Debris Detection in SAR Imagery Using Statistics of Simulated Texture

Silvia Kuny, Karsten Schulz
Department Scene Analysis
Fraunhofer Institute of Optronics, System Technologies and Image Exploitation IOSB
Ettlingen, Germany
silvia.kuny@iosb.fraunhofer.de

***Abstract*—This paper presents a preliminary approach for debris detection in SAR images based on simulated training areas. For this purpose radiometrically correct simulations of heaps of debris are produced. Based on statistics of the first and second order they are analyzed for their textural characteristics. The resulting feature information is used for the localization of debris-like signatures in real SAR imagery. Results are presented and discussed.**

Keywords—SAR simulation; Haralick features; texture; damage detection; debris

I. INTRODUCTION

When natural disasters like earthquakes occur in urban areas a dire need for fast emergency response arises. One key aspect for the support of rescue efforts is the timely analysis and interpretation of remote sensing imagery. For this purpose SAR imagery often is the first available data, since it is not dependent on weather and illumination conditions like optical data. Many approaches for damage detection in SAR imagery have been introduced, some of them breaking new ground by using the assistance of SAR simulation [1], [2], [3] in cases where no pre-event SAR image is available and thus change detection approaches fail. However, this subject still remains an open research issue.

Most often heaps of debris surrounding buildings are the cause for the most distinct signature of a damage site, their texture differing considerably from that of intact buildings. On these grounds the usage of statistical texture features such as Haralick features is quite promising. However, a differentiation between debris and non-debris by means of its texture statistics can be problematic, since suitable training areas cannot easily be found in real SAR images without prior knowledge of the location of destroyed buildings. Even if such buildings can be found it remains challenging to define the extent of the heap of debris without including textures of surrounding areas.

In this paper we introduce a preliminary study exploring whether the simulated SAR signature of a heap of debris instead is suited for the detection of debris in real SAR images. First results attained using a basic detector are presented.

II. DEBRIS AND ITS SAR TEXTURE

The proposed processing structure described in the following is illustrated in Fig. 1. As test data a TerraSAR-X image of the Christchurch (New Zealand) area is used, acquired shortly after the devastating earthquake in 2011. Corresponding reference information is provided in the form of optical imagery recorded after the earthquake.

The proposed direct comparison between real and simulated SAR images requires an accurate radiometric simulation. This requirement is met by the CohRaS® SAR simulator, a coherent SAR image simulator based on ray tracing. CohRaS® has been described in detail in [4]. It uses the so-called narrow-beam approach to SAR simulation, i.e. no raw data are created. CohRaS® takes into account the coherent nature of radar imaging by simulating both amplitude and phase of the returned signal. Using a fast ray tracer, CohRaS® is able to simulate large amounts of images from different incidence and aspect angles in very little time and is thus ideally suited for the purpose at hand.

A. Simulation of heaps of debris

In order to attain a realistic simulation of debris, which is suited as texture for the training area, two 3d models of heaps of debris were chosen as input. Both consist of an accumulation of brick stones of different sizes and orientations, yielding a surface of a rather average unevenness. Consequently, the characteristics of a good portion of real heaps of debris are represented.

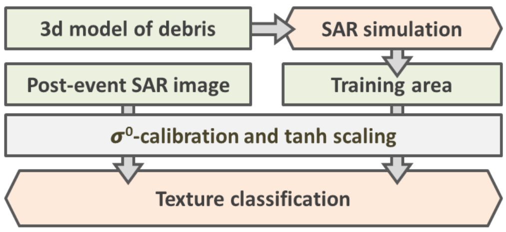

Fig. 1. Flow chart of processing structure.

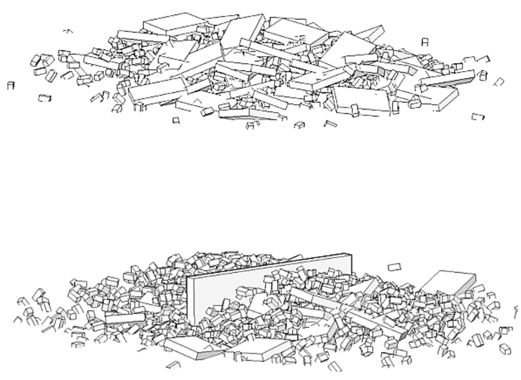

Fig. 2. 3d models serving as input for the simulation of the training texture.

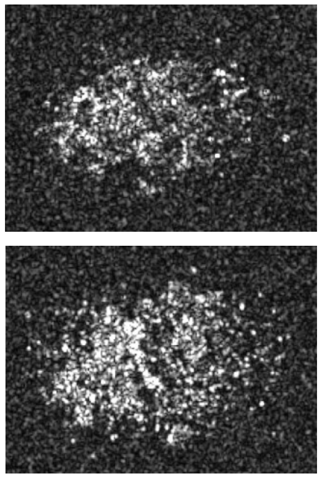

Fig. 3. Simulated amplitude images serving as training texture.

The second model additionally features a vertical wall across the heap. Thus it is also accounted for, that heaps of debris very often occur in front of still standing building parts and consequently the signature of debris often is directly adjoined to a dihedral building corner. The generation of the 3d models with regard to their macroscopic surface roughness was described in detail in [5]. In Fig. 2 both 3d models are depicted.

The simulation of the heaps of debris was conducted with the sensor and acquisition parameters of the TerraSAR-X image used in this work. Furthermore, the material properties were chosen so that the amplitudes of a corresponding heap of debris in the TerraSAR-X image were imitated. In Fig. 3 the resulting simulated amplitude images are shown. Note that both heaps of debris have been created with enough spatial extent so that the textural features can be computed for multiple windows.

The following steps require the calibration of the amplitude images A. So both the TerraSAR-X image and the simulations are Sigma Naught calibrated [6], thus making the image radiometry comparable to other SAR images of e.g. different acquisition angles. Obviously no calibration scaling factor or information about the noise power is provided for the simulations. However, since these were generated imitating the actual TerraSAR-X amplitudes, the calibration can be conducted using the same metadata.

B. *Statistical Texture Analysis*

In this approach to textural analysis statistical texture features of the first and second order are included. From the many existing first order texture features, computed directly on the SAR image in a sliding window of size 15x15 pixels, the following were chosen:

- Mean
- Variance
- Median

The second order features, defined by Haralick [7] and also widely used in texture analysis are computed on the gray level co-occurrence matrix (GLCM).

The GLCM considers the gray level combination for two pixels of a given spatial relation, listing probabilities how often specific gray level combinations occur in an image. For this the image has to be quantized to a manageable number of gray levels. To ensure that the sought for texture information is not lost in this step the gray level distribution of SAR imagery has to be considered.

On the one hand the setting of arbitrary thresholds has to be avoided, cutting off large gray level values. On the other hand care must be taken that not too many details are lost in dark regions. A suitable scaling method was introduced in [8], which maps the intensities I in accordance with the following equation to the range]-1,+1[.

$$\tanh(\ln A) = \frac{e^{2\ln A} - 1}{e^{2\ln A} + 1} = \frac{I - 1}{I + 1}$$

For the generation of the GLCM the scaled gray values are then quantized to 6 bit values, since it was established that there is no further information gain by choosing more than 64 gray levels, as mentioned in [9]. This finding has been validated for the approach discussed in this paper in [5].

Another issue in the usage of GLCM is the prospect of an ideal window size to compute the texture features for. Several runs have confirmed a size of 15x15 pixels to be reasonable regarding debris. A window size of 11x11 pixels or smaller leads to somewhat unstable results, whereas a size of 19x19 pixels already appears to be too large to contain just one type of texture. Since the GLCM is sensitive to rotation it is computed not only for neighboring pixels in the horizontal, but also for the vertical and the diagonal neighboring pixels, thus eliminating possible directional dependencies in the SAR texture.

Not all of the 14 Haralick features have to be used, since many of them are correlated. Rather it is important to use the right combination for the problem at hand. In our case, those features were discarded that show a lack of robustness regarding single strong scatterers and those that vary too strongly within the texture of the training area, thus holding no class information. The seven Haralick features used in the following are listed below.

- Energy
- Correlation
- Variance
- Sum Average
- Sum Variance
- Sum Entropy
- Entropy

C. *Defining feature value intervals for debris*

For every pixel in the two appointed training areas the GLCM and then the Haralick features as well as the statistics of the first order are computed. As a result there are two intervals for each feature describing the texture of the two simulated heaps of debris. For comparison this is also done for two training areas in the TerraSAR-X image showing real debris. However, as expected, this leads to feature intervals too large to include only debris. The reason for this is the challenge of capturing just the part of the signature actually representing debris.

Accordingly the features are computed for each pixel in the TerraSAR-X image. The subsequent process of classifying each pixel as debris or non-debris is carried out by a simple test of inclusion for each feature interval. For further processing the resulting binary mask is then decomposed into connected components.

III. RESULTS

The binary mask, featuring all pixels with the defined texture properties, shows many very small areas. Since it is not the objective or even expectation of this study to detect small heaps, but rather debris at least of the size of a small building, those small areas are discarded. This is done by decomposing the binary mask into connected components and a subsequent filtering step removing all regions consisting of less than 500 pixels. In Fig. 4 the components left over after the filtering step are displayed for the inner city of Christchurch.

The actual locations of potentially visible heaps of debris were assembled using the optical imagery mentioned in Section II. Debris that in the SAR image would be located in the shadow of a building and thus is undetectable deliberately is not included. Of the fifteen thus declared debris sites there are twelve that exhibit the texture properties defined in the simulated training areas. The remaining three sites have only few pixels indicating debris and hence were discarded in the filtering step. In Fig. 4 the correctly declared areas are marked green whereas components known to be falsely declared as well as components for which no clear information on the texture source could be provided are marked red. A more detailed quantitative assessment of the 66 marked regions is listed in Tab. 1. It is obvious that there are many markings not actually showing debris sites. In particular the texture of trees is very similar to that of debris, as is demonstrated in Fig. 5. In fact the feature intervals overlap to a great extent with those of trees, so there are definitely many false declarations to be seen on this account.

TABLE I. QUANTITATIVE ASSESSMENT

debris	vegetation	non-debris / non-vegetation	unclear source
13	11	17	25

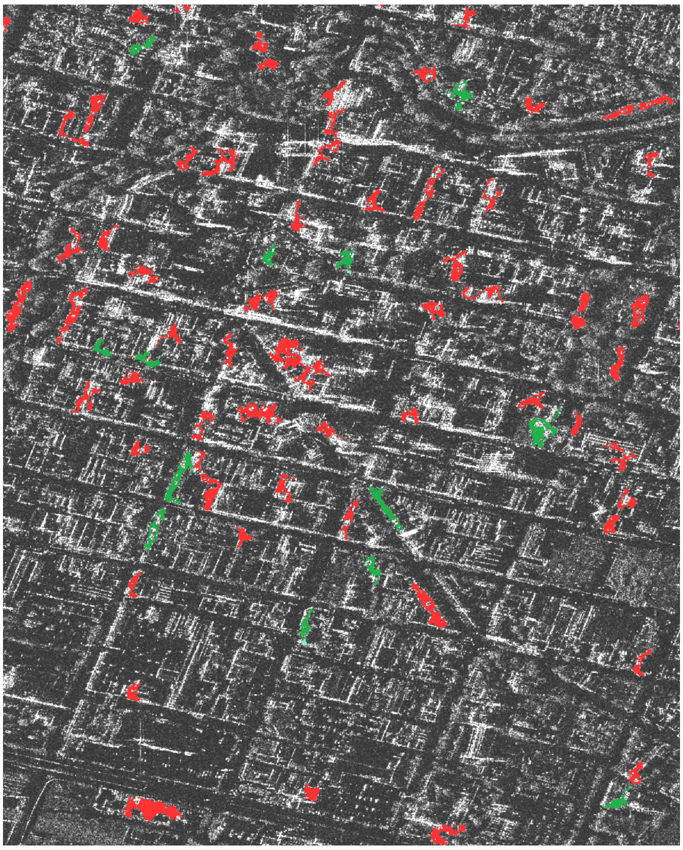

Fig. 4. Filtered classification result: actual debris sites (green), non-debris and unknown sources (red).

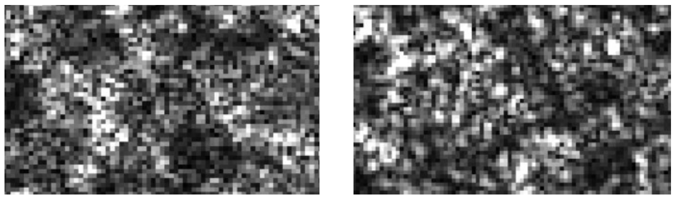

Fig. 5. SAR texture of trees (left) and simulated SAR texture of debris (right).

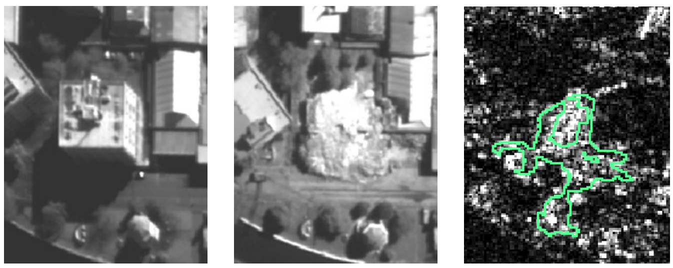

Fig. 6. Exemplary damage site.

Furthermore, some buildings with a lot of alcoves and nooks seem to yield a rather similar texture as well, resulting in false declarations. However, for some markings it remains unclear if debris may be the cause for the texture similarities, since the optical data was recorded a few days after the SAR image. Hence there is a possibility that debris was already cleared away.

In Fig. 6 a close-up of an exemplary damage site is depicted, which is correctly declared as texture of debris. However, the discrimination between a neighboring tree and the debris fails in this example also. A better distinction between trees and the heaps of debris is expected to be possible using further texture features and a multi-class classifier instead of a one-class classifier.

IV. CONCLUSION & OUTLOOK

The objective of this study was to use simulated SAR textures of modelled heaps of debris to detect regions of massive destruction in real SAR imagery. Statistical texture features of first and second order were computed for the simulated training area and the real SAR image. On the basis of these, a binary image was calculated indicating areas of the image that are similar to the heaps of debris with respect to the features used.

Almost all damage sites known to us were declared correctly, thus confirming the suitability of the simulated textures as training area. However, there also are many false declarations, many of which can be attributed to trees, which have a texture that is rather similar to that of the heaps of debris.

It is planned to add more textural and direct features as well as to switch to a discriminative multi-class classification in order to obtain a better distinction between debris and non-debris. In the course of this, the macroscopic surface roughness of the heaps of debris is to be taken into account more closely. Also, if data of different sites become available, the derived feature intervals will be tested against these new data. It is expected that since calibrated data are used, the intervals should also be able to identify heaps of debris in other X-band data sets. Finally, a comparison to already established techniques in debris detection will be conducted.

REFERENCES

[1] T. Balz and M. Liao, “Building-damage detection using post-seismic high-resolution SAR satellite data”, Intern. Journal of Remote Sensing, Vol. 31, No. 13, pp. 3369-3391, 2010.

[2] J. Tao, S. Auer, and P. Reinartz, “Detecting changes between a DSM and a high resolution SAR image with the support of simulation based separation of urban scenes,” Proc. of EUSAR 2012, 4 p., CD-ROM, 2012.

[3] D. Brunner, “Advanced methods for building information extraction from very high resolution SAR data to support emergency response,” Ph.D. Thesis, University of Trento, 2009.

[4] H. Hammer and K. Schulz, “Coherent simulation of SAR images,” Proc. of SPIE, Image and Signal Processing for Remote Sensing XV, Vol. 7477, Berlin, Germany, pp.74771G-1-9, 2009.

[5] S. Kuny, K. Schulz, and H. Hammer, “Simulation based texture analysis of heaps of debris for damage assessment in high resolution SAR data,” IEEE Proc. of Intern. Conf. on Recent Adv. In Space Techn. RAST 2013, Istanbul, Turkey. pp. 1169-1172, 2013.

[6] Airbus Defence and Space (2008), „Radiometric calibration of Terra-SAR-X data,” TSXX-ITD-TN-0049-radiometric_calculations_I1.00.doc, October 2008. IEEE Trans. on Geosc. and Remote Sensing, Vol. 43, No. 3, March 2004.

[7] R. M. Haralick, K. Shanmugan and I. Dinstein, “Textural features for image classification,” IEEE Transactions on Systems, Man, and Cybernetics, Vol. 3, No. 6, pp. 610–621, 1973.

[8] A. Schmitt, “Änderungserkennung in multitemporalen und multipolarisierten Radaraufnahmen,” Ph.D. Thesis, Karlsruhe Institute of Technology, 2012.

[9] L.-K. Soh and C. Tsatsoulis, “Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices,” IEEE Trans. on Geosc. and Remote Sensing, Vol. 37, No. 2, pp. 780–795, 1999.