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<th>Journal:</th>
<th>Transactions on Geoscience and Remote Sensing</th>
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<tr>
<td>Manuscript ID:</td>
<td>TGRS-2005-00496</td>
</tr>
<tr>
<td>Manuscript Type:</td>
<td>IGARSS 2005 Special Issue paper</td>
</tr>
<tr>
<td>Date Submitted by the Author:</td>
<td>30-Sep-2005</td>
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<tr>
<td>Complete List of Authors:</td>
<td>Gamba, Paolo; Universita' di Pavia, Dipartimento di Elettronica Lisini, Gianni; University of Pavia, Electronic Dell'Acqua, Fabio; Universita, Dipartimento di Elettronica</td>
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<tr>
<td>Keywords:</td>
<td>Synthetic aperture radar, Image processing</td>
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Change Detection in SAR Data Combining Feature-Based and Pixel-Based Techniques

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The authors are with Dipartimento di Elettronica, Università di Pavia, Via Ferrata, 1, 1-27100 Pavia, Italy. This paper is a revised and enlarged version of the paper: “Joint feature and pixel-based change detection in high resolution SAR data,” by P. Gamba, F. Dell’Acqua, and G. Lisini, presented at IGARSS’05.
Abstract

In this paper, the problem of change detection from SAR images is addressed. Feature-level change detection algorithms are still in their preliminary design stage. Indeed, while pixel-based approaches are already implemented into existing, commercial software, this is not the case for feature comparison approaches. Here we propose a joint use of both approaches. The approach is based on the extraction and comparison of linear features from multiple SAR images, to confirm pixel-based changes. Though simple, the methodology proves to be effective, irrespectively of misregistration errors due to re-projection problems or difference in the sensor’s viewing geometry, which are common in multi-temporal SAR images.

The procedure is validated through synthetic examples, but also two real change detection situations, using airborne and satellite SAR data over the campus of the University of California, Los Angeles as well as over an area around the city of Bam, Iran, recently stroke by a serious earthquake.

I. INTRODUCTION

As far as a change detection task is concerned, the availability of Synthetic Aperture Radar (SAR) data promises high potentialities, thanks to the insensitivity of SAR imagery to atmospheric conditions and cloud cover issues; the short revisit time planned for future SAR-based missions will make SAR data even more appealing. Hence, multitemporal SAR imagery is expected to play a relevant role, for instance, with respect to ecological and environmental monitoring applications or to disaster prevention and assessment.

Leaving the sensors and considering the algorithms, we may say that change detection methods could be categorized based on their unsupervised or supervised nature. Roughly speaking, the first category consists of different ways of comparing raw multi-temporal data, while the second involves supervised classifiers.

In unsupervised change detection techniques, the focus is more on the detection than on the classification of the change which took place. Pixel-based or parcel-based (area-based, in short) techniques are enough to reveal extent and location of changes in the observed area. This is especially true when using medium resolution satellites, which provide low-cost data that may be co-registered and corrected using standard techniques already available in COTS software.

To be more specific, unsupervised change detection may be obtained through very simple combinations of the raw images at two dates. The basic methods for SAR data consists of computing the ratio between the two images [1], but the task has been approached also using
statistical tools [2], [3] as well as refined segmentation analysis [4], and even, although less frequently, using fuzzy classification [5] or neural networks. Finally, interferometric measures like phase or coherence or simply the amplitude correlation have been explored ([6]-[8]). Even if these simple methods may be effective, they usually require the setting of thresholds, which implies subjective evaluations unless some automatic or semi-automatic approach is developed. This has been done in [9], where the Bayesian theory is used to automatically determine the correct threshold to be applied to a difference image. In particular, this image is analyzed by considering the spatial-contextual information included in the pixel neighborhood, relying on Markov Random Fields (MRFs) to exploit inter-pixel class dependency contexts. An iterative method based on the Expectation-Maximization (EM) algorithm is used to estimate the statistical terms that characterize the distributions of the changed and unchanged pixels in the difference image. The authors report to have made experiments on both satellite and airborne multi-spectral data: results appear to be good, and the robustness of the algorithm against noise is highlighted. An extension of this work is presented in [10], where a more application-oriented tool for monitoring land-cover changes is proposed. The proposed technique relies on the definition of the unsupervised change-detection problem in terms of the Bayes rule for minimum cost (BRMC), which in turn allows the generation of change-detection maps in which the more critical type of error is minimized according to end-user requirements.

Most of these approaches start from the assumption that the multi-temporal sequence is already co-registered. Many techniques exist for co-registration of optical images or multiple SAR images of the same area taken by the same sensor and the same viewing geometry. It is however much more difficult to accomplish the task of a good co-registration at the pixel level when images are taken from different vantage positions with respect to the target scene. Papers in technical literature dealing with the effect of data misregistration/miscalibration on change detection are indeed already available [11]-[14]. In any case, achieving reliable results even in presence of such data inconsistencies is becoming increasingly important with new high resolution sensors. This is particularly true for SAR images, and especially for high resolution SAR images output by the forthcoming new generation of low earth orbit satellites, like TerraSAR-X and Cosmo/SkyMed. Different layover and shadowing effects contribute to making the registration task a tricky one, to the extent that some misalignments at the local scale are to be considered an unavoidable plague. As a matter of fact, approaches to change detection somehow incorporating the awareness
of registration problems are already available. In [17] the authors assume a slight residual misalignment between images. They propose an adaptive estimation of the distribution of the so called “registration noise” followed by a decision strategy for producing the actual change-detection map. Since misregistrations affect unevenly the different portions of the images, as noted above, it is recommended to apply the proposed technique after partitioning the original image into a number of sub-images. In [15] the authors exploit the spatial correlation between adjacent pixels using Markov Random Fields. They find that the method is particularly robust against noise and misregistration. Finally, in [16] objects are first extracted from each image to be analyzed, and a site model is built; then, site models extracted from different images are compared and the differences highlighted. Besides robustness against misregistration, this method provides higher-level information and potentially allows some degree of scene understanding; moreover, addition of more imagery helps to perfect the model and thus tends to improve detection results.

In order to improve even further the results of the change detection analysis, in this work it is proposed to investigate on the usefulness of feature-based approaches for change detection. Indeed, misregistration problems may be reduced using feature-based co-registration techniques[18]-[20]. Why not improving, using the same idea, area-based change detection results? That would also blaze a trail towards improving results by the large database of area-based techniques already available. In this sense, we don’t expect that feature-based approaches may be able to achieve alone better results than area-based algorithms, but they may help to overcome some of the above mentioned problems, notably misregistrations or difference in viewing angles, and to reduce misclassified changes. To this aim, we propose to find first all possible edges in the multiple images to be compared. Then, features are compared and the corresponding change detection map, previously found by refined area-based methods, is corrected according to this comparison.

The paper is organized as follows. Section II introduces the proposed procedures, describing the feature-based change detection algorithm and the combination with a pre-existing pixel-based change map. Section III shows the results on synthetic and real images, and finally Section IV draws some conclusions and discusses the open issues for future research.
II. THE PROPOSED PROCEDURE

The conceptual work flow of the proposed procedure is described in fig. 1. As described in the introduction, the aim of the procedure is the improvement of pre-existing change detection results by considering detected changes in features. The procedure starts with two or more images depicting the same area. An unsupervised feature extraction algorithm is then applied to each image, and the results of this extraction are compared, to find out where changes have taken place, if any. Finally, feature changes are fed into a fusion routine, aimed at introducing these results into the pre-existing change detection map.

The procedure thus requires two fusion steps, which will be more precisely delineated in next subsections.

- First, an algorithm at the feature level is implemented, i. e. a procedure for the extraction of features from the input images and consequently their comparison.
- Then, a second step at the information level fuses the changes extracted with a feature-based technique and those extracted with an area-based technique.

We wish here to stress that this conceptual framework, though simple and very general, has not been exploited for change detection purposes until now, and it shows interesting advantages over pure area-based techniques. Moreover, it may be implemented using different routines, starting from the choice of the features to be considered on one side and the techniques to detect feature changes on the other side, which are strictly related. Therefore, while being well suited to change detection in SAR data, the following procedure may be adapted to different situations and still work better than traditional area-based approaches.

A. Feature extraction and comparison

The choice of geometric features to be extracted in SAR images is necessarily limited. Due to geometrical problems and distortions, it is indeed difficult, when considering these data, to reach beyond plain point scatterers and linear features. However, even if point scatterers have shown a great potential in interferometric applications, constituting the base for accurate co-registration and subsidence approaches, their change analysis offers limited advantage over traditional area-based change detection algorithms. Therefore, we are somehow forced to use linear elements, i. e. edges, as basic elements for a feature-based change detection algorithm. Moreover, this choice is based on two other comments.
Edges, or their combinations, have already been used as the more frequent choice in the above mentioned approaches for feature-based refined co-registration. So, they are a good candidate for improved change detection, which is somehow the complementary problem.

In real-world images, edges refer mostly to man-made or artificial objects (e.g. streets). In turn, their change is among the most important information we may extract from the analysis of two temporally different scenes of the same area. So, the particular feature-based change analysis may be useful by itself too.

Many algorithms for edge extraction are proposed in technical literature, some of them particularly suited for SAR images. We rely on the work previously done by our group and use an approach originally developed as a first step for street extraction [21].

The procedure is aimed at the extraction of elongated areas in a pre-filtered image, where the input may be simply a thresholded version of the data, or a directionally filtered version of the same. It looks for connected components (called “blobs”) and discards those not compliant with some very basic rules. In summary, the algorithm first compares each blob with a very general model for linear regions. The algorithm checks for the “fullness” ratio, the location of the region edges and their parallelism. Then, each considered region is compared with a set of 16 basic segment prototypes, computing a matching index based on the spatial correlation between it and the best prototype. Finally, a skeletonization step is applied, which takes into account the changes in both direction and thickness of the region to partition it into segments and to provide a linear approximation of the original connected region.

Once the extraction procedure is completed, we are left with two feature sets representing the edges in the two compared images, that need to be matched. This comparison needs to face at least two problems: the limited reliability of the extraction results and the different location, structure or even topology of the corresponding features, due to geometrical distortions, misregistration and misalignment. For instance, experience shows that it is very difficult to extract the locations of corresponding linear features in high resolution images of an urban area [18], where layover and shadowing effects dominate. The first problem may be solved only by a more refined extraction procedure and suggests to manage carefully the result of any feature-based analysis. From this point of view the availability of a quality index for the extracted linear feature would be useful to pass the reliability information along the various steps of the procedure. The approach in [21] exploited in this work indeed allows the user to evaluate this reliability. In
fact, the matching between the elongated area retrieved from the image and prototypes is used to compute a reliability index. The larger the index, the more the extracted feature is similar to an actual edge. Since a normalized version of this index may be somehow considered as a fuzzy characterization of the likelihood of the region to be an edge, the comparison between a couple of linear features in the two sets may be labeled with the fuzzy AND operator applied to their reliability, resulting in the minimum value. This allows assigning to the final result a measure, useful for further combination with the area-based change map.

The second problem may be solved by designing a careful approach for linear feature matching. The goal of this algorithm is to identify for each segment of the first group one or more corresponding segments of the second group, where “corresponding” is defined according to some given rules. As a matter of fact, we expect that linear features match if they have nearly the same location, the same orientation and length. Tolerances should be set, and weights assigned for each of the compared geometrical characteristics. Moreover, a maximum difference level must also be set, in order to define the “unmatched” status for any linear features which has no corresponding element. In order to explain how these tolerances were considered in the proposed approach, in the following the steps of the procedure are introduced. The reader is referred to fig. 2 for a visual representation of the algorithm.

1) First, for each segment from the first set, a bounding box with cross size (width) equal to \( \Delta \) pixels is drawn;
2) then, the routine computes the number of pixels of any element of the second feature set that fall into that box;
3) finally, the ratio between this value and the matched segment length is used to validate the match and retain the connection between the feature pair, if the ratio is higher than a minimum threshold.

The procedure is ruled by two parameters: \( \Delta \) and the minimum matching threshold, \( \rho \in [0, 1] \). Their combination allows to retain pairs of linear elements with the same length and the same direction, but displaced by \( \pm \Delta /2 \), but also pairs with the same location for their centers but with a directional mismatch of less than \( \tan^{-1} \left( \frac{\rho}{\sqrt{\Delta^2 + 1}} \right) \). Different locations for the two centers in a pair contribute to the result in shrinking the tolerance for directional mismatch. Therefore, by choosing the above mentioned parameters it is possible to have a precise definition of the
geometrical tolerances while maintaining a connection with the problem that started this analysis, i. e. misregistration. As a matter of fact, $\Delta$ may be computed as twice the mean misalignment between the two images to be compared, in turn easily obtainable for instance through their correlation.

To complete the discussion, we should note that equal lengths for the compared linear features has been assumed until now. However, since a difference in lengths is the most common case, the matching measure is not commutative, and we need to compute again the match after exchanging the two sets and then consider their mean value. Through this procedure it is possible to build a so called “correspondence matrix”. In this matrix, each extracted segment is associated with all the overlapping ones (following the above mentioned criterion) in the other set. The match reliability may be also computed, as explained above, and associated to the matrix element as valuable information for further processing. Please note that using the same approach, if a GIS or a manually extracted feature layer is available, a quantitative evaluation of the extracted data set may be computed, considering the completeness and correctness indexes [22]. After feature matching, the mismatched elements in the two sets represent features that were extracted only from one image and hence potential candidates for changes in the scene. They might be a results of noise, however, or false extractions as well. It’s not wise to rely on them for a precise change detection, and some fusion procedure with independently obtained area-based change map is to be planned.

B. Information Fusion Routine

Once both feature-based change detection and area-based change detection have been computed, their combination is, as noted above, an information fusion problem. As a matter of fact, we have two uncorrelated information sources, since the two procedures are based on different algorithms and suffer from different drawbacks. From information theory it is well-known that the best combination of the information sources would be the one weighted by a measure of their mean reliability (called “source entropy”). However, in the change detection problem there is no common ground for the computation of the reliability of area-based and feature-based approaches. Thus, we are forced to the sub-optimal solution, which is the equal-weight combination. As a result, the sub-optimal approach to information fusion in area-based and feature-based change detection is a logical AND operator between the two results, which means
that only changed areas validated by both algorithms will be considered. In order to compare
the changes a geometric approach very similar to the one in the comparison routine is required.
Each linear matched pair, i.e., any linear feature not representing a change is assumed to be
representative of a boxed area around it, computed with the same $\Delta$ parameter as above. This
area did not undergo any change and, if it was labeled as change by the area-based approach, it
is switched back to no-change label. Similarly, if an unmatched linear feature does not overlap
a change area in the change map, it is labeled as no-change and deleted from the set. The final
results of this approach are both a refined change map and a reduced set of unmatched linear
features.

III. EXPERIMENTAL RESULTS

In order to prove the usefulness of the proposed approach, we show some results in this section.
First of all, we show results for two synthetic pairs, where the second image was obtained by
manually processing an actual airborne SAR image. The second set of test images are instead
two multi-temporal pairs, analyzed after a manual co-registration step provided by an expert
operator.

A. Synthetic examples

The two synthetic pairs are based on an AIRSAR image of Santa Monica, California and are
shown in fig. 3. The original image has been recorded on August 5, 1994, from the height of
11,000 m, and georeferenced on a grid with 5 m posting. The second image in the pair was
manually shifted to the right by 10 pixels, to simulate a misregistration effect (“shift test”). In
the second situation, two parts of the roads in the area were masked, in order to simulate a
change in the area (“modify test”).

The validation of the procedure requires first the linear feature extraction and the availability
of a change map. In order to simplify the situation and maximize the effect of the feature-based
and area-based combination, the simple ratio between the two SAR images, suggested as the
easiest approach for area-based change detection, was used to provide the change map. After
ratioing, a threshold was applied to detect the changes. Fig. 4(a) shows the corresponding change
map for the “shift test”, and fig. 4(b) the segments extracted from the original AIRSAR image
(the second extractions is made by the same set with all segments shifted by 10 pixels to the right).

The final results are only a function of $\Delta$ and $\rho$. Setting the latter to 0.5, which seems a reasonable choice, the value of 5 (pixels) for $\Delta$ would results in no match and thus in no improvement of the change map. Choosing instead $\Delta = 15$, the algorithm finds out almost the totality of matches (see fig. 4 c). Thus, fig. 4(d) depicts the change map without the zone where the common segments are located. Note that there remains a dark area which represents the locations where a change has possibly taken place. In fact, this is a mistake, but since we don’t have any information from linear features in the areas, we are unable to exclude them from the map.

For the “modify test”, the thresholded ratio image provides the change map in fig. 5(a), while the linear feature matching results in the image in fig. 5(b) ($\Delta = 8$), to be compared with the extraction from the original AIRSAR image, in fig. 4(b). Naturally the missing segments were not considered and the change is recognized by both the area-based and the feature-based change detection algorithms. In fig. 5(b) it is shown the corresponding road extraction. In this situation their combination does not cause dramatic improvements in the change map (fig. 5 c). Just note a few more white no-change areas on the left road, where it was crossed by two other roads, which are clearly visible in both the images.

B. Real multitemporal examples

The actual image pairs used for demonstration corresponds to an airborne SAR pair and a satellite SAR pair over urban areas. The choice is related to the need to validate the approach on very different images, considering different sensors, different viewing angles, and different spatial resolutions. In particular, the first multitemporal pair (fig. 6 a,b) is actually a multi-sensor set. The oldest image is a portion of the same AIRSAR data set including the Santa Monica test image, and was recorded in 1994. The second image depicts the same area in the year 2000 and was provided by Intermap Technologies Inc. This is a 1.25 m posting georeferenced image from the airborne Star-3i sensor. Both images show the area of the University of California, Los Angeles (UCLA) campus, but they are taken from different viewing angles, and also the spatial resolution plays its role in making the results of any area-based change detection scheme more fuzzy.
The information content of the images gets clearer if we look at the linear features (mainly, the road network) in both images, depicted in fig. 7(a,b). Note that the largest number of features in the second image is due to the more detailed (higher spatial resolution) original data set. Fig. 7(c) shows the change map. The darker areas (change areas) represent both slots where changes really took place (new built structures) but also difference in contrast and backscattering field values. After comparison with the feature maps and feature matching (again, $\Delta = 8$), the refined change map is shown in fig. 8(d), with the areas around common segments masked out. The majority of the false change detections have been removed, and the remaining areas refer to real changes in the 6 years’ period between the AIRSAR and the Star-3i image. In particular, a new building is highlighted in green.

Finally, the second multitemporal set is made of two ENVISAT Advanced SAR (ASAR) sensor images of the area around the city of Bam (Iran), shown in fig. 6(c,d). Both images are coarse resolution ones, with 12.5 m posting, and were chosen with the purposes of detecting the effect of the major earthquake that stroke the town on December 27, 2003. In fact, the first image was recorded on the 3rd of December, 2003, while the second one was recorded a few days after the disaster, on 7th of January, 2004.

The aim of this test is to extract the areas that were affected by the earthquake without introducing false positives, i.e. areas outside the town where the change is only due to misregistrations or slight changes in the viewing direction of the sensor. Indeed, looking at the feature extraction results (shown in fig. 8 a,b), the hilly areas around the town present the same edge pattern in both images, while the pattern is different inside the affected area, as we expected. By using the mask depicting the areas with common edge patterns after the matching procedure ($\Delta = 8$), which is shown in fig. 8(c), it is possible to obtain the final refined change map, starting as in all our test from a less precise map obtained by ratio thresholding. Fig. 8(d) provides the final map superimposed in red to the original pre-earthquake image.

IV. CONCLUSIONS

This paper presents a method for change detection from multitemporal SAR data that includes a data fusion procedure. It has been shown that improvements in the change map using both pixel- and feature-information are available. Moreover, the technique is able to overcome to some degree some common problems in multitemporal image analysis, like misregistration or
miscalibration. The procedure has been validated using synthetic pairs, to show its potentials, and real pre- and post-event images, which helped in understanding its real abilities. Summing up, it is possible therefore to draw some conclusions.

- From a very general point of view, the procedure shows that the joint use of two (in principle) uncorrelated sources of information, namely pixels and geometrical features, may achieve better detection results than using one source alone. This is very similar, in signal theory, to the task of looking for a known signal (like a discontinuity, i.e. a change) using two different detectors. This is a well-know result, and in this sense this work is a sheer assessment.

- The amount of improvement in the change map due to the joint use of area-based and feature-based approaches is variable as a function of the two algorithms. In the examples in this paper the basic ratio detector (standard for SAR images) was used for deriving the first, rough change map. The reason is that it is available in many standard, commercial and free software components. More complex algorithms require specialized software and will surely push the improvement forward, but to the expense of a larger programming effort and heavier CPU load. SAR edge detectors are instead available in the same packages, and the only work needed for this approach is the implementation of the comparison and the fusion routines.

- Some specific problems, like misregistration, are easier to solve using this combined approach than more complex area-based procedures [17]. A misregistration (see the “shift test”) is not a problem at all, and can be completely recovered. The same is true using the above mentioned area-based method, but a shift coupled with a multi-sensor data set is out of the reach for current area-based analyses, while the first part of the problem (i.e. misregistration) may be decoupled from the second one using the joint pixel/feature approach.

Future lines of research may be related first to using several linear feature extraction algorithms; then, to improving the reliability of the feature-based change detection results. Another research line may be a more locally refined, even if still suboptimal, combination of the two (or more) information sources. Adaptive approaches taking care of the local combination of the different change detection procedures are therefore the final recommendation for this work, since they naturally follow the mainstream of multiple classification fusion, which is dramatically
increasing in importance in current lines of research.

REFERENCES


Figure Caption

- Fig. 1: Conceptual work flow of the proposed procedure.
- Fig. 2: Visual representation of the feature match computing procedure. $\Delta$ is a parameter to be set (see text).
- Fig. 3: Synthetic examples: (a) original AIRSAR image; (b) the same image shifted to the right by 10 pixels; (c) the same image with two road parts masked out.
- Fig. 4: “Shift test”: (a) change map obtained by thresholding the ratio between the two images; (b) linear features extracted from the original AIRSAR image; (c) matched feature pairs; (d) refined change map.
- Fig. 5: “Modify test”: (a) change map obtained by thresholding the ratio between the two images; (b) matched feature pairs; (c) refined change map.
- Fig. 6: Actual multi-temporal pairs: (a) AIRSAR image of UCLA campus; (b) Star-3i image of the same area; (c) ASAR pre-earthquake image of Bam, Iran; (d) ASAR post-earthquake image.
- Fig. 7: Results for the UCLA image pairs in fig. 6(a,b): (a),(b) road extraction of the corresponding original images; (c) original change map; (d) refined change map.
- Fig. 8: Results for the Bam image pair in fig. 6(c,d): (a),(b) feature extraction from the original images; (c) common segment mask; (d) refined change map (in red) superimposed on the pre-earthquake SAR image.
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