (i.e. clutter). In case of change detection the CFAR detector is applied to the ratio image.

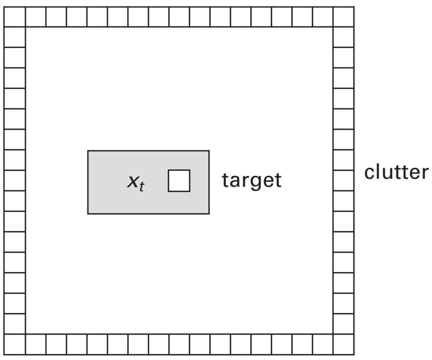


Figure 2. Common CFAR kernel.

In the CFAR detector for every pixel, background statistics are computed. Based on these statistics is decided whether the central pixel is (part of) a target or not. The following equation is used:

$$\frac{x_t - \mu_c}{\sigma_c} > k_{CFAR} \tag{1}$$

Here x_t is the tested pixel, μ_c and σ_c the mean and standard deviation of the background pixels, and k_{CFAR} the CFAR constant. The latter is the number of standard deviations the tested pixel must stand out above its background to be (part of) a target. Equation (1) corresponds to the so-called classical CFAR detector, but it can be rewritten for order-statistics. The order-statistics CFAR detector is more robust in case more targets enter the kernel. Change detection by CFAR detection is generally applied when the changes are small compared to the resolution, i.e. when changes cover a few pixels.

3.2 *Adaptive filtering*

The second method is based on an adaptive filter that is applied to reduce the speckle-noise in the ratio image (Dekker 1998). Because filters make errors in estimating the underlying radar cross-section, it is more effective to apply one filter to the ratio image, than one on the original SAR images. Therefore the work flow is as follows:

- create ratio image
- logarithmic scaling to make the multiplicative speckle-noise additive
- adaptive filtering
- thresholding

Logarithmic scaling is applied because additive noise is easier to filter than multiplicative noise, as in the original SAR and ratio images. The filter that is referred to preserves edges, lines and point-targets. The point-target detector is a kind of CFAR detector, but with a different kernel. The threshold is global, for the whole ratio image, while in CFAR detection the threshold is local, for every kernel.

An advantage of applying the adaptive filter, compared to the CFAR detector, is that it can be used to detect distributed changes as well. But even then this method can be more effective in case of small changes (e.g. Dekker 2000). An example of change detection by adaptive filtering is shown in Figure 3(a). Here the method is applied to the PHARUS SAR images of The Hague of Figure 1(a). The threshold was set to ± 9dB. Figure 4 shows a result of the method on two Radarsat-1 images (resolution 10 m) of new dwellings under construction, south of Esfahan, Iran. The results were generated within the framework of GMOSS (Global Monitoring for Security and Stability, http://gmoss.jrc.it/).

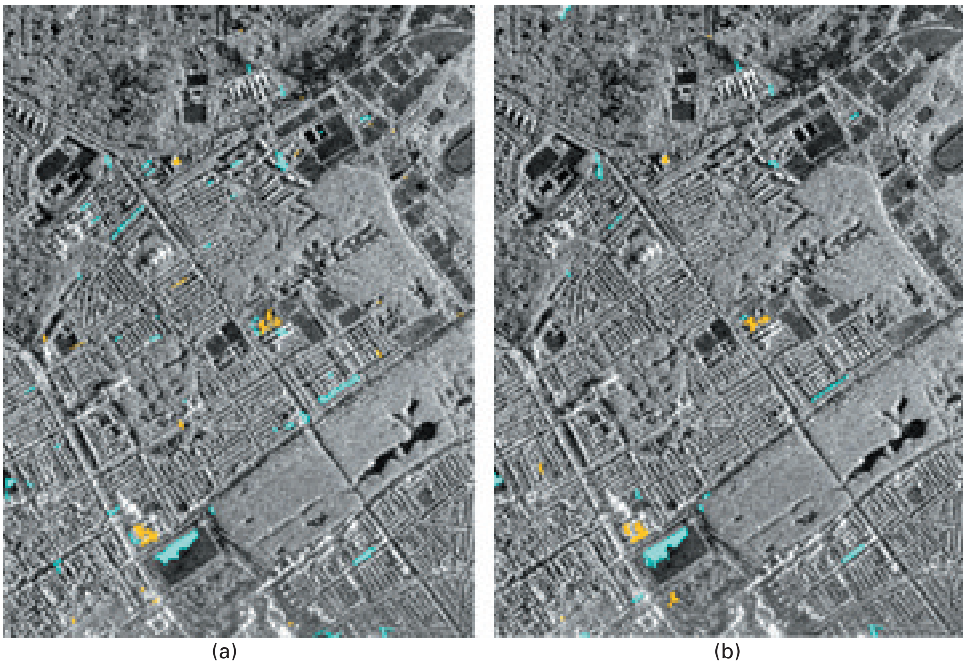


Figure 3. Results of pre-classification change detection using the adaptive filter (a) and multi-channel segmentation (b). New objects = orange; disappeared objects = blue.

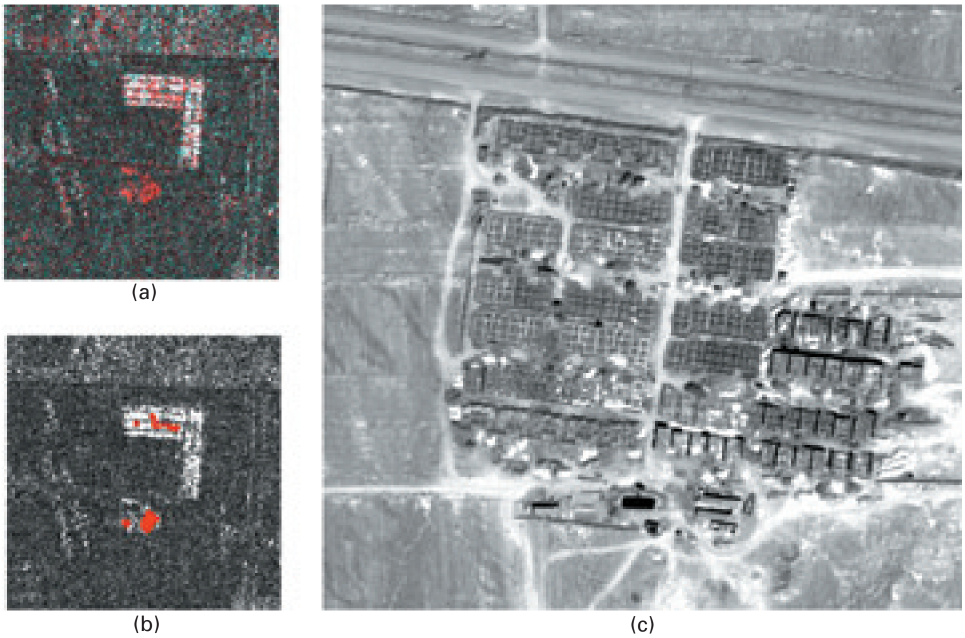


Figure 4. Results of change detection by adaptive filtering applied to two Radarsat-1 images of new dwellings under construction, south of Esfahan, Iran (29 July 2003 = red; 20 September 2002 = cyan). (a) Shows the colour composite, (b) the detected changes, and (c) the corresponding Quickbird image of 19 September 2003 of the lower dwellings.

3.3 *Multi-channel segmentation*

The third method of pre-classification change detection is based on multi-channel segmentation (Caves and Quegan 1995). Segmentation is the process of grouping adjacent pixels into multi-pixel homogeneous objects that can be further processed as one entity. The advantage of this method is that, in case of not too much speckle noise (about more than 3 looks), it reduces the remaining speckle. In case of multi-channel segmentation, the grouping process is applied to two or more images instead of one. Figure 3(b) shows an example of multi-channel segmentation change detection using the software of Benz et al. (2004). The same threshold was applied as in Section 3.2.

Compared to the result of the adaptive filter the number of changed objects has decreased. Especially smaller objects are missing. On the other hand, the shape of the changed objects is better reproduced. The apparent similarity is caused by the relatively high equivalent number of looks of the SAR images, which is 5.

3.4 *Hybrid methods*

To improve the change detection capabilities, methods can be combined. An example is multi-channel segmentation. This method can be improved (1) by adding an adaptive filter to reduce speckle-noise for segmentation of distributed changes and (2) by adding a CFAR detector to detect smaller changes such as vehicles (Dekker et al. 2004). Here the speckle-filtered ratio and the results of CFAR detection are both input to the segmentation and thresholding process, see Figure 5. The output is a set of polygons representing the changed objects. In case the georeferencing of the original SAR images is not accurate enough, they can be co-registered automatically using a FFT-based correlation procedure.

The method was applied to two 0.5 m resolution SAR images of Borculo (The Netherlands). The images were acquired by the Intermap AeS-1 X-band SAR system. The time interval between the images is less than 2 hours. Changes are due to the relocation of digging machinery (i.e. draglines, shovels, tractors). Chosen was for a CFAR constant of 2.0. Segmentation was applied to both layers. Features that were used to classify the changes are the mean of the filtered ratio and

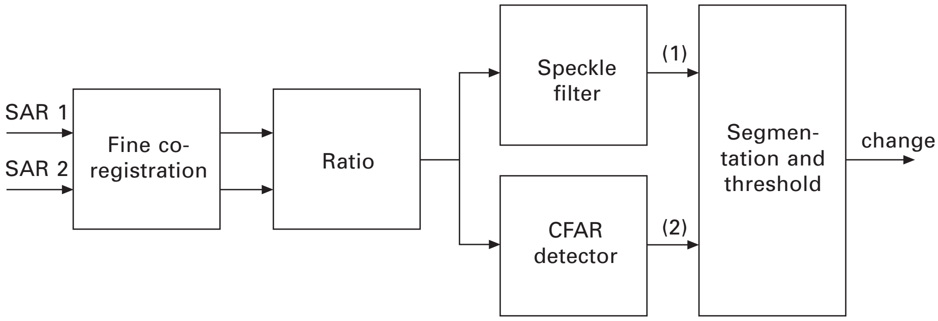


Figure 5. Architecture for SAR change detection covering distributed changes (1) and small changes such as vehicles (2).

the area. The latter was set to 1 m^2 for both positive and negative changes, to reject all changes that are smaller. Figure 6 shows the results. In this case nine out of ten relocated machines were detected. Two false alarms occur at the edges of the farm buildings (lower right). The results of this scene are actually quite good because it is rural. Other scenes show less detections and more false alarms. The results were generated within the framework of PRESENSE (Pipeline Remote Sensing for Safety and the Environment, http://www.presense.net/).

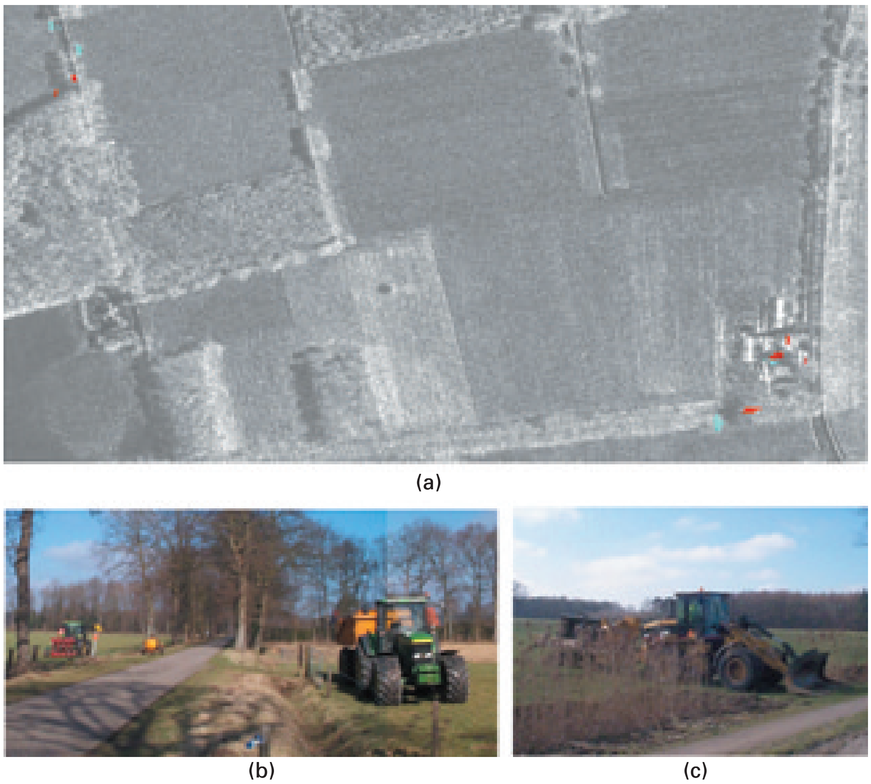


Figure 6. (a) Changes in Intermap AeS-1 SAR images of Borculo (The Netherlands), detected using a hybrid change detection method. Detected are relocated machines and a water tank (b) (upper left), and relocated machines and farm activities (c) (lower right).

4 CONCLUSIONS

Five methods of SAR change detection for environmental earth observation and security were presented and evaluated. The performance of the first one, post-classification change detection, is strongly dependent on the accuracy of classification. Because the latter can be a problem in SAR images, this is not a proper method. The second one is CFAR detection. This method is only suitable when the changes are small compared to the resolution (i.e. when changes cover a few pixels). The third method, using an adaptive filter, is able to deal with distributed changes as well. Besides, it can be more effective in case of small changes. A disadvantage of this method is that the shapes of changes are not always well reproduced. The fourth method makes use of multi-channel segmentation, a method that reproduces the shape of changes well for multi-look images, but lacks in the detection of small changes. The fifth method is a combination of CFAR detection, adaptive filtering and multi-channel segmentation. This method combines the appropriate detection of distributed and small changes, even for noisy SAR images. As a result there is a preference for the last three methods, but what method can best be used is dependent on the application too.

REFERENCES

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. and Heynen, M. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing. Vol. 58*: 239-258.

Caves, R.G., and Quegan, S. 1995. Multi-channel SAR Segmentation: Algorithm and Applications. *Proc. European Symp. on Satellite Remote Sensing II*, Paris: 241-251.

Dekker, R.J. 1998. Speckle filtering in satellite SAR change detection imagery. *International Journal of Remote Sensing, Vol. 19, No. 6*: 1133-1146.

Dekker, R.J. 2000. Monitoring the urbanisation of Dar es Salaam using ERS SAR data. *International Archives of Photogrammetry and Remote Sensing. Vol. XXXIII, Part B1*: 62-69.

Dekker, R.J. 2003a. Object-based updating of land-use maps of urban areas using satellite remote sensing. *MSc dissertation,* Vrije Universiteit Amsterdam, June 2003.

Dekker, R.J. 2003b. Texture Analysis and Classification of ERS SAR Images for Map Updating of Urban Areas in The Netherlands. *IEEE Transactions on Geoscience and Remote Sensing, Vol. 41, No. 9*: 1950-1958.

Dekker, R.J. Lingenfelder, I., Brozek, B., Benz, U., and van den Broek, A.C., 2004. Object-based detection of hazards to the European gas pipeline network using SAR images. *5th European Conference on Synthetic Aperture Radar (EUSAR),* Ulm, Germany: 1035-1038.

Greidanus, H.S.F., Hoogeboom, P., Koomen, P.J., Snoeij, P., and Pouwels, H. 1996, First Results and Status of the PHARUS Phased Array Airborne SAR. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS),* Lincoln, Nebraska: 1633-1635.

Novak, L.M., and Hesse, S.R. 1991, On the performance of order-statistics CFAR detectors. *IEEE Conference Record of the 25th Asilomar Conference on Signals, Systems and Computers, Vol.2*: 835-840.

Rignot, E.J.M., and van Zyl, J.J., 1993. Change Detection techniques for ERS-1 SAR data. *IEEE Transactions on Geoscience and Remote Sensing, Vol. 31, No. 4*: 896-906.