Simulation based texture analysis of heaps of debris for damage assessment in high resolution SAR data

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***Abstract*—This paper presents a preliminary study for damage detection in SAR images based on simulated data. We conduct a signature analysis of heaps of debris with the focus on a dependence on surface formation. Based on several series of 3d models, high resolution SAR images were simulated. We use grey level co-occurrence matrices and textural parameters to analyze the signatures. The discussion focuses on the behavior of the features for systematically changing formation of the surface.**

Keywords—SAR simulation; damage assessment; textural analysis

I. INTRODUCTION

If natural disasters such as earthquakes strike urban areas, a fast emergency response is most crucial. In order to get a good overview of the affected area, SAR sensors are the systems of choice for their independence on weather conditions and on illumination by the sun. However, the extraction of viable information from SAR data is not an easy task, especially if no pre-event data of the area are available.

It has been noted before that areas of destroyed buildings show a higher backscattering intensity in SAR data than their surroundings [1]. This is caused by heaps of debris stemming from the destroyed building. Small rubble results in the formation of many dihedral and trihedral corner reflectors and thus produces high backscattering intensity. In this paper such a formation is called “macroscopically rough”. Planar areas on the contrary reflect the beam away from the sensor. Thus, different compositions of the heaps lead to different brightness of the overall backscattering intensity and smoothness of the signatures. So as a first step to analyze the signature of destroyed buildings, in this paper the appearance of heaps of debris in SAR data is investigated. As the signature of one such heap is depending on many factors, which cannot all be taken into account, this analysis concentrates on the changes in signature caused by a systematic altering of the macroscopic roughness. Since not enough real data for a systematic analysis are available, SAR simulation is used. In [1] the concept of simulating a heap of rubble for individual cases has been introduced, however we are not aware of any publications dealing with a systematic signature analysis regarding SAR signatures of heaps of rubble. The simulations shown in this paper were produced with the SAR simulator CohRaS developed at Fraunhofer IOSB [2].

II. SIMULATOR

CohRaS (Coherent Raytracing SAR Simulator) is a simulation tool for creating processed SAR images (i.e. no raw data are calculated). It uses ray tracing for direct returns (narrow-beam approximation) and for determining areas not illuminated by the sensor. Specular reflections are simulated using geometrical and physical optics. The specularly reflected energy is then processed to the correct place in the simulated image using a very simple Range-Doppler processor. One of the main features of CohRaS is that it simulates both amplitude and phase of the returned signal. Thus, different signals in the same resolution cell are added coherently. This offers the opportunity to create speckle by randomly distributing point scatterers in a resolution cell and then adding their respective returns coherently. The simulated phase also enables the creation of interferometric images. From the input 3d model of the scene with material properties attached to the different polygons in the scene, CohRaS creates a so-called Reflectivity Map - an ideal SAR image that would be recorded by a system with infinite bandwidth. This image is then coherently downsampled to the system resolution, oversampled to the pixel size chosen by the user by means of a *sinc* interpolation step and then convolved with the point spread function corresponding to the chosen window function. More details about the CohRaS simulator can be found in [2].

III. DEBRIS CONSTRUCTION

Since heaps of debris usually are very chaotic structures that cannot be totally accounted for in a 3d model, the synthetic heaps used in this study are reduced to their essential elements. A heap of debris is modeled out of various randomly piled up cuboids, so that its horizontal concentration is normally distributed and its height is limited by the Gaussian probability density function. By picking a sufficient amount of cuboids there exist only few bricks that are not attached to others (e.g. floating above the heap). These few do not seriously interfere with realistic SAR imaging. Each cuboid is rotated randomly along all three main axes, with a restriction concerning large flat cuboids. It would be rather unrealistic to assume that those occur very often in badly sloped, almost upright states without support. Hence large cuboids are restricted to smaller pitch angles.

The algorithm used to generate the heaps leads to the occurrence of numerous intersections between the cuboids. This, however, bears no conflict with a realistic surface, which exclusively is accountable for the resulting signatures. In Fig. 1 the 3d model of such a heap is displayed.

The generation of heaps was carried out in an automated way, so that the macroscopic roughness of the surface could be changed systematically by altering size, form, count and combination of the cuboids stepwise.

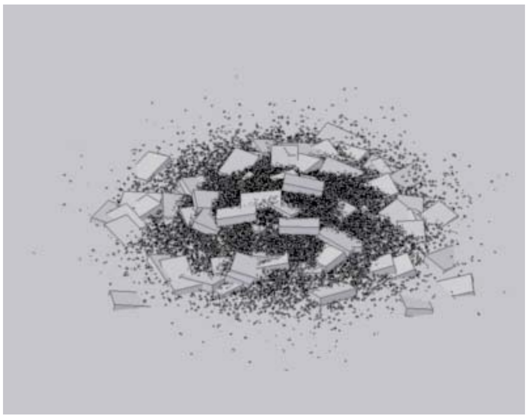

Fig. 1. Example of model showing heap of debris

IV. EXPERIMENTAL LAYOUT

In this paper two series of models of heaps are analyzed on a textural basis. In both cases the models are generated such that the macroscopic roughness of their surface is decreasing systematically for 20 heaps each, using different methods. The first series was modeled by increasing the size of the cuboids step by step, with the restriction on the pitch angle in mind. In the second series the decrease of roughness was achieved by a stepwise exchange of many small cuboids at the surface with large flat ones.

In order to assign realistic material parameters to the models, backscattering properties were derived from real SAR images showing a concrete wall. The parameters were adjusted such that the intensity profiles of the backscattering of this wall and of the corresponding simulated signature were alike. This led to parameters describing a rather specular material. Additionally a second material of a more diffuse kind was chosen.

Simulation parameters were picked according to high resolution TerraSAR-X parameters, using a pixel spacing of 45 cm in range and 87 cm in azimuth, and a wavelength of 3.1 cm. In order to mitigate the effect of randomly generated corner reflectors within the heaps on the textural analysis it would have been ideal to have a set of models for each of the 40 kinds of heaps, and then to average the analytic results. This would have been too time-consuming though, instead each model was simulated for 35 aspect angles in steps of 10°. Each of these simulations was conducted for several incidence angles, two of which are shown in this paper (30°, 50°), and for the two described materials. Samples of the simulation results are shown in Fig. 2. While the simulated amplitudes are not calibrated and consequently cannot be directly compared to real SAR amplitudes, the comparison amongst the simulations is valid.

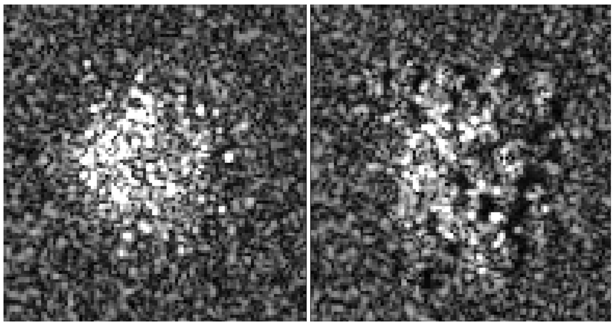

Fig. 2. Examples of simulated SAR signatures of heaps of debris (left: rough; right: less rough)

V. TEXTURAL ANALYSIS

The textural features introduced by Haralick [3] based on the gray level co-occurrence matrix (GLCM) are an established approach for textural analysis, that have been used in other publications for the analysis of textural features in SAR data [4, 5]. However, we are not aware of any publications applying these features to simulated SAR data.

The GLCM encodes how often different combinations of pixel gray levels occur in a given image window [3]. Effectively, the matrix generation is influenced by several important parameters, such as window size, the offset of the two pixels in direction as well as distance, the quantization method and the number of gray levels the image is quantized to. In order to maximize the gain of image based information, it is necessary to adjust these parameters to the sort of data at hand:

A. Quantization

The first step in generating the GLCM is to break down the given data to fewer gray level bins. There are different methods for this quantization process, which are chosen depending on the data gray level distribution and the information sought: There is uniform quantization, a simple method of scaling the gray levels linearly to a number of bins, not contemplating the data gray level distribution. For data that can be assumed to be normally distributed, Gaussian quantization seems suitable and last but not least there is the equal probability quantization. Since our data is not Gaussian distributed and since uniform quantization is reported to produce better results in SAR images than the equal probability quantization, at least concerning sea ice [4], we decided on the uniform quantization method.

The number of bins is a fundamental parameter, which, if chosen too low, leads to a fatal reduction of information. On the other hand fewer bins reduce noise-induced effects and since the number of bins determines the size of the co-occurrence matrix it directly affects the computing cost. This trade-off was discussed in [5], with the conclusion that the loss of information due to quantization is not compensated by the information gained by noise reduction, however, large numbers are unnecessary. As a threshold, Soh [5] suggests a number of 64 bins for sea ice in SAR images. Our test series confirmed these tendencies, there was but little change for high values. However, a number of 128 gray levels yielded best results for our application.

B. Window size

In our case, the bigger the window the more textural information of the object signature is gained, as long as the cutout does not expand beyond the signature of the debris. This is due to the fact that there is no risk of including regions that may have objects belonging to different categories. So the window size was adjusted to the dimensions of the simulated debris signatures, namely 25x25 pixels.

C. Direction

Since we did not expect the SAR images to be spatially invariant, we chose to look at four directions separately, namely θ = 0°, 45°, 90°, 135°, but have come to the conclusion, that for the purpose at hand the spatially invariant features, computed on the basis of all four directions are sufficient.

D. Distance

The ideal distance for the pixel offset depends on the level of detail of the texture that is analyzed. The GLCM cannot capture textural information of a fine texture if a large pixel offset is used. Accordingly, for our test series a displacement of 1 has tended to produce the best results regarding the change of features for the different test heaps, so we have stuck to this value.

By applying statistics on the normalized GLCM, the textural features defined by Haralick [3] are derived. Though there is an abundance of 14 features, many of them are correlated, so the important issue is not to evaluate them all, but to identify the suitable features. After some testing we decided on the five texture features listed below:

Contrast $$\sum P_{ij}(i-j)^2 \qquad (1)$$

Homogeneity $$\sum \frac{P_{ij}}{1+(i-j)^2} \qquad (2)$$

Angular Second Moment $$\sum {P_{ij}}^2 \qquad (3)$$

Entropy $$\sum P_{ij}(-\ln P_{ij}) \qquad (4)$$

Correlation $$\sum P_{ij}\left[\frac{(i-\mu_x)(j-\mu_y)}{\sqrt{(\sigma_x{}^2)(\sigma_y{}^2)}}\right] \qquad (5)$$

Here $P_{i,j}$ denotes the number of occurrences of gray levels i and j and $\mu_x, \mu_y, \sigma_x, \sigma_y$ are the means and standard deviations for the rows and columns of the co-occurrence matrix.

Both Contrast and Homogeneity belong to the group of features applying weights to the matrix entries, depending on their distance to the matrix diagonal. For Contrast the weights increase with the distance from the diagonal, for Homogeneity the weights decrease, consequently the two features are inversely correlated. High Contrast values emerge in case of large local variations, whereas high Homogeneity values represent uniform areas.

Angular Second Moment (ASM) and Entropy are features describing the orderliness in the image. An image that has many similar gray level transitions will result in few but high entries in the GLCM and thus a high ASM value. In contrast the Entropy, also called “Chaos”, reaches its maximum when each pair of gray levels is equally probable, which is the case for an irregular image. The GLCM Correlation is a feature using descriptive statistics on the co-occurrence matrix, measuring linear dependencies of gray level values. For more details on the features derived from GLCM and their properties we refer to [3].

VI. EXPERIMENTAL RESULTS

Regarding the backscattered intensities a distinct decrease of the mean amplitudes, as well as an increase of the maximal values could be observed as shown in Fig. 3. Thus the assumption of the backscattering intensities correlating with macroscopic roughness could be confirmed.

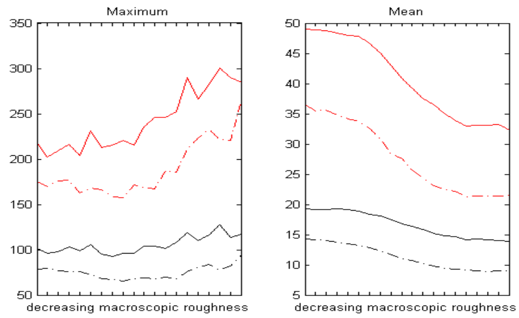

Fig. 3. Maximal and mean amplitude values occuring in image window for decreasing macroscopic roughness in second series of heaps. (red: material 1, black: material 2, continuous: 30°, dashed: 50° incidence angle)

The changes the used features undergo for systematically decreasing macroscopic roughness are displayed for the first series of heaps in Fig. 4 and for the second series in Fig. 5. Since there is no concise measure for the level of macroscopic roughness, the x-axis only represents the number of the simulated images used to calculate the respective features, sorted in decreasing order of macroscopic roughness.

For both series of heaps a distinct rise in Homogeneity and a decline in Contrast can be observed. This is due to the many trihedral corner reflectors occurring for a macroscopically rough surface and the resulting local image variations. The rougher the surface, the more large gray level differences appear and the less probable similar gray levels in neighboring pixels are. Since material 1 is the more specular one, the resulting signatures feature distinctly higher values for the corner reflectors than those simulated with material 2. This entails the corresponding GLCM to contain more entries with a large distance to the diagonal and thus to a large Contrast value.

The increase for Angular Second Moment indicates that the same gray level differences are occurring more often. This can be explained by the appearance of larger and more numerous flat areas in the models of reduced roughness. These, for small image areas, cause more or less the same gray levels and thus lead to some gray level transitions appearing more often. Contrary to that, a rough surface results in all sorts of gray level combinations, rendering it much less probable that a specific gray level transition occurs several times. The increase was expected to some extent, as the Angular Second Moment is a feature that describes how regular the pixel values are within a window and without large enough cuboids causing consistent areas there is no source for any regularity in the heaps.

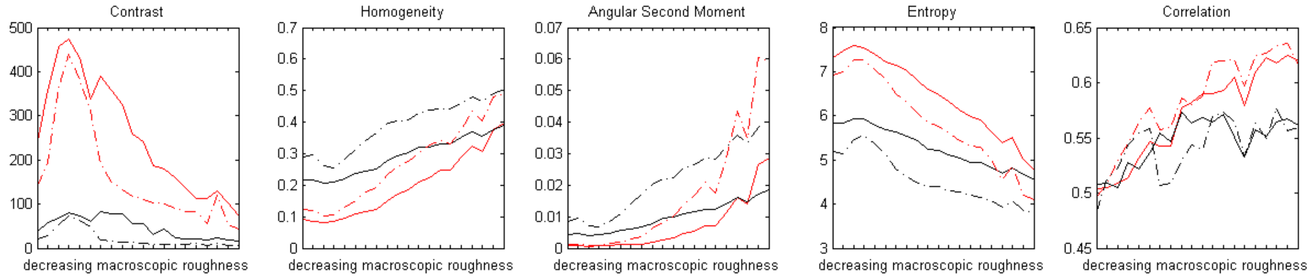

Fig. 4. Behavior of five textural features for decreasing macroscopic roughness in the first series of heaps. (red: material 1, black: material 2, continuous: 30° incidence angle, dashed: 50° incidence angle)

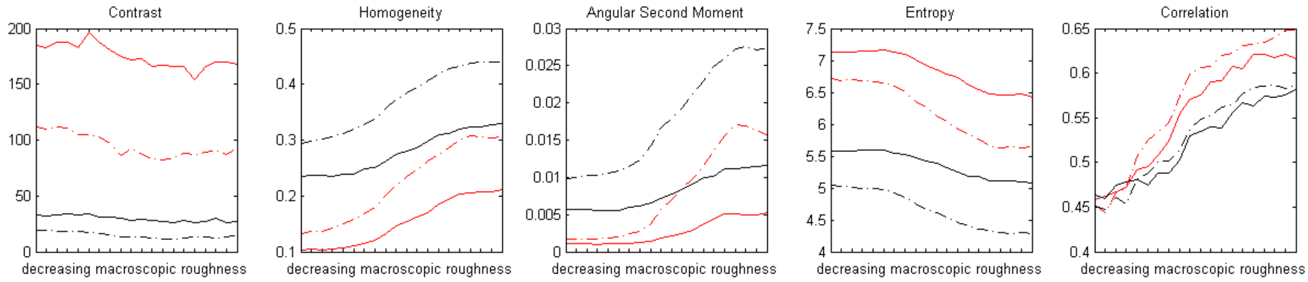

Fig. 5. Behavior of five textural features for decreasing macroscopic roughness in the second series of heaps. (red: material 1, black: material 2, continuous: 30° incidence angle, dashed: 50° incidence angle)

Accordingly, a decrease of Entropy, another feature related to orderliness, was expected. Since the signatures of the many corner reflectors lead to a very irregular image, the entries in the co-occurrence matrix are rather regular and thus yield a higher Entropy value than the signatures that seem to have some kind of pattern, like the simulations of the heaps with lesser macroscopic roughness.

The increase in Correlation is incurred by a rising linear dependence of the gray level values. This is caused by the signature of larger cuboids extending over several pixels and forming a line structure at the border.

For the first series of heaps (see Fig. 4) several of the features show a differing tendency for the very rough heaps than the rest of the series. This may be caused by the fact that in these cases the dimensions of the individual cuboid are considerably smaller than the resolution cell of the simulated image. Even though the two materials lead to different results, the changes they undergo for decreasing roughness are comparable. The same applies for the two different incidence angles.

VII. CONCLUSIONS

Using several series of SAR simulations the signatures of heaps of debris were analyzed. This signature depends upon many factors, which could not all be covered in this paper. Thus, we focused on macroscopic roughness. In particular the effect a systematic change in macroscopic roughness has on the signatures was examined and evaluated by means of textural analysis. It is intended to validate the results of this textural and radiometric analysis by means of real SAR images, use them to perform a screening of possible damage areas in SAR images and, extending the simulation to more complicated types of damage of urban structures, to classify the damages occurring at the buildings under consideration.

REFERENCES

[1] T. Balz and M. S. Liao, "Building-damage detection using post-seismic high-resolution SAR satellite data," International Journal of Remote Sensing, 31 (13) (2010), pp. 3369–3391, 2010.

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

[3] 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.

[4] D. A. Clausi, "An analysis of co-occurrence texture statistics as a function of grey level quantization," Can. J. Remote Sensing. v28 i1. 45-61, 2002.

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