Generalized Interpretation Scheme for Arbitrary HR InSAR Image Pairs

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ABSTRACT

Land cover classification of remote sensing imagery is an important topic of research. For example, different applications require precise and fast information about the land cover of the imaged scenery (e.g., disaster management and change detection). Focusing on high resolution (HR) spaceborne remote sensing imagery, the user has the choice between passive and active sensor systems. Passive systems, such as multispectral sensors, have the disadvantage of being dependent from weather influences (fog, dust, clouds, etc.) and time of day, since they work in the visible part of the electromagnetic spectrum. Here, active systems like Synthetic Aperture Radar (SAR) provide improved capabilities. As an interactive method analyzing HR InSAR image pairs, the CovAmCoh method was introduced in former studies. CovAmCoh represents the joint analysis of locality (coefficient of variation – Cov), backscatter (amplitude – Am) and temporal stability (coherence – Coh). It delivers information on physical backscatter characteristics of imaged scene objects or structures and provides the opportunity to detect different classes of land cover (e.g., urban, rural, infrastructure and activity areas). As example, railway tracks are easily distinguishable from other infrastructure due to their characteristic bluish coloring caused by the gravel between the sleepers. In consequence, imaged objects or structures have a characteristic appearance in CovAmCoh images which allows the development of classification rules. In this paper, a generalized interpretation scheme for arbitrary InSAR image pairs using the CovAmCoh method is proposed. This scheme bases on analyzing the information content of typical CovAmCoh imagery using the semi-supervised k-means clustering. It is shown that eight classes model the main local information content of CovAmCoh images sufficiently and can be used as basis for a classification scheme.

Keywords: SAR, High Resolution, InSAR, interpretation scheme, classification, CovAmCoh, k-means, clustering.

1. INTRODUCTION

In contrast to optical remote sensing satellite imagery, spaceborne SAR offers some significant advantages. Since SAR is an active method, it is mainly independent of weather conditions like dust, fog and clouds. Furthermore, the time of day plays no role in planning the acquisition dates [1]. These are the reasons which make SAR remote sensing well-suited for (e.g.) monitoring tasks and time series analyses. Concerning the geometric resolution, nowadays, many SAR satellites offer acquisition modes which deliver images with high resolution (HR) of less than one meter. One of them is the German system TerraSAR-X (TSX), which was launched in 2007. One can order images covering the same location with identical acquisition parameters in an 11 days repeat pass cycle. Two images, which were acquired by this constellation, establish one interferometric image pair.

For the interactive interpretation of such image pairs, the CovAmCoh analysis ([2]) is a suitable method. It offers opportunities to derive additional information about physical backscatter characteristics of the acquired scene. In contrast to the analysis of amplitude or intensity images, a CovAmCoh image can deliver important complementary useable information content which simplifies the exploitation process. CovAmCoh images consist of three layers: Coefficient of Variation (Cov), Amplitude (Am) and the Coherence (Coh) of the interferometric image pair. These layers, arranged to a RGB image (Cov = Red, Am = Green, Coh = Blue), show the CovAmCoh image signature.

Amplitude images can be calculated from so-called SLC (Single Look Complex) imagery. Those images are complex-valued datasets consisting of the real (first layer) and the imaginary (second layer) part of the complex backscatter
information. Let \( a \) be the real and \( b \) the imaginary part of the complex number. Then the amplitude image can be derived by:

\[ \sqrt{a} \]

In order to generalize the CovAmCoh method, the input images are radiometrically calibrated (sigma naught \( \sigma^0 \)). Thus, in the generalized version of CovAmCoh, intensity images are used instead of the amplitude images used in the original version of the algorithm. For TSX data, the calibration step is done by the following calibration rule ([3]):

\[ (k \quad |DN| \quad N) \]

where \( k \) is the calibration factor, \( DN \) represents the complex gray values, \( NEBN \) denotes the Noise Equivalent Beta Naught and \( N \) is the local incidence angle of the SAR signal. In a final step, the two resulting \( \sigma^0 \) images are averaged. The second layer for the CovAmCoh images then results from:

\[ \text{[-----]} \]

The Cov represents a statistical measure which is calculated on both of the two calibrated amplitude images resulting from the interferometric repeat pass cycle. Using a window of a predefined size \( n \times n \) (e.g., \( 5 \times 5 \)), the two Cov images are calculated as follows:

\[ \left[ \frac{1}{n^2} \right] \]

with the standard deviation \( \sigma \) of the local pixel values and the local mean value \( \bar{x} \). The Cov image contains information about the locality, precisely about the local homogeneity (heterogeneity). For example, urban or even forest areas which are characterized by a relative high local heterogeneity lead to high values in the resulting Cov image. As two calibrated amplitude images are considered, the Cov layer of the CovAmCoh image is established by:

\[ \left[ \frac{1}{\bar{x}} \right] \]

The complex correlation between two InSAR images – the coherence – is a well-known parameter to assess the stability of the interferometric phase for interferogram generation. Analyzing this coherence image, one can also distinguish between temporally stable and unstable regions with respect to the difference in time of both InSAR images. Due to the fact that the coherence is very sensitive to very small changes it represents the basis for Coherent Change Detection (CCD) approaches. In terms of CovAmCoh analysis, the coherence is estimated considering a \( n \times n \) sized window (e.g., 5) using the following formula:

\[ \frac{s_1 \cdot s_2}{\sqrt{(s_1^* \cdot s_2)} \sqrt{(s_1 \cdot s_2^*)}} \]

where \( s_1 \) and \( s_2 \) are the measured complex-valued signals at the two acquisition times and \( s_1^* \), \( s_2^* \) are the matching complex conjugated parts. Coherence values are fixed to the closed interval between \([0;1]\), where zero denotes a complete decorrelation between the two signals and a value of 1 represents optimal correlation. Arranging the CovAmCoh image, the coherence is used as the third layer in the blue channel.

The three CovAmCoh component layers described above are stacked to a raw RGB image. To get the final image product with the correct visualization, the layers are stretched in a knowledge-based way which leads to the generalization step of the method ([4]). The generalized CovAmCoh analysis represents the basis of the proposed interpretation scheme presented in this paper. Using k-means clustering, the generalized information content of CovAmCoh imagery is investigated. The resulting clusters lead to a scheme which can be used, for example, for classification tasks.
2. GENERALIZED COVAMCOH ANALYSIS

The motivation for generalizing the CovAmCoh analysis was to get visually comparable imagery independent on sensor and procession parameters (size of Cov and coherence windows). For this, unique and adaptive borders for CovAmCoh layer scaling were developed as described below. For detailed information, see also ([4]).

First of all, the Cov layer is calculated from the amplitude (intensity) layer, whereby the stretch borders for the second CovAmCoh layer were generalized. For this purpose, the Noise Equivalent Sigma Zero (NESZ) was used, since it describes the “backscatter” in regions with no signal echo excluding the system noise. Those are mainly radar shadow regions or very smooth surfaces like calm water or wet asphalt. The NESZ value (used as lower stretch border of amplitude layer) varies for each sensor. In terms of using HR X-Band SAR data (TSX, COSMO-SkyMed (CSK)) a value of about -22 dB was found by scientific literature research. In ([5]), it was found out that as upper stretch border a value of 10 dB is suitable, due to the fact that this value is measured in high backscattering industrial areas.

Deducing a lower stretch border for the Cov layer, local structures were investigated for several window sizes (5 x 5, 7 x 7 and 9 x 9) on simulated intensity images. The structures are lines in different sizes depending on the window size (Figure 1). The lines were set to the upper stretch border of the amplitude layer (10 dB). The background of the structures in the local window was set to the lower threshold of -22 dB. Furthermore, full-developed speckle noise was added to the local windows. The following stretch borders were found: [0.71;1.65] for 5 x 5; [0.78;1.85] for 7 x 7 and [0.82;2.0] for 9 x 9. In default state, CovAmCoh images are calculated using the 5 x 5 windowing.

Investigating the generalized stretch borders for the coherence layer, two simulated images of size 1000 x 1000 containing equal distributed gray values in the interval [0;1] were considered. From these, two phase images containing equal distributed gray values in the interval [0;2π] and two intensity images with a mean value of -22 dB (see above) were calculated and finally stacked to two single look complex images (SLC). Additionally, coherence images of varying window sizes (3 x 3, 5 x 5, 7 x 7, 9 x 9, …) were calculated from these SLC images. To derive proper stretch borders, the mean values (lower border) and the maximum values (upper border) calculated in these windows were used. As example, using a 5 x 5 window, the resulting thresholds are approximately [0.18;0.8].

![Figure 1: Generalization of Cov (left) and coherence (right) layers stretch borders. Both visualizations show the results considering a 5 x 5 sized local window.](image-url)
The so-calculated adaptive, generalized stretch borders were evaluated using a multitude of TSX and CSK data. It is shown, that the visual information content does not change, independent of the sensor or the chosen window size (Figure 2). Furthermore, the CovAmCoh analysis has been evaluated on 11 TSX datasets of different locations at different seasons and on four CSK datasets of one location at different dates. In addition, first tests using C-Band data (RADARSAT-2) have been accomplished as well. It was shown, that the visual information content of all CovAmCoh imagery is comparable.

![Figure 2: Subsets of TSX (left) and CSK (right) CovAmCoh images representing rural (upper row), urban/industrial (middle row) and activity areas (lower row). The images were calculated with varying window sizes for the Cov and Coh layers (5x5, 7x7 and 9x9).](image)

3. GENERALIZED INTERPRETATION SCHEME

Aiming on the development of a general interpretation scheme, the first question is: “What is the general information content of the images?” Furthermore: “How many and which kind of classes are represented in the data?” Finding answers to these questions lead to the so-called clustering algorithms. One of these algorithms is given by the k-means method ([6]). It represents a semi-supervised, statistical approach which can be described by two basic steps:

- **Assignment step**
- **Re-estimation step**

Before the assignment step can be applied, the number of clusters has to be defined by the operator in an initializing step (bottom-up method). For each of these clusters, one so-called centroid is randomly placed which represent the cluster center of mass. In a first assignment step, the distances (e.g., Euclidian distances) between the instances (pixels) and the centroids are calculated. In detail, one instance is assigned to that centroid (cluster) where the distance shows a minimum. If all instances are assigned to precisely one cluster, the re-estimation step is performed. This means that the positions of the centroids are re-calculated based on the currently assigned instances. Both steps are repeated iteratively until convergence regarding the centroid positions is reached.

In this study, the aim was to get an idea about the number of classes existing in typical CovAmCoh imagery. Since the k-means method requires this number at the start of the algorithm, our strategy was applied as follows: As (visual) reference data, the generalized, 8-bit scaled CovAmCoh datasets of different sceneries were chosen. Hereby, the focus...
was set on preferably heterogeneous image content. Then, several numbers of classes (8, 16, 32) were tested as previous information to run the k-means clustering algorithm. For first tests considering large subsets of CovAmCoh images, eight classes were chosen referring to the additive color mixing principle (Figure 8). In the particular clustering results, each assigned instance (pixel) was color coded referring to its cluster centroid. In this way, a re-constructed RGB image results depending on the initially chosen number of classes. To derive conclusions about the suitable number of classes describing a CovAmCoh image, the re-constructed RGB image was then compared with the reference data. At this point, it should be considered that the re-constructed image is “built” by the mean colors of the centroids. The best-fitting number of classes is found when best visual accordance with the reference data is observable.

This strategy was tested using different subsets containing heterogeneous image content (rural / forest, urban / industrial, activity areas) at different image sizes (big and local subsets). The investigated TSX images show Frankfurt (Main), Greding, Berlin Schoenefeld (all Germany), and St. Louis (USA). Considering the large subset of the St. Louis image, it can be seen that eight classes are probably not suitable to model the image content sufficiently. Apparently, the use of 16 or even 32 classes lead to results which better match to the visual reference (Figure 3).

![Figure 3: Large subset of TSX CovAmCoh image St. Louis. Upper left: Reference; upper right: Re-constructed RGB image (eight clusters); lower left: Re-constructed RGB image (16 clusters); lower right: Re-constructed RGB image (32 clusters).](image)

At this point, it should be kept in mind that the k-means method is a statistical clustering algorithm. Instances (pixels) which are in the minority compared to other instances might be assigned to “wrong” clusters. Hence, by using a small number of classes, there might be a high probability that “minority” pixels are assigned to “foreign” classes. Referring to CovAmCoh imagery, those “minority” pixels are mainly appearing as white colored elements at magenta colored structures (e.g., urban).

Thus, detailed subsets of the datasets described above are considered (Figure 4). Doing so, it is expected to find the main CovAmCoh colors which model the basic information content. Taking a view on Figure 4, this expectation can be confirmed: Eight classes are sufficient to model the typical CovAmCoh image content. However, in the Berlin Schoenefeld subset, the cyan colored structure is merged to bright grey / white. This is caused by the “minority” of this structure compared to the others. The same effect can also be observed for the Greding subset showing a typical activity area. There, small white regions are merged with magenta structures.
Aiming on a proposal of an interpretation scheme for CovAmCoh imagery, another subset of the St. Louis scene was chosen (Figure 5). This subset was chosen so that it contains typical CovAmCoh information (urban, vegetation, activity areas, water surfaces, very coherent structures) and such that all classes are represented by a roughly equal number of pixels. The subset was analyzed using the k-means clustering algorithm considering eight classes. The resulting centroid colors were extracted and are visualized in Figure 6.

Furthermore, in Figure 7, images referring to the extracted centroids are given to visualize the several class instances extracted by the algorithm. It can be observed that magenta, blue, green and white / bright are meaningful colors in a typical CovAmCoh image. Furthermore, dark or black structures are also easily extractable. The remaining three centroid colors represent mixture colors, for example, orange colored objects represent high activity or changing structures. Focusing on objects colored dark violet and taking a look on the matching image visualizing the class affiliation in Figure 7, this color represents very low backscattering structures with high coherence values. This color dominates the water surface region.

In summary, with respect to the results explained, a generalized interpretation scheme for CovAmCoh images can be proposed. As it was shown, for most of the examples, eight classes (clusters) are sufficient to model the main information content of CovAmCoh imagery in a sufficient way. In the following, the eight colors describing the additive color model are taken as basic colors representing the main CovAmCoh classes and building the foundation for a more detailed scheme. Precisely, as any other RGB imagery, CovAmCoh images also consist of multiple mixture colors, which can be interpreted using the main eight colors of the scheme.
Figure 6: Centroid colors extracted from re-constructed RGB image of St. Louis CovAmCoh subset (Figure 5).
Figure 7: Images of St. Louis visualizing the class affiliations of the instances according to (Figure 5), and (Figure 6) respectively. The listing is according to (Figure 6).
<table>
<thead>
<tr>
<th>Color</th>
<th>CovAmCoh rule</th>
<th>Real world examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dark / black</td>
<td>Non-local, low backscattering and non-coherent structure</td>
<td>Shadow, water surfaces, infrastructure (depending on surface smoothness, acquisition mode, sensor, …). Infrastructure can appear low bluish.</td>
</tr>
<tr>
<td>Bright/ white</td>
<td>Very local, high backscattering and coherent structure</td>
<td>Corner (building facades, roof structures, fences, …).</td>
</tr>
<tr>
<td>Red</td>
<td>Very local, low backscattering and non-coherent structure. Pure red is rare in CovAmCoh images. Magenta or yellow tones are more frequently appearing.</td>
<td>Shadow edges</td>
</tr>
<tr>
<td>Blue</td>
<td>Bright blue: Very coherent and high backscattering structure; less backscattering: Deeper blue.</td>
<td>Candidates in general: Temporarily stable man-made structures (e.g. urban areas, …)</td>
</tr>
<tr>
<td>Magenta</td>
<td>Very local, low backscattering and coherent structure.</td>
<td>Small elements of infrastructure and urban areas: Traffic lights, traffic signs, guardrails, small corners, …</td>
</tr>
<tr>
<td>Yellow</td>
<td>Very local, high backscattering and non-coherent structure.</td>
<td>Man-made changes / activities or changes / activities of man-made structures: Wastewater treatment plants, airport gates, …</td>
</tr>
<tr>
<td>Cyan</td>
<td>Non-local, high backscattering and coherent structure.</td>
<td>E.g. train routes, …</td>
</tr>
</tbody>
</table>

Figure 8: Proposed interpretation scheme for arbitrary CovAmCoh images.
4. EXAMPLE

In this section, the proposed scheme (Figure 8) is used to interpret a CovAmCoh image. For this, a subset of three TSX HR SpotLight images of Berlin Schoenefeld (Germany) was chosen. The images were acquired at the following dates: 2010/04/14; 2010/05/06; 2010/05/28 (22 days repeat pass cycle), resulting in two CovAmCoh images. The chosen subset given in Figure 9 shows in the center a building site of rail access to the planned new airport “BER”. Subsequently, the areas of interest (AOI) 1 to 4 marked in (Figure 9) are interpreted.

![Figure 9: Subsets of the two Berlin Schoenefeld TSX CovAmCoh images. Left column: 2010/04/14, 2010/05/06. Right column: 2010/05/06, 2010/05/28. Upper row: Second CovAmCoh layer (mean amplitude). Lower row: CovAmCoh image. The overlayed numbers represent the areas of interest, which are exemplary interpreted.](image)

**AOI 1:** Due to its bright bluish coloring, it can be assumed that this structure is very coherent (temporarily stable) between the acquisition dates. Furthermore, it is relatively high backscattering and its shape is narrow elongated. In the interpretation scheme, temporarily stable man-made objects are mentioned. In this case, this structure represents a railroad the CovAmCoh signature of which (bright blue) is caused by the gravel between the sleepers.

**AOI 2:** Comparing this structure to AOI 1, it can be seen that the shapes are basically similar (narrow man-made), but the signatures differ. In the center, AOI 2 is dark bluish to black, and at the edges magenta coloring can be observed. Referring to the scheme, magenta coloring represents in general small-scaled, man-made objects like traffic lights or guardrails. In this case, the signature and the shape lead to the assumption that this structure is a road or a highway, respectively. Magenta coloring combined with high backscatter (bright) is also typical for urban regions (AOI 2b), where small corners of walls, fences and roofs appear.

**AOI 3:** Interpreting this AOI, the additional benefit of CovAmCoh imagery in contrast to amplitude images can easily be seen. This structure represents an agricultural field, which appears similar in the two amplitude images (Figure 9). Analyzing the amplitude signature, one can conclude that it might be a field. Taking a view on the two corresponding CovAmCoh images, a color change (green to blue) can be seen. In other words: The structure becomes coherent between the two CovAmCoh images. This is caused by harvesting volume scatterer objects placed on the field.

**AOI 4:** This structure is mainly characterized by a yellow colored signature. Referring to the interpretation scheme (Figure 8), this coloring stands for very local, high backscattering and non-coherent (temporarily unstable) objects or
structures. In general, we have to emphasize that each region without bluish coloring in a CovAmCoh image is a candidate for a change/activity area. In case of this AOI and furthermore regarding its man-made, narrow and elongated shape, this structure represents a traffic building site. The benefit of CovAmCoh imagery can also be observed by analyzing the differences of the image pair. Their signature change represents the progress of the construction work. This information/backscattering change would be difficult to extract analyzing the corresponding amplitude images alone.

5. CONCLUSION AND OUTLOOK

In this paper, an interpretation scheme for CovAmCoh imagery was presented. Since this scheme is developed using the generalized CovAmCoh method, it is transferable on arbitrary InSAR image pairs.

The concept for the generalized and adaptive scaling of the three CovAmCoh layers was presented. It was shown that the visual information content does not change for varying window sizes (Cov and Coh) using TSX and CSK data. Aiming on the development of an interpretation scheme, the generalized 8-bit scaled CovAmCoh images of different scenes (Frankfurt (Main), Berlin Schoenefeld, Greding, St. Louis) were considered. The general information content of those images was analyzed using the semi-supervised k-means clustering method. In summary, it was shown that eight clusters (classes) are sufficient to represent the main local information content of CovAmCoh images. These eight basic classes match to the number of colors inherited in the adaptive color mixture principle. Finally, the interpretation scheme was proposed and an example analyzing a subset of two TSX CovAmCoh images of Berlin Schoenefeld was presented.

As future work, the proposed interpretation scheme will be applied on further C-Band SAR data. Furthermore, the generalization of the CovAmCoh analysis will be extended considering un-biased methods calculating the coherence layer.

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