IMPLEMENTATION OF NEW SAR CHANGE DETECTION METHODS: SUPER-RESOLUTION SAR CHANGE DETECTOR

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ABSTRACT

SAR systems can provide good all-weather reconnaissance imagery allowing fairly large areas to be covered quickly. Following independent autofocus and phase-correction processing, the images are co-registered automatically by cross-correlation of small areas. However, to automatically detect changes between images of the same site it is necessary to overcome the speckle noise; evaluating the differences between pairs of images is not sufficient to pin point the changes.

In general it appears clearly from the literature that the main unsolved problem of change detection in SAR imagery is the lack of accurate and reliable methods capable of performing unsupervised change detection in a complete automatic way. Three recently released change detection methods will be analysed in this paper as well as the concept of computer-aided change detection. The implementation of these methods has been carried out in the frame of an ESA project (“Products in Support of the Common Foreign Security Policy”) with the development of an automatic SAR change detector.

1. BACKGROUND IN RADAR CHANGE DETECTION

SAR systems can provide good all-weather reconnaissance imagery. One of the advantages offered by synthetic aperture radar is not only the all-weather imaging capability, but the high data rate allowing fairly large areas to be covered quickly. The ability to produce focused and coregistered SAR imagery allows us to make a direct comparison between two or more images of the same scene formed at different times. Following independent autofocus and phase-correction processing, the images are coregistered automatically by cross-correlation of small areas. However, to automatically detect changes between the scenes we need to overcome the speckle noise within the images arising from the interference of random scatterers within each resolution cell. For single-look SAR this is equivalent to multiplicative noise. Thus taking differences between pairs of images is not sufficient to pin point the changes. The uncertainty in the image values due to unavoidable speckle makes automatic image analysis very difficult. This problem is obviously more acute when the image objects are of a size comparable with the system resolution. Indeed, in such situations human observers may not be able to make even simple decisions such as differentiating between buildings and vehicles. In such cases some form of collateral information is desirable, if not essential. The simplest form of collateral information to consider is another SAR image of the same area. The change or even the appearance of an object can be of benefit in its identification. Consequently change detection between two or more images, is of interest for automatic image interpretation. However, as mentioned before, an equally attractive benefit results from the data reduction offered by change detection.

Another of the significant obstacles to the use of SAR techniques for temporal change detection arises from the strong dependence of the image characteristics on imaging geometry. When the flight paths used by the SAR platform during acquisitions are crossed (ASC/DESC), important features in the resulting images can appear, change dramatically or disappear entirely. Even when the flight tracks are parallel but widely separated (different tracks) geometric distortions arise due to the resulting look angle difference since the backscattering from any given area remains a function of both the surface characteristics (essentially shape and orientation) and the local radar incidence angle. For typical targets such as grass, forest, shrub and water, the variation due to radar geometry can be stronger than backscattering changes due to actual surface change, making measurement of the latter difficult; a critical case would be that of a crop field with changing row directions.

Our work involves the use of C-band, orbit-based SAR data for radar backscattering intensity comparisons. We take advantage of high spatial stability of the repeat pass orbit, resulting in look angle differences between imaging passes of fractions of a degrees (to obtain
the ground. If the scatterers change in position during scatterers located within the associated scattering cell on represents the sum of the returns from the many point scattering model, each pixel in a complex image technique based on phase coherence. In a simple from those revealed by repeat-pass interferometry, a changes which can be detected using radar backscattering intensity interferometric applications of repeat-pass orbital data is also very significant. The changes that are not easily determined from measurements of temporal decorrelation however, is not necessarily accompanied by changes in the backscattering intensity. Conversely, the sense and extent of backscatterer intensity changes are not easily determined from measurements of temporal decorrelation. By comparing the intensity of radar return in images acquired on repeat-pass orbits and by averaging adjacent pixels intensities (multilooking), we optimize our ability to observe processes which alter the surface backscatter intensity. To give a glimpse of the difficulties that arise when comparing two SAR images, in the next section the selection of the difference or the ratio between the pixel intensities of two images will be studied.

2. METHODOLOGICAL APPROACHES FOR URBAN CHANGE DETECTION

Synthetic aperture radars have been less exploited than optical sensors in the context of change detection. This is due to the fact that SAR images suffer from the presence of speckle noise that makes difficult to analyze such imagery, and in particular, to perform unsupervised discrimination between changed and unchanged classes. Despite of the presence of speckle noise, the use of SAR sensors in change detection is potentially attractive, and definitively challenging, from the operational viewpoint. These active microwave sensors present the advantage that (unlike optical ones) they are independent of atmospheric and sunlight conditions (“all-weather” operation). This makes it possible to plan and ensure the monitoring of a region (by repeat pass imaging) with advance timing according to end-user requirements. In the context of SAR image analysis, the problem of unsupervised change detection has been addressed focusing on different aspects, including image despeckling, choice of the comparison operator and optimal threshold selection.

The first automatic change detection methods were based on the Bayesian theory [1-5]. To detect and quantify eventual changes in radar backscatter and mapping out ensembles of pixels of spatially and radiometrically homogenous and similar changes, a Bayes classifier was developed. This probabilistic approach allowed selecting comparison threshold levels as a function of the accepted probability of error. They also showed that for change detection in SAR data it is better to use the ratio of the backscatterer intensity than the difference.

With the launch of the ESA’s ERS-1 in July 1991, the Japanese first Earth Resources Satellite (JERS-1) in February 1992, and the Canadian RADARSAT in 1995, multidate SAR data started to be generated and archived on a regular basis, over the entire planet, resulting in huge data archives: even nowadays the biggest part of this archive remains unexploited. This new generation of SAR sensors was characterized by an enhanced image quality (in particular a stable and reliable calibration of the data), and a significant increase in data volume, data rates, and duration of the mission. As a consequence, there was an important need for developing automated procedures of change detection for SAR data that could help human interpreters or subsequent computer algorithms analyze the data and relate the observed changes in radar backscatter with changes in the structural and dielectric properties of the remotely sensed areas (inversion methods to recover bio-physical parameters).

Change detection techniques for SAR data can be divided into several categories, each corresponding to different image quality requirements. In a first category, changes are detected based on the temporal tracking of objects or stable image features of recognizable geometrical shape. Absolute calibration of the data is not required, but the data must be rectified from geometric distortions due to differences in imaging geometry or SAR processing parameters, and the accurate spatial registration of the multi-date data is essential. Applications include sea-ice monitoring and motion tracking, monitoring of glaciers, landslides, and oceanic features. In a second category, changes are detected based on temporal differences in radar backscatter. The requirements are a stable calibration accuracy of the data, and an accurate spatial registration of the multidate data. Typical applications include monitoring of crops, volcanic activity, snow extent and conditions, glacial melt, soil moisture, and vegetation water content.

3. SELECTED CHANGE DETECTION METHODS

The latest developments in this field represent a big step towards unsupervised and robust change SAR
detections methods. Some of them come from the generalization and evolution of previous methods while the others introduce new concepts to the SAR change detection field, such as the use of wavelets and computer vision. These methods improve the quality of change detection output maps and enhance change detection capability over speckle noise.

Three of the most recent and advanced techniques for SAR computed aided change detection have been selected to be implemented during the project mentioned before. They can be found on: Gaussian method [6], Wavelet method [7], Adaboost method [8]. The aim of this project is the demonstration of several innovative products and services from SAR data to support the routine operations of the European Union Satellite Centre (EUSC), the final user in the project. One of these products is the change detection of multi-temporal SAR images. That means, that for example, a multi-temporal or superresolution SAR image (SSI) obtained with several acquisitions in one winter will be compared to another multi-temporal image of another winter. The superresolution term is in this case referring to an increase in the radiometrical resolution, which implies a huge reduction of the speckle. Filtering the noise using the multi-temporal approach improves dramatically the performance of change detection estimators. However, in some case, it will be necessary to compare single images to detect subtle changes and it will be mandatory to reduce the level of speckle.

Also, we introduce the concept of computer-aided change detection as the operator will deal with the results of these three image classifiers and will select the optimum linear combination in order to enhance the desired change detection pattern (big areas, small features, etc). As it will be shown in the next sections it is not possible to entirely (spatially) filter the noise of an image while preserving the spatial resolution and for a given pattern of change detection, a compromise between resolution and noise filtering must always be defined. These three methods offer this crucial trade-off to the photo-interpreter while share some common features as unsupervised training.

4. GAUSSIAN METHOD

The Gaussian method is a novel automatic and unsupervised change-detection approach specifically oriented to the analysis of single-channel single-polarization synthetic aperture radar images, which is the case of the current project. The images to be used come from ERS-2 and Envisat satellites.

Figure 1. These 4 images show the effect on the log-operator difference image of the number of iterations in the filtering step. The last image shows a manually threshold binary image where the performance of the filtering effect is clearly visible, of course at the expense of the reduction in the detection of small local changes. Madrid new Airport Terminal was used as test site.

The approach is based on a closed loop process made up of three main steps:
- A preprocessing based on a controlled adaptive iterative filtering
- A comparison between superresolution or multitemporal images carried out according to standard log-ratio operator (see Fig. 1)
- A novel approach to the automatic analysis of the log-ratio image for generating the change-detection map

The first step is a controlled preprocessing based on Adaptive Filtering which aims to reduce speckle noise to maximize the discrimination capability between the unchanged and the changed classes. The multilooking process reduces speckle noise at the expense of spatial resolution but generally a further step is required to make the image suitable for the desired analysis. In our case, we are not comparing only two images, so the reduction of speckle is also carried out by the multitemporal average. The main problem with filtering is related to the determination of the best number of filtering iterations for the specific change-detection application. In this method, the number of iterations will be determined through a closed loop in the performance index evaluation.

The comparison of multitemporal images is based on a pixel-by-pixel ratio operator evaluation which is much
robust against calibration errors and which enabled change detection in both high and low intensity areas. Finally, we analyze the log-ratio image which is formulated on the context of Bayesian decision theory and where pixel spatial independence is assumed. The threshold selection procedure is carried out with a modified Kittler-Illingworth (KI) algorithm which is able to differentiate between changed and unchanged classes. This modification of the algorithm is based on the adoption of the generalized Gaussian assumption for modeling distribution of changed and unchanged classes. The behavior of the KI algorithms is used to determine the number of iterations in the filtering process. This method was validated by the authors using ERS-2 datasets with different number of speckle. They demonstrated that their method achieved change-detection accuracies similar to those that can be achieved by manual supervised thresholding, thus confirming the self-consistency of their approach. Fig 1 shows the effect of the number of iterations in the filter process applied to the log-operator evaluated image.

5. WAVELET METHOD

Unsupervised change detection in SAR image usually is based on a three step procedure (as shown in the previous section for the Gaussian method): 1\textsuperscript{st} preprocessing, 2\textsuperscript{nd} pixel-by-pixel comparison of two images; and 3\textsuperscript{rd} image thresholding. The aim of preprocessing is to increase the SNR of the considered images (by reducing noisy speckle components). Many adaptive filters for speckle reduction have been proposed, i.e. Lee, Kian, Gamma Map, etc. Despite their spatial adaptive characteristic, which intends to preserve the signal’s high-frequency information (information of feature borders), filter applications often give the desired speckle reduction but also an undesired degradation on the geometrical details of the scene. Pixel-by-pixel comparison is carried out according to a ratio (or a log ratio) operator in such a way as to take into account the multiplicative model of the speckle. The decision threshold can be selected either with a manual trial-and-error procedure (according to a desired tradeoff between false and missed alarms) or with automatic techniques.

Depending on the kind of preprocessing applied to the multitemporal images, these techniques can achieve different tradeoffs between detail preservation and accuracy in the representation of homogeneous areas in change-detection maps. In other words, high accuracy in homogeneous areas usually requires an intensive despeckling phase, which in turn degrades the geometrical details. In order to address these drawbacks of standard methods, the authors of this method propose a scale-driven adaptive approach based on:
1. multi-scale decomposition of the log-ratio image.
2. selection of reliable scales for each pixel (the scales at which the considered pixel can be representative without border problems)
according to an adaptive analysis of its local statistics. See Fig. 2.

3. On a scale-driven combination of the selected scales.

The rationale of the proposed method is to exploit only high-resolution levels in the analysis of the expected edge (or detail) pixels and to use also low-resolution levels in the processing of pixels in homogeneous areas. The proposed method offers both a high sensitivity to geometrical details (borders of changed areas are well preserved) and a high robustness to noisy speckle components in homogeneous areas.

Based on a set of multi-scale images, it is necessary to identify reliable scales for each considered spatial position in order to drive the next fusion stage with this information. By using this information we can obtain change-detection maps characterized by high accuracy in homogenous and border areas.

Reliable scales are selected according to whether the considered pixel belongs to a border or a homogeneous area at different scales. It is worth noting that the information at low-resolution levels is not reliable for pixels belonging to the border area. At those scales details and edge information have been removed from the decomposition process. Thus, a generic scale is reliable for a given pixel if the pixel at this scale is not in a border region or if it does not represent a geometrical detail.

6. ADABOOST METHOD

To identify changes between two SAR images, this detection algorithm is made up of five steps:

1. Preprocessing of SAR images: because images have already been coregistered and radiometrically calibrated, it is only necessary to concentrate on the speckle noise. Due to the low speckle noise of the multi-temporal images to be compared, it would be possible to overcome this step.

2. Texture feature extraction: in this step the authors define four kind texture features to detect changes in the bitemporal SAR images. These features are the Kullback-Leibler distance between the local neighborhood pixel intensity distributions, the mean, the variance and the median differences of the local neighborhood pixel intensity. Due to the lack of knowledge of the best neighborhood window size for the change detection application, each kind of texture feature is extracted with ten different windows size, ranging from 3x3, 5x5, ... to 21x21. Therefore, forty texture features are extracted from the compared bitemporal SAR images.

3. Weak classifier design: For each texture feature extracted from the pair of multitemporal SAR images, a weak classifier is designed. A weak classifier does not give high accuracy. Thresholding is adopted to obtain a rough separation of the changed and unchanged pixels.

4. Construction of the strong classifier using the AdaBoost algorithm: The basic idea of boosting is to combine several weak classifiers to a strong one. In this step, the AdaBoost algorithm is employed to choose several suitable classifiers from all the forty ones and
the final strong classifier is made up of a linear combination of them. Figure 3 shows an example of the Adaboost algorithm.

5. Change detection: using the strong classifier learned from the AdaBoost algorithm, the change detection result is satisfying. We will use our validation test site ground map to train the weak classifiers as well as the strong one.

Forty texture features structures are extracted from two SAR images, and therefore there is one weak classifier for each of them. It is found that both the Kullback-Leibler distance and the difference of the mean, variance and median get a low value when there is no change while a high one when there is change. Because very high accuracy is not necessary in weak classifier design, thresholding, a simple approach with relatively low computation complexity is adopted. The threshold for every classifier (texture feature) is obtained by minimizing the error rate in the training examples.

When this Adaboost method is compared to methods based on Bayesian decision theory or using K-means clustering approach, the results are very satisfying. For instance, the overall error (formed by false alarms and miss alarms) goes from around 10% (Bayesian, K-means methods) to 1.3%. The Fig 4 shows 6 views of the feature texture values of the test site image (which are fairly representative of the total 40 combinations).

7. CHANGE DETECTION IMPLEMENTATION

Two of the previous algorithms have been implemented during the project (Gaussian and Wavelets methods), resulting into the Superresolution SAR Change Detector application (see Fig. 5).

A set of SAR images calibrated, coregistered and orthorectified are needed as input images in the Superresolution SAR Change Detector application. This works with dynamic images, i.e., the set of SAR images involved in the SSI production (before and after) are present in two moving windows with a temporal interval ordered according to the images dates (see Fig. 5). SSI showed in each window will depend on the user election in the time bar.

Thus, first of all, we must select the time interval that it is used to generate every multitemporal or superresolution image. It is important to consider that the level of speckle noise of a multitemporal image is decreases with the number of images that has been used to produce it. Subtle changes between single images will be masked by the multi-temporal averaging. The developed end user tool allows modifying interactively the time interval of the pair of multitemporal images to enhance the desired kind of change pattern.

Several algorithms and its linear combinations are available for the users: log (A/B) and linear (A-B) operators, Wavelet Detail Preserving (corresponding to Wavelet method), Generalized Gaussian (corresponding to Gaussian method), Wavelet+Gaussian, max(Wavelet,Gaussian) and their adaptative ways, i.e., the amplitude of the image obtained in each algorithm is normalized to attenuate the effects of generalized changes. Users can choose the algorithm more adequate according to the characteristics of the area to study.

Thus, for example, adaptative log will be used to detect subtle changes in big areas as shown (Fig. 6). Whereas, adaptative linear will be useful in the detection of abrupt changes near border or edge pixels (Fig. 7).
In order to provide a better detection of the changes found in each site, a visualization tool, called Activity Monitoring Tool, was developed after the generation of the products. This tool allows to load the set of images for each site all together, to catch them at a time (or the interval that the user chooses) and to pass them as a movie. Thus, all the changes present in the images of each site are easily visualized. Furthermore, two zoom windows complete the tool, for a detailed inspection of each change.

The GUI of the Activity Monitoring Tool is shown in Fig. 8. Left window stores the images at screen native resolution while right sub-windows are used to display cursor point region using inverse equalizations. The user can use mouse wheel button to shift between SSI images easily and locate change visually. The complexity of SAR monitoring is hugely reduced with this technique which shares some of the developments achieved during this project. For instance, the Point Target Enhancement feature reduces signal saturation using a non linear RGB image equalization and can help in the production process as changes in point targets are detected easily. Furthermore, the mouse wheel solution adds a third dimension to images and target change location becomes simpler.

8. SUMMARY

We have described the state of art in the field of SAR Change Detection. The speckle noise, which is multiplicative, makes these methods very different from the ones used for optical sensors. The utilization of Superresolution SAR images as input data, to avoid the speckle noise, reduces the complexity of the detection. We have observed how bad ideas were rejected and that new ways of looking to the problem, lead to an
evolution towards robust and high quality change detection algorithms for synthetic aperture radar images. Three new methods for SAR change detection have been explained:

The **Gaussian method** is specially designed to detect texture changes in homogeneous regions and uses a probabilistic adaptive approach to filter the speckle noise which makes possible the comparison of intensity images. It will be used to detect subtle changes in big areas as shown in Fig 1. The **wavelet method** is used for the opposite purpose. Its multi-scale capability offers a huge advantage in the detection of abrupt changes near border or edge pixels. This algorithm maintains the system geometrical resolution allowing the detection of small feature changes. Finally, the **Adaboost algorithm** is a mixture of the previous algorithms and represents a considerable step in the unsupervised change detection methods using one of the most advanced computer vision techniques. It will learn from the already available ground truth map developed to validate the procedure. It will automatically gather the human change identification patterns and use it to produce a robust detector of the changed and unchanged classes in the field of SAR imaging.

Two of these methods have been implemented in the Superresolution **SAR Change Detector** application: Gaussian and Wavelet, being used during the development of our project.

9. **ACKNOWLEDGEMENTS**

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10. **REFERENCES**