Anomaly detection schemes in complex-valued SAR imaging

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Anomaly Detection

What are anomalies?

- An anomaly refers to an observation that deviates significantly from the expected data pattern.

What can be considered as anomalies in SAR images?

- Depend on the context and scenario
- Abnormal pixel or pixels significantly different from adjacent, surrounding or global background pixels

What are the challenges?

- Natural presence of speckle which induces many false alarms.
- Lack of labeled data
- Multidimensionality and Complex-valued nature of SAR signals

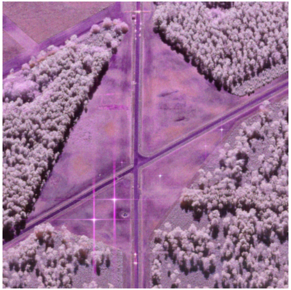


Figure: ONERA SETHI X-band image with anomalies.

Statistical approaches

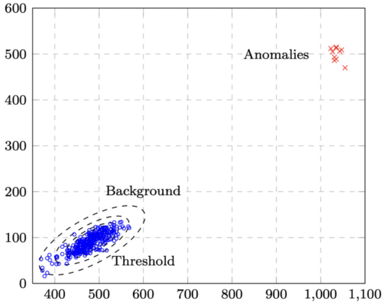


Figure: Point-to-distribution distance to determine an anomaly score for each outlier.

Binary hypothesis test of anomaly detection problem:

$$\begin{cases} H_0 : \mathbf{x} = \mathbf{c}, & \{\mathbf{x}_i = \mathbf{c}_i\}_{i \in [\![1,n]\!]} , \\ H_1 : \mathbf{x} = \mathbf{c} + A\,\mathbf{p}, & \{\mathbf{x}_i = \mathbf{c}_i\}_{i \in [\![1,n]\!]} . \end{cases}$$

The Reed-Xiaoli Detector:

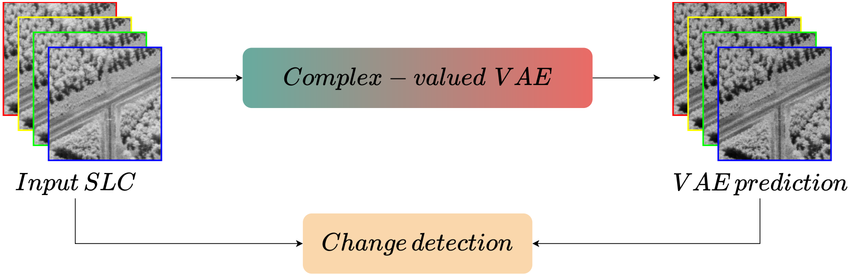
$$RXD(\mathbf{x}) = \mathbf{x}^H \hat{\boldsymbol{\Sigma}}^{-1} \mathbf{x} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

where $\hat{\boldsymbol{\Sigma}}$ the Covariance Matrix of the secondary data, estimated via the SCM or the Tyler M-estimator methods.

I. Reed and X. Yu (1990), Adaptive multiple-band cfar detection of an optical pattern with unknown spectral distribution. *Acoustics, Speech and Signal Processing, IEEE Transactions on, vol. 38, no. 10, pp. 1760–1770*

J. Frontera-Pons (2014), Robust target detection for Hyperspectral Imaging. *PhD thesis, STITS, Supélec*

Proposed scheme



SAR Anomaly Detection in 2 steps:

- Determining the general distribution of the clutter and use the learned features to **reconstruct an anomaly-free image** with a complex-valued VAE.
- **Detecting changes** between the input image and the reconstructed image.

Variational AutoEncoder

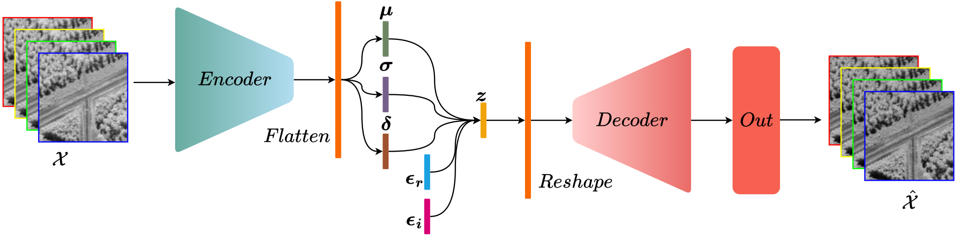


Figure: VAE architecture. $\mathcal{X}$ and $\hat{\mathcal{X}}$ denote respectively SLC and reconstructed SAR images.

- Learn the anomaly-free distribution of SAR images.
- Preserve the intrinsic magnitude-phase relationships of the data

Gabot Q. et al. (2024). Preserving polarimetric properties in polsar image reconstruction through complex-valued auto-encoders *2024 International Radar Conference (RADAR). IEEE, 2024, pp. 1–6*

Loss function

Optimizing a VAE consists in minimizing the *Evidence Lower BOund* or ELBO loss function:

$$\mathrm{ELBO} = \mathcal{L}_{rec} - D_{KL}(q(\mathbf{z}|\mathcal{X})\|p(\mathbf{z}))\,, \tag{1}$$

where $\mathcal{L}_{rec} = \mathbb{E}_{q(\mathbf{z}|\mathcal{X})}\left[\log\left(p(\mathcal{X}|\mathbf{z})\right]\right.$, $p(\mathcal{X}|\mathbf{z})$ is the generative distribution.

For the complex Gaussian prior distribution:

- $\mathcal{L}_{rec}$ is formulated as a L^2 loss function
- The Kullback-Leibler criterion is expressed as below:

$$D_{KL}(q(\mathbf{z}|\mathcal{X})||p(\mathbf{z})) = ||\boldsymbol{\mu}||^2 + \mathbf{1}_q^T\left(\boldsymbol{\sigma} - 1 - \frac{1}{2}\log^{\circ}\left(\boldsymbol{\sigma}^{\circ 2} - (|\boldsymbol{\delta}|^{\circ})^{\circ 2}\right)\right). \tag{2}$$

A. Rouzoumka et al. (2025). Complex-valued variational autoencoders for radar detection in joint compound Gaussian clutter and thermal noise. *33rd European Signal Processing Conference (EUSIPCO)*

Reparameterization trick

- The latent space $\mathbf{z}$ needs to be reparameterized.
- Complex-valued reparameterization trick using complex circular Normal distribution:

$$\boldsymbol{z} = \boldsymbol{\mu} + \boldsymbol{k_r} \odot \boldsymbol{\epsilon}_r + i\, \boldsymbol{k_i} \odot \boldsymbol{\epsilon}_i \,, \tag{3}$$

where $\begin{cases} \boldsymbol{k}_r = 2^{-\frac{1}{2}} (\boldsymbol{\sigma} + \boldsymbol{\delta}) \oslash (\boldsymbol{\sigma} + \mathrm{Re}(\boldsymbol{\delta}))^{\circ\frac{1}{2}} \,, \\ \boldsymbol{k}_i = 2^{-\frac{1}{2}} \left(\boldsymbol{\sigma}^{\circ 2} - (|\boldsymbol{\delta}|^{\circ})^{\circ 2}\right)^{\circ\frac{1}{2}} \oslash (\boldsymbol{\sigma} + \mathrm{Re}(\boldsymbol{\delta}))^{\circ\frac{1}{2}} \end{cases}$,

and where $\boldsymbol{\epsilon}_r \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$, $\boldsymbol{\epsilon}_i \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$.

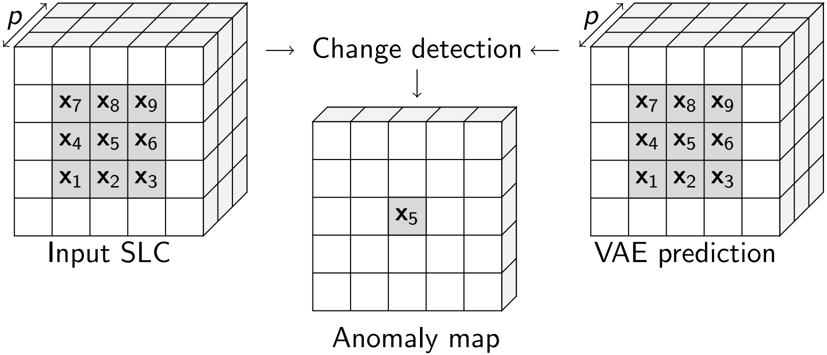
T. Nakashika (2020). Complex-valued variational autoencoder: A novel deep generative model for direct representation of complex spectra. *Interspeech, pp. 2002-2006*

Problem definition

What type of change?

- Complex-VAE learns the anomaly-free distribution of the data
- Reconstruction errors are outliers

$\rightarrow$ We use appropriate detectors to best filtering out false detections due to the learning imperfection, and concentrate on the anomalies



Frobenius-based Change Detector

The anomaly map is obtained by comparing the squared Frobenius norm between the input image and the reconstructed image. For each pixel, let

$$A = \left\| \hat{\boldsymbol{\Sigma}}^{\hat{\mathcal{X}}} - \hat{\boldsymbol{\Sigma}}^{\mathcal{X}} \right\|_F^2 ,$$

be the anomaly score of pixel k, l for $k \in [|0; h-1|], l \in [|0; w-1|]$.

The Sample Covariance Matrix is computed for each boxcar $\mathcal{B}$:

$$\hat{\boldsymbol{\Sigma}}^{\mathcal{X}} = \frac{1}{|\mathcal{B}|} \sum_{i,j \in \mathcal{B}} \mathcal{X}_{i,j}, \mathcal{X}_{i,j}^H ,$$

Data

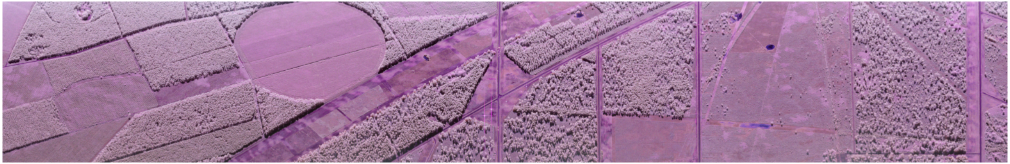


Figure: ONERA Sethi X-band quad-polarization images. Considering HV = VH by the principle of reciprocity, the image is displayed using (HH, HV, VV) represent (R, G, B) channels respectively.

Synthetic data:

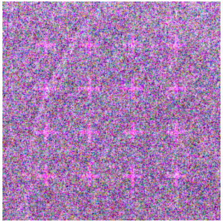


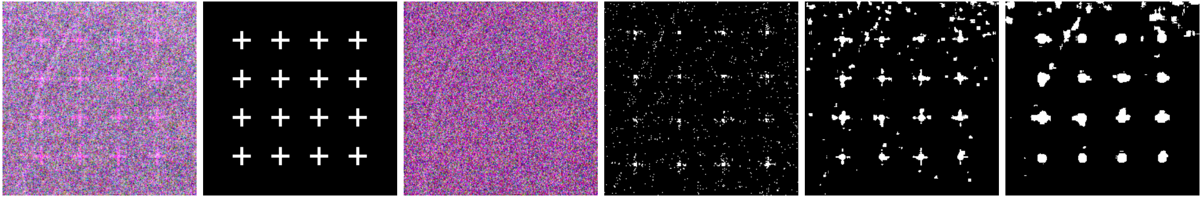
Figure: Cross-shaped synthetic anomalies

$$SNR(\mathbf{x}_t) = A^2 \, \mathbf{p}^H \, \hat{\boldsymbol{\Sigma}}_{SCM}^{-1} \, \mathbf{p} \,, \tag{4}$$

where:

- $\mathbf{p} = (1, 0, 0, 1)^T$ the steering vector of the co-polarized HH and VV channels
- $\hat{\boldsymbol{\Sigma}}_{SCM}$ the estimated covariance matrix of the homogeneous clutter

Anomaly map



(a) Original (b) Ground truth (c) VAE's prediction (d) RXD - SCM (e) Frobenius 5×5 (f) Frobenius 9×9

Figure: Anomaly maps generated by the RXD-SCM detector and the complex-valued VAE with a Frobenius-based change detector. Anomaly maps are displayed at PFA=0.02.

ROC curves

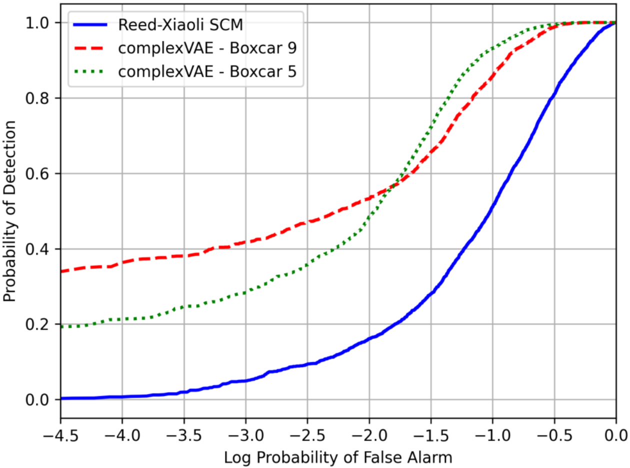
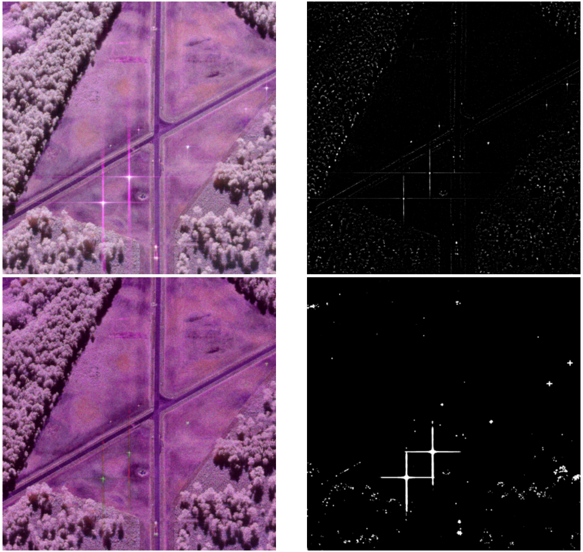


Figure: Probability of Detection versus $\log_{10}(P_{fa})$ for an anomaly with an SNR=5 dB.

Reconstruction quality

a
b

c
d

a - Single Look Complex	b - RXD-SCM
c - VAE's prediction	d - Frobenius 9×9

Table: Image notations

Figure: Qualitative comparison between the RXD built with SCM and the complex-valued VAE with a Frobenius-based change detector. (b and d) are displayed at PFA=2%.

Conclusion & Perspectives

- Improve anomaly detection by extending the reconstruction-error analysis with covariance change detector.
- Promising qualitative and quantitative results.
- Study the contribution of multi-band and multi-look data.
- Explore other anomaly-free distribution learning (ex. flow models) and advanced statistical detection schemes.

Thank you for your attention!

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