Anomaly detection schemes in complex-valued SAR imaging

Work progress presentation

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Outline

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

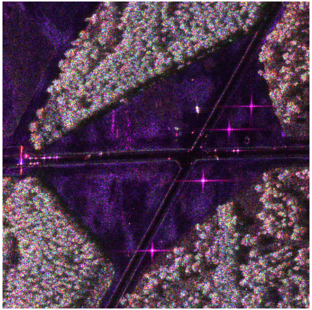

Figure: ONERA SETHI L-band image with anomalies.

Data

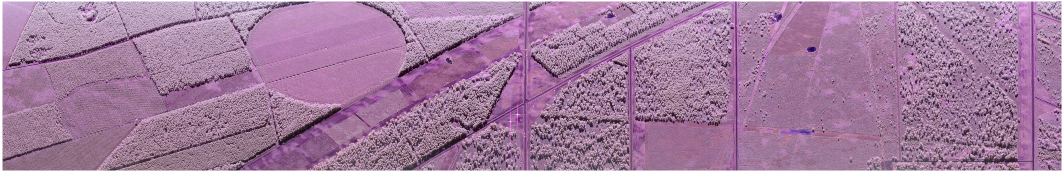

Figure: ONERA Sethi X-band quad-polarization images. HH, HV, VV represent R, G, B channels respectively.

Mathematical formulation:

$$\begin{cases} H_0 : \mathbf{x}_t \sim P_{\mathbf{x}_s} \text{ (no anomaly)}, \\ H_1 : \mathbf{x}_t \not\sim P_{\mathbf{x}_s} \text{ (anomaly)}, \end{cases}$$

where $P_{\mathbf{x}_s}$ is the distribution of the surrounding pixels.

Zone of study:

- Test each pixel $\mathbf{x}_t$ individually
- Measure the distance between test pixel $\mathbf{x}_t$ and the background distribution $P_{\mathbf{x}_s}$.

Methodologies

What do we expect? An anomaly map that helps us answer these key questions:

- Are there any anomalies in this study area?
- Where are they?
- What should the tolerance boundary of the false alarms be?

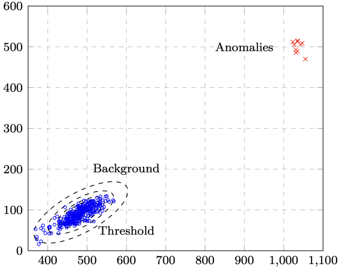

Figure: Measuring the point-to-distribution distance to determine an anomaly score for each outlier.

Traditional detector: Reed-Xiaoli

$$RXD_{SCM}(\mathbf{x}_t) = (\mathbf{x}_t - \hat{\boldsymbol{\mu}}_{SMV})^H \hat{\boldsymbol{\Sigma}}_{SCM}^{-1} (\mathbf{x}_t - \hat{\boldsymbol{\mu}}_{SMV}) \underset{H_0}{\overset{H_1}{\gtrless}} \lambda$$

With $\hat{\boldsymbol{\Sigma}}_{SCM}$ and $\hat{\boldsymbol{\mu}}_{SMV}$ the Sample Covariance Matrix and the Sample Mean Vector, respectively.

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*

Anomaly detection scheme

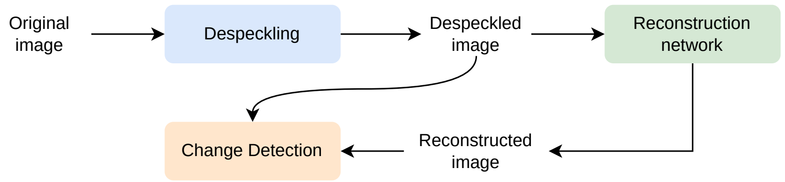

Figure: M. Muzeau et al. Self-supervised learning based anomaly detection in synthetic aperture radar imaging. *IEEE Open Journal of Signal Processing, 3:440-449, 2022*

SAR Anomaly Detection in 3 steps:

- **Despeckling** to reduce the probability of false alarm
- Determining the general distribution of the clutter and use the learned features to **reconstruct an anomaly-free image** with a deep convolutional neural network.
- **Detecting changes** between the despeckled image and the reconstructed image.

SAR despeckling

Despeckling with the **coMplex sElf-supeRvised despeckLINg** algorithm (MERLIN):

- Hypothesis: independence of the real and imaginary components of the complex-valued signals.
- Minimize the distance between the real and the imaginary.
- State-of-the-art performance against SAR2SAR, with a simpler training strategy due to self-supervised learning techniques and does not require time-series data.
- MERLIN works in single-channel, and must be applied to each polarimetric channel HH, HV, VH, VV individually.

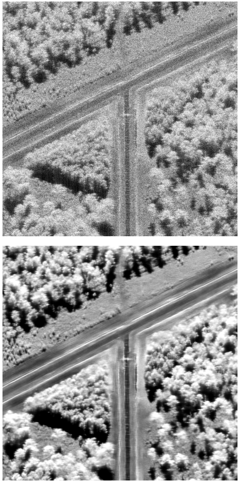

Figure: Single-Look complex image (top) vs despeckled image with MERLIN (bottom).

Dalsasso E. et al. (2021). As if by magic: Self-supervised training of deep despeckling networks with MERLIN. *IEEE Transactions on Geoscience and Remote Sensing: 60, pages 1-13*

Variational AutoEncoder

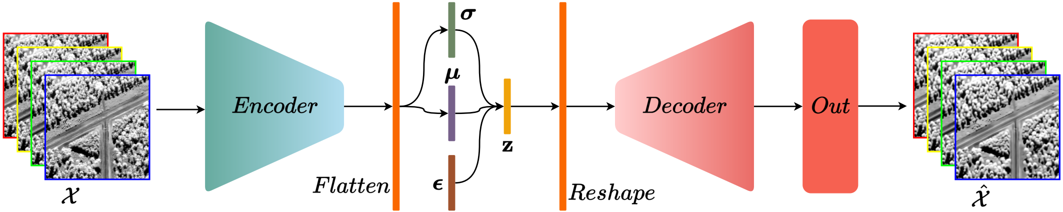

Figure: VAE architecture. $\mathcal{X}$ and $\hat{\mathcal{X}}$ denote respectively despeckled and reconstructed SAR images.

What is VAE?

- A deep generative network designed to learn the underlying distribution of data and to generate new samples that resemble the training data.
- An AutoEncoder with a probabilistic approach, based on Bayes theories.
- The latent space $\mathbf{z}$ is regularized with a prior distribution via Kullback-Leibler criterion.

Kingma D. P., Welling M. (2013). Autoencoding variational Bayes

Variational AutoEncoder

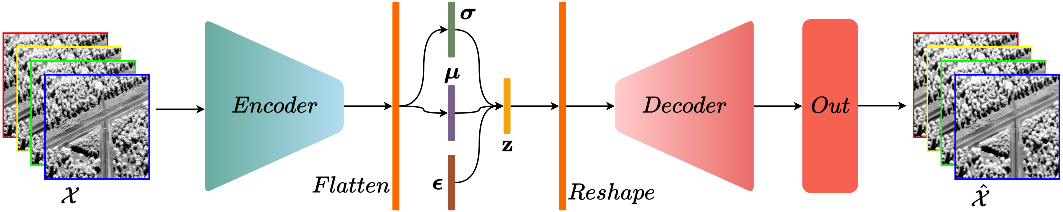

Figure: VAE architecture. $\mathcal{X}$ and $\hat{\mathcal{X}}$ denote respectively despeckled and reconstructed SAR images.

Why should we use VAE?

- To generate an anomaly-free image.
- Anomalies are rare, therefore have few impact on the reconstruction loss function.
- Anomalies are outliers in latent space. The Kullback-Leibler criterion will force the latent vector not to preserve these data points.

Encoder & Decoder

Mirror operations:

- 5 encoding blocks - 5 decoding blocks
- Spatial compression by Encoder with $\mathrm{MaxPooling}$ operations.
- Nearest Neighbors algorithm decodes output images from the latent space.

Finally, the reconstructed image $\hat{\mathcal{X}}$ is obtained with

$$\hat{\mathcal{X}} = \mathrm{Sigmoid}(\mathrm{Conv}(\mathcal{G}_N))\,,$$

where $\mathrm{Sigmoid}$ is the final activation function and Conv is the convolution operation.

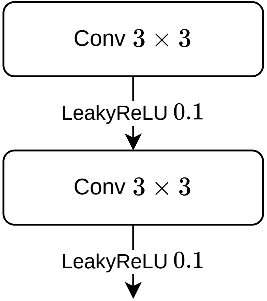

Figure: Configuration of each encoder and decoder block.

Reparameterization trick

VAEs are used to model an a posteriori distribution $p(\mathbf{z}|\mathcal{X})$ with the encoder output data distribution $q(\mathbf{z}|\mathcal{X})$. However, the sampling operation is not straight forward and can bloc the backpropagation gradient flow.

The reparameterization trick consists in:

- sampling a separate Normal distribution for $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
- performing a variable change $\mathbf{z} = \boldsymbol{\mu} + \boldsymbol{\sigma} \odot \boldsymbol{\epsilon}$

This leads to

$$\boldsymbol{z} \sim \mathcal{N}\left(\boldsymbol{\mu}, \mathrm{diag}\left(\boldsymbol{\sigma}^{\circ 2}\right)\right) ,$$

where $\boldsymbol{\mu}$ et $\boldsymbol{\sigma}$ are two estimated parameters representing the mean and the standard deviation components of $\mathbf{z}|\mathcal{X}$.

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.

Using a Gaussian prior distribution, the Kullback-Leibler criterion is expressed with μ_j and σ_j components of the mean $\boldsymbol{\mu}$ and standard deviation $\boldsymbol{\sigma}$ vectors:

$$D_{KL}(q(\mathbf{z}|\mathcal{X})||p(\mathbf{z})) = -\frac{1}{2}\sum_{j=1}^{J}\left(1 + \log(\sigma_j^2) - \mu_j^2 - \sigma_j^2\right) \,, \tag{2}$$

To improve the image reconstruction quality, we consider an extension, the β-annealing VAE. The new loss function becomes:

$$\mathcal{L}_{VAE} = \mathcal{L}_{rec} - \beta\, D_{KL} \,, \tag{3}$$

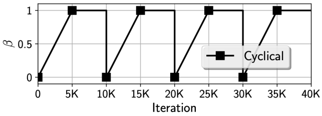

Figure: β annealing strategy.

Fu H. et al. (2019). Cyclical annealing schedule: A simple approach to mitigating KL vanishing. *arXiv:1903.10145*

Change detection

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

$$A_{k,l} = \left\| \hat{\mathbf{\Sigma}}^{\hat{\mathcal{X}}}_{k,l} - \hat{\mathbf{\Sigma}}^{\mathcal{X}}_{k,l} \right\|_F^2,$$

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

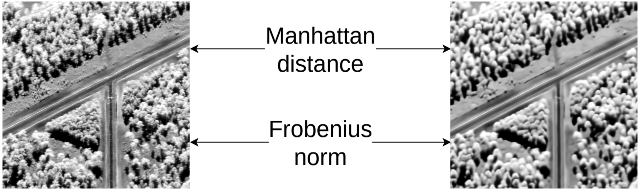

Figure: Detecting changes between despeckled image (left) and reconstructed image with VAE (right).

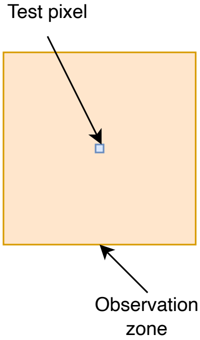

Figure: Local boxcar $\mathcal{B}_{k,l}$ for each test pixel k, l used to compute the Frobenius norm.

Reconstruction quality

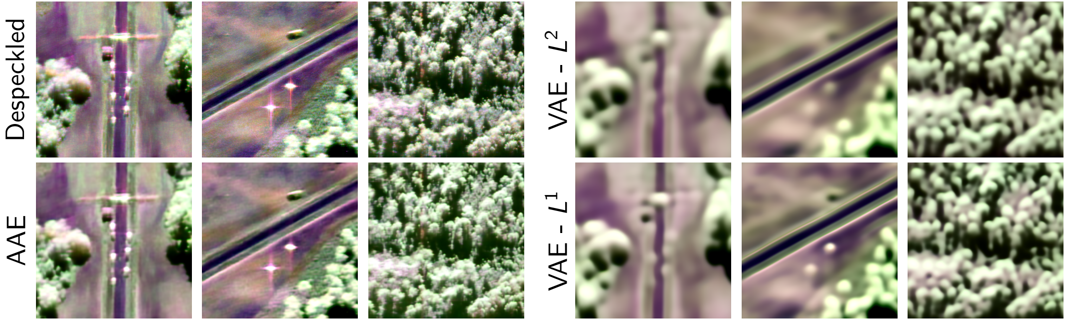

Figure: Qualitative comparison

Metrics	AAE	VAE - L^2	VAE - L^1
PSNR	33.19	31.46	32.41
SSIM	0.866	0.886	0.892

Table: Quantitative comparison

Anomaly map

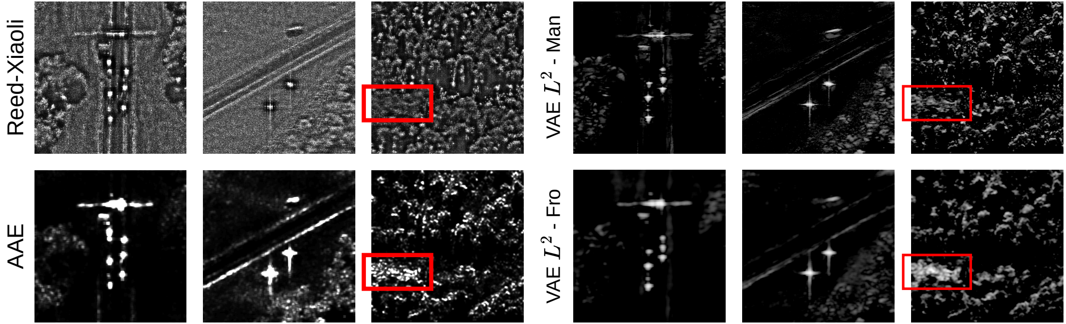

Figure: Comparison between anomaly maps, computed with the Frobenius norm for AAE and VAE vs Reed-Xiaoli Detector.

Thank you for your attention!

The Pytorch Complex-Valued Neural Networks **torchcvnn** library is under active development, feel free to join us on this effort!

- Library available on `https://github.com/torchcvnn`
- Examples available on `https://github.com/torchcvnn/examples`
- Documentation `https://torchcvnn.github.io/torchcvnn`

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