An analysis on the contribution of the phase component for scene class recognition in TerraSAR-X scenes

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ABSTRACT and MOTIVATION

Traditional approaches for SAR image classification and target recognition in high resolution acquisitions discard phase information and are solely based on the detected data. When one makes use of several SLC image acquisitions, the phase variation is the main source of information. We propose a method for feature definition and extraction which combines single SAR acquisitions with interferometric information. Not only that phase becomes less random, but it describes the changes that occur on the received scene reflectivity. In the hypothesis that two successive acquisitions are taken on a stationary scene (tandem acquisitions), combined information from these data can be employed to describe the scene content. Thus, we propose the usage of spectral based descriptors that make use of the full complex signal from two or more SLC acquisitions to construct robust image descriptors. The experiments show that the interferometric information can be very valuable for the recognition of coherent targets, increasing the recognition rate. Our approach relies on the estimation of the SAR image spectra, from which features are derived in two stages: the estimation of the model order and the extraction of the most relevant descriptors. The set of descriptors is extracted from the complex spectrum of the SAR image, using a spectral decomposition method. We consider the problem of estimating the parameters of complex-valued two-dimensional sinusoidal signals observed in noise. Our approach considers not just isolated objects but also takes into account the complexity of high resolution urban scenes, where there is a large variety of structures, which can be best understood in their context. This is why we propose to extract the feature vectors from image patches which cover a relevant area on the ground (200 x 200 m), compared to the object size. Experiments are performed on data acquired in the context of scientific proposals LAN 1613, MTH 1628, and OTHER0502.

SAR Signal Model

The 2-D complex-valued signal obtained with the synthetic aperture represents the phase history of the imaged target and is obtained through the integration of the reflected signal along the elevation direction. Sinusoidal signal model for the 2-D complex SAR signal:

SIGNAL MODEL IN MATRIX FORM

$$Y = \omega(f_k, \bar{f}_k)\begin{bmatrix}\alpha_1 \\ \vdots \\ \alpha_k\end{bmatrix}$$

COMPLEX AMPLITUDE AND FREQUENCY ESTIMATES

$$\hat{\alpha}_k = \arg\max_{\alpha_k} C(f_1, \cdots, f_k, \bar{f}_1, \dots, \bar{f}_k, \alpha_1, \dots, \alpha_k)$$

$$\hat{\alpha}_k = \left[\omega(f_k,\bar{f}_k)^H \omega(f_k,\bar{f}_k)\right]^{-1} \omega(f_k,\bar{f}_k)^H y_k = \omega(f_k,\bar{f}_k)^H y_k/(N\bar{N})$$

$$\{\hat{\omega}(f_k,\bar{f}_k)\} = \arg\max_{\omega(f_k,\bar{f}_k)} \left\{\frac{|\omega(f_k,\bar{f}_k)^H Y|^2}{N\bar{N}}\right\}$$

COST FUNCTION

$$C(f_1,\cdots,f_k,\bar{f}_1,\dots,\bar{f}_k,\alpha_1,\dots,\alpha_k) = \left\|Y - \textstyle\sum_{k=1}^{K}\omega(f_k,\bar{f}_k)\alpha_k\right\|^2 \quad C = \|Y - \hat{Y}\|^2$$

Experimental Data

- TerraSAR-X SM scene, which covers the city of Bucharest, in Romania
- Database of 14.532 image patches obtained by applying a regular grid over the original image (SLC/InSAR). The databases were constructed in such way so that we could ensure a very large variability and diversity of scene classes, types of landcover, urban architecture and other man-made targets.
- The complex image resolution is of 1 m, thus each patch covers 200 x 200 meters on the ground. This size allows for large structures to be visible in their urban context, making it easy for the user to identify and classify the structures which are present in a certain patch of interest. Each tile in test database has a representative label, which indicates the position of the tile in the original image, the dominant class of the tile and the most significant secondary class.

Constrained RELAX algorithm for feature set estimation

Model order selection: minimization of the Akaike Information for model order selection; estimated order through AIC: N_comp_AIC =30 components.

Given a random sample y from the distribution of the random process X , and the estimated parameter θ the MLE based on the model and data :

$$E_y E_x\left[\log g\left(\cdot\,\middle|\,\hat{\theta}(y)\right)\right] \approx \log\left(\mathcal{L}(\hat{\theta}|y)\right) - k \qquad AIC = -2\log\mathcal{L}(\hat{\theta}|y) + 2k$$

In order to increase the consistency of these results we have introduced a second approach for model order estimation, based on the entropy of the spectrum of the SAR image patch, which accounts for the statistical properties of complex random processes and makes use of the pseudo-covariance matrix.

MODIFIED COST FUNCTION (introduces an Entropy constraint on the spectrum)

$$C = \|Y - T\{S\}\|^2 \quad T = \arg\min_T\{C\} = \arg\min_T \|Y - T\{S\}\|^2$$

1. $k = 1 \Rightarrow estimate\ \hat{f}_1, \alpha_1\ from\ y(n,\bar{n})$
2. $k = 2 \Rightarrow estimate\ y_2(n,\bar{n})\ from\ \hat{f}_1, \alpha_1$
3. $estimate\ \hat{f}_2, \alpha_2\ from\ y_2(n,\bar{n})$
4. $estimate\ y_1(n,\bar{n})\ from\ \hat{f}_2, \alpha_2$
5. $Iterate\ until\ practical\ convergence\ is\ achieved$
   $\longrightarrow cost\ function\ doesn't\ change\ significantly$
6. $Onwards, for\ every\ k^{th}\ iteration:$

$$\left\{estimate\ \{\hat{f}_k, \hat{\alpha}_k\}\,\middle|\, f_j, \alpha_j, \quad where\ j \in \{1,2,\dots \max(k,j)\} \setminus \{k\},\ and\ (f_j,\alpha_j) = \arg\max_{f_j,\alpha_j} H(T\{S_k\})\right\}$$

7. $Iterate\ until\ practical\ convergence\ is\ achieved$
   $\longrightarrow cost\ function\ doesn't\ change\ significantly$

The feature vector of each patch consisted of the value of the sinusoids' amplitude, which were ordered based on the position of the corresponding spectrum peaks . Three test scenarios were proposed for the analysis:

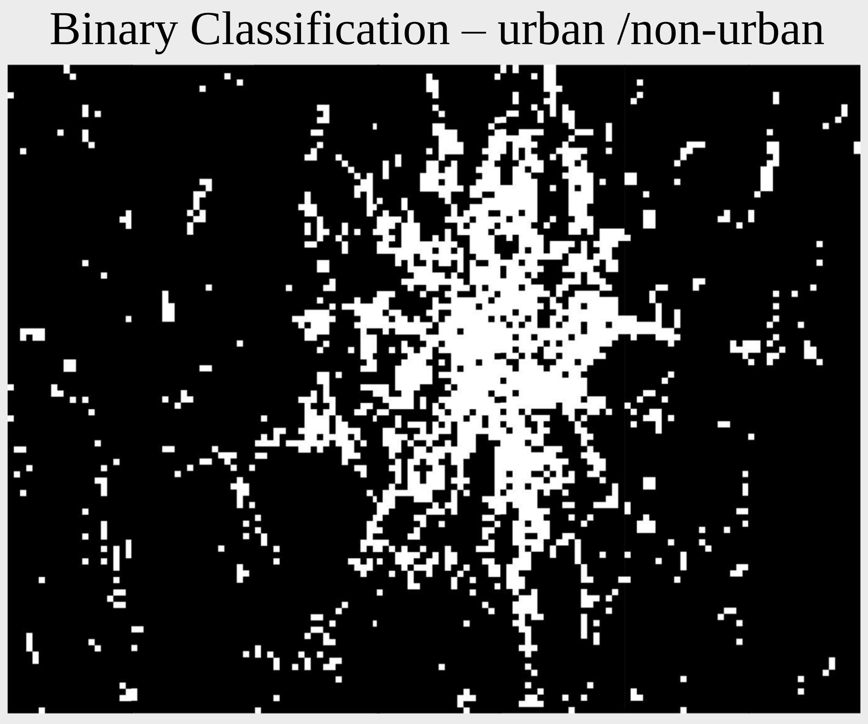
I. Form feature vectors using the complex amplitude of the first 40 estimated spectral components;

II. Form feature vectors using the absolute value of of the first 40 estimated spectral components;

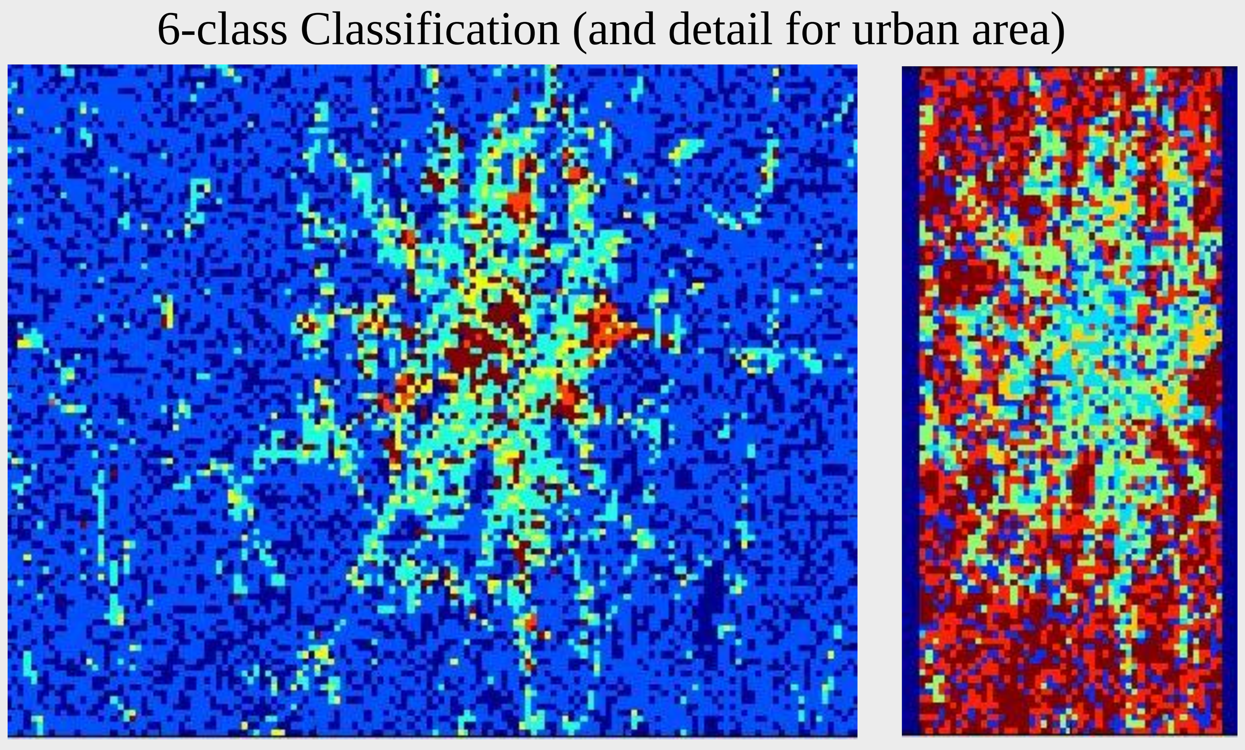
III. Form feature vectors using the absolute value of the first 10 spectral components selected in the Entropy Constraint framework ;

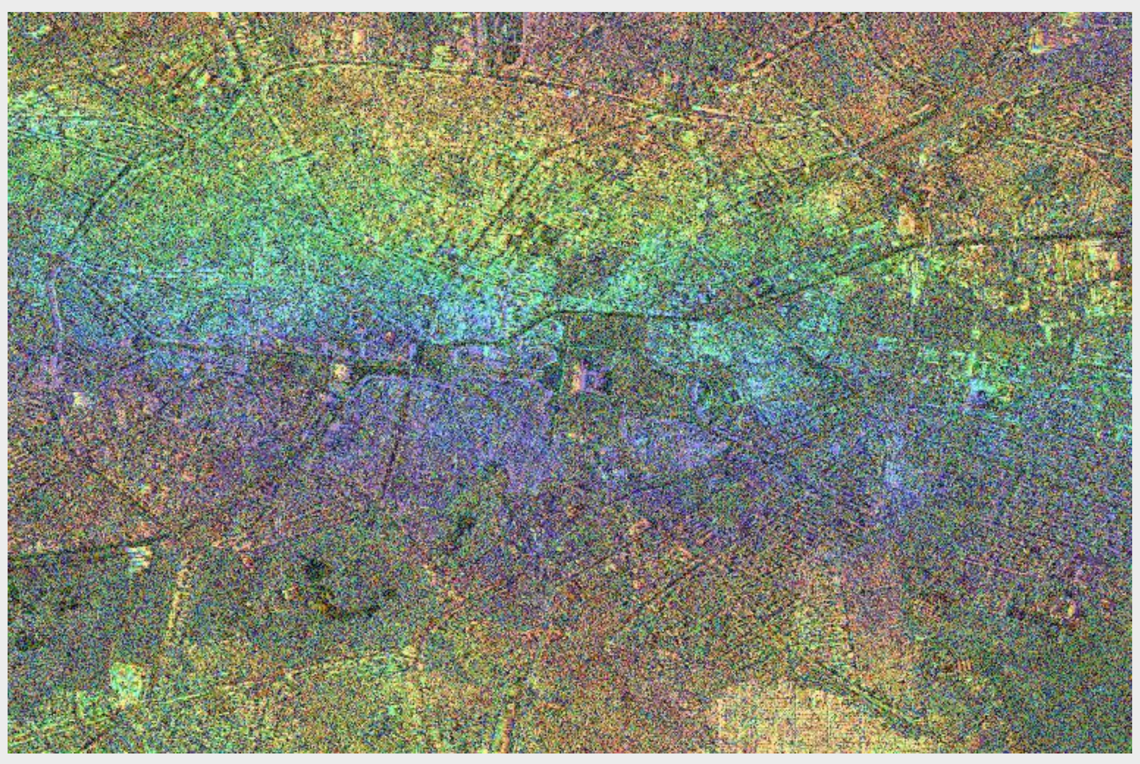
Results

Binary Classification – urban /non-urban



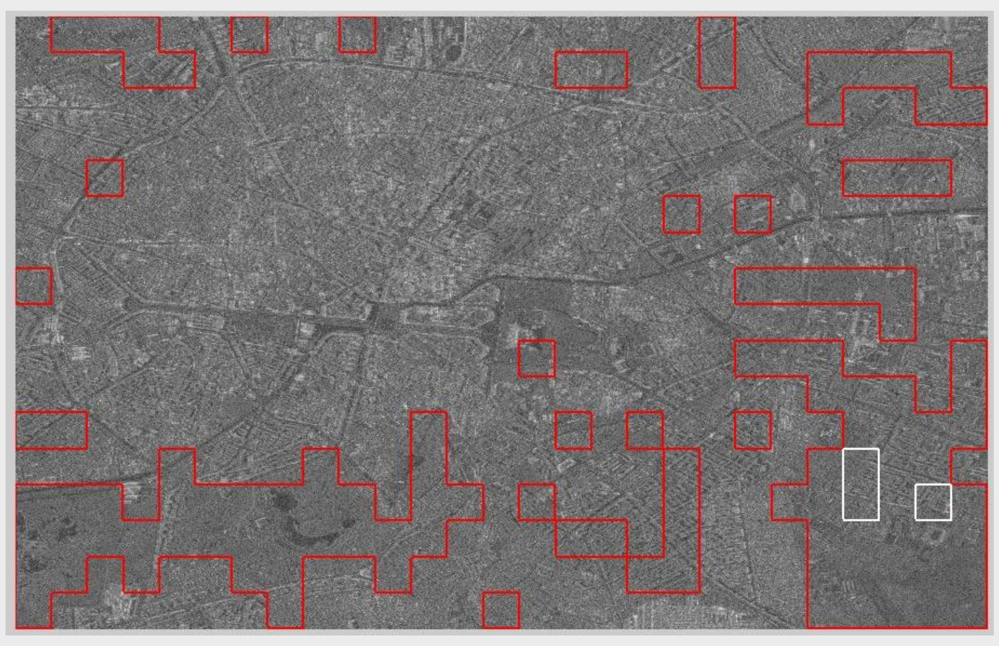
6-class Classification (and detail for urban area)





Using solely the SLC data we can separate with a good approximation the urban areas from non-urban areas. However, large inter-class confusions appear when trying to discriminate between different scene classes within the general Urban area class. The usage of the phase information allows us to delineate with better approximation not only between urban an non-urban areas in the scene, but also between different types of strong scatterers (typically buildings).

Green Urban Areas



One class of Buildings with strong scattering

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