VAE for anomaly detection in SAR imaging

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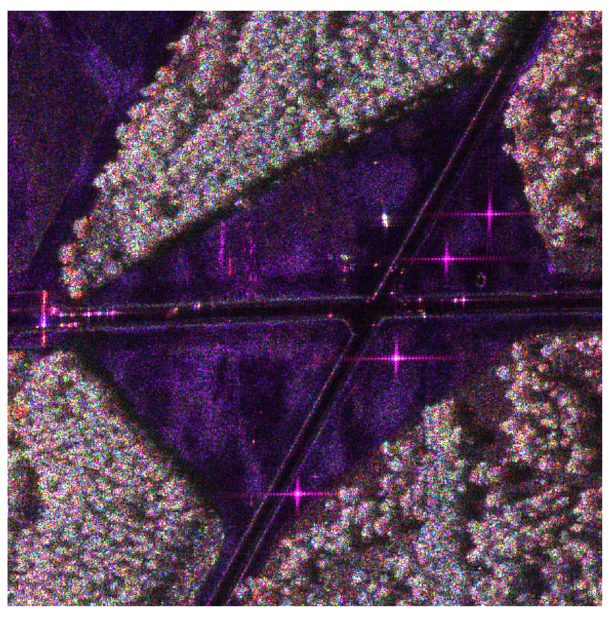
Anomaly detection

Anomalies refer to observations that deviate significantly from **the expected data pattern**. Anomaly detection in SAR imaging is challenging, due to the presence of *speckle* which induces many false positives and to the lack of *labeled data*.

Mathematical formulation:

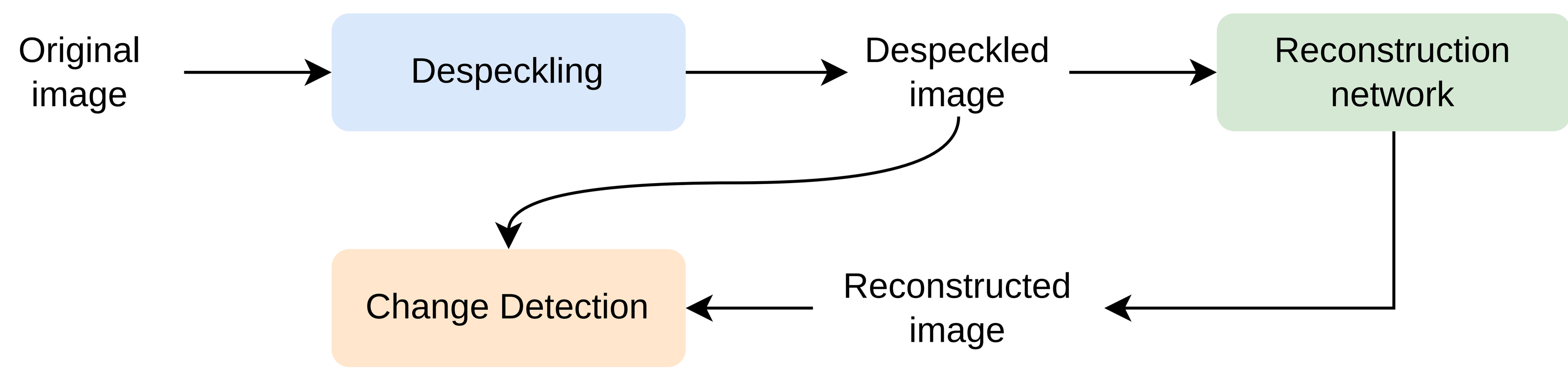
$$\begin{cases} H_0 : \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2 \text{ (no anomaly)}, \\ H_1 : \boldsymbol{\theta}_1 \neq \boldsymbol{\theta}_2 \text{ (anomaly)}, \end{cases}$$

with $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ are estimated parameters vectors of the pixel values distribution.



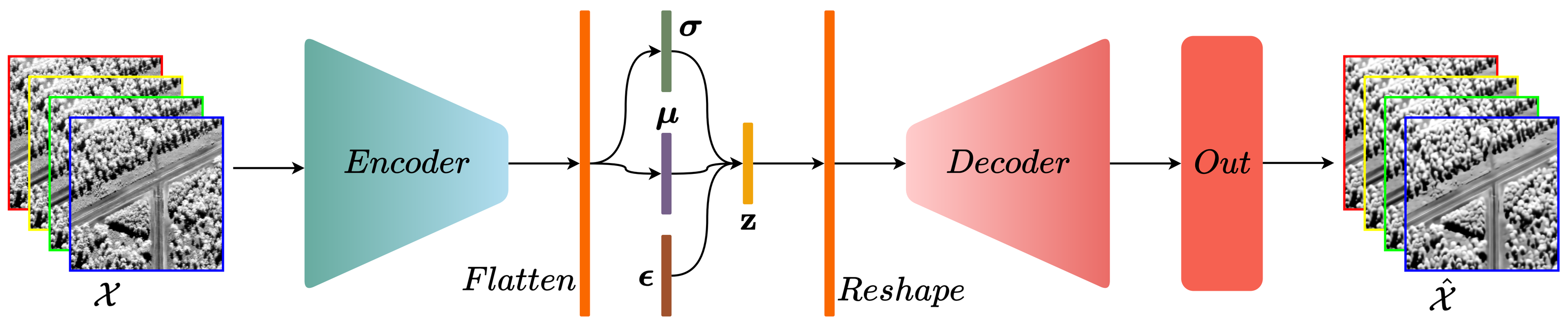
ONERA SETHI L-band image with anomalies.

Anomaly detection scheme



We adopt the anomaly detection methodology proposed in [3], which locates abnormous pixels by computing the deviation of a zone characteristics to the normal distribution. Instead of using the proposed AAE, we study an extension of the VAE family, called β-annealing VAE [2].

β-*annealing* VAE



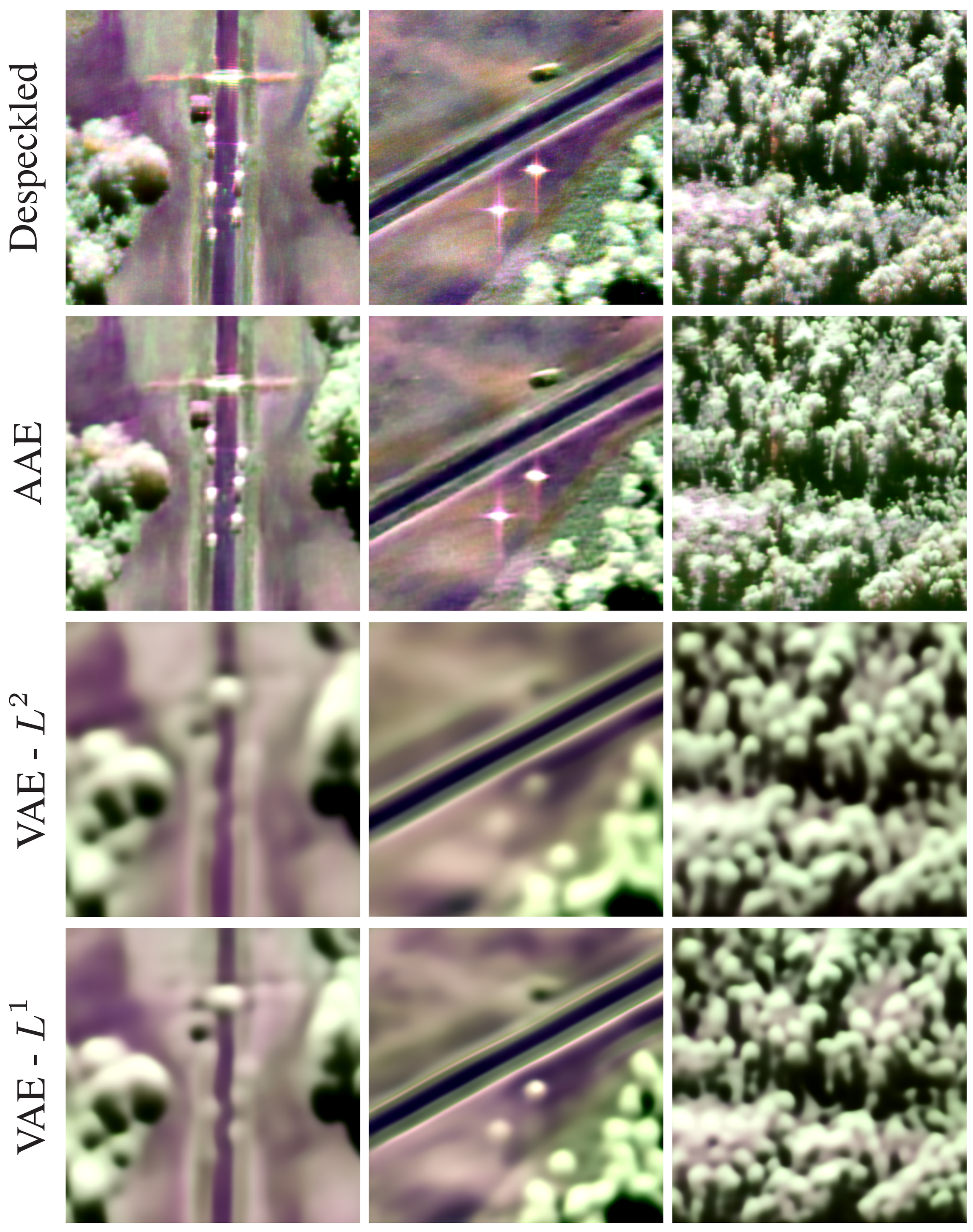
VAE architecture. $\mathcal{X}$ and $\hat{\mathcal{X}}$ denote respectively despeckled and reconstructed SAR images. To obtain $\mathcal{X}$, we apply MERLIN algorithm [1] on a Side Look Complex SAR image.

Loss function:

Optimizing β-annealing VAE means minimizing the *Evidence Lower BOund* loss function, whose formulation is expressed as $\mathcal{L}_{ELBO} = \mathcal{L}_{rec} + \beta\, D_{KL}$ where $\mathcal{L}_{rec}$ can be an L^1 or L^2 distance and

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

Reconstruction images:



Quantitative comparison:

Metrics	AAE	VAE - L^2	VAE - L^1
PSNR	**33.19**	31.46	32.41
SSIM[4]	0.866	0.886	**0.892**

Observations

Image reconstruction quality:

- Our VAE generates blurrier results than AAE's, but mitigates stronger high energetic targets.
- VAE with L^1 reconstruction loss outputs less blurry images than L^2

Anomaly map:

- Both AAE and VAE give lower false positives than Reed-Xiaoli detector.
- Reed-Xiaoli detector isolates better high-bounce targets.

Change detection

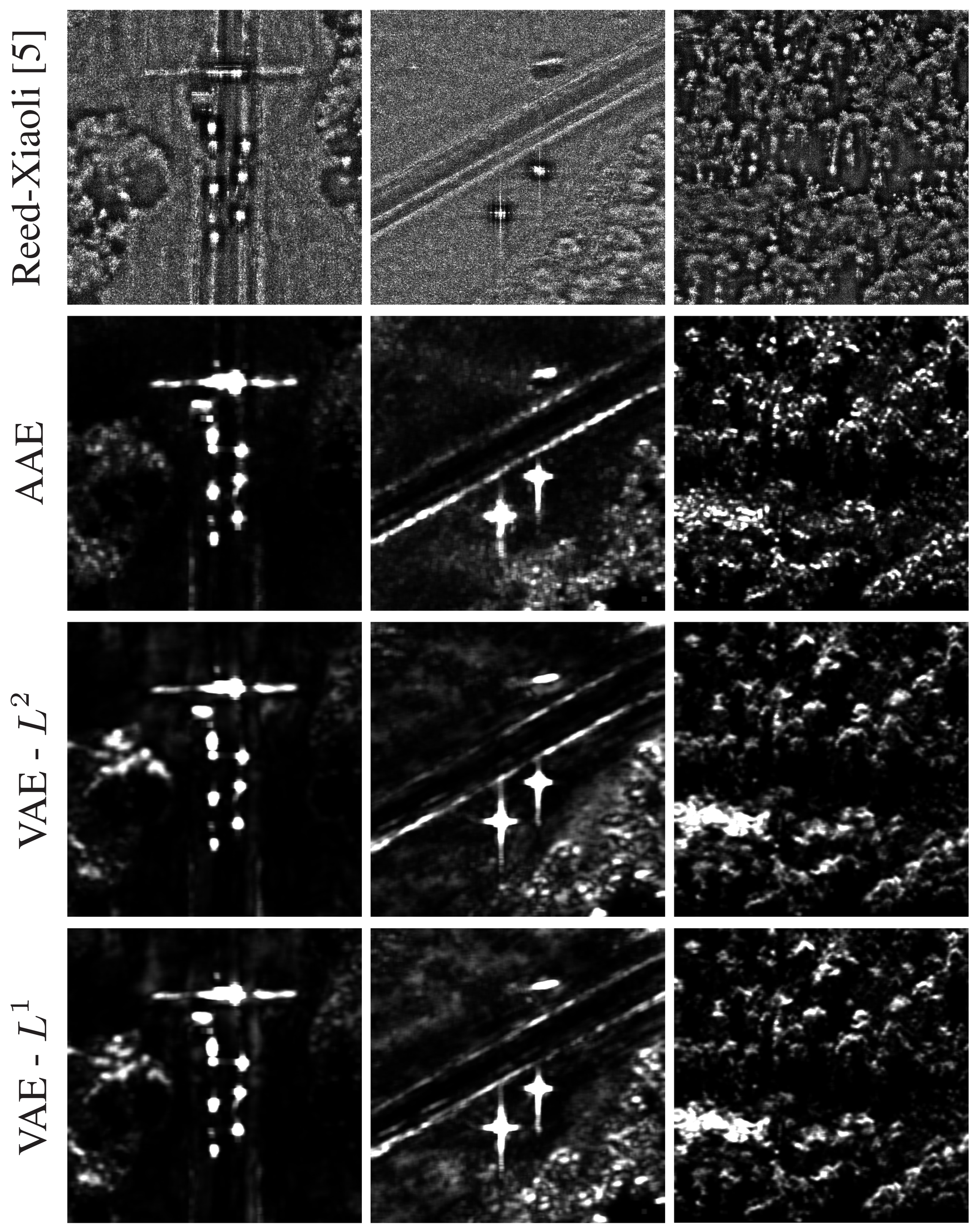
The anomaly detection process ends with the comparison between reconstructed images by the β-annealing VAE and the despeckled images. SAR images, having a high spatial and spectral dynamic range, therefore necessitate calculating statistics locally. We use the Frobenius norm as distance metric:

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

where $\boldsymbol{\Sigma}_{k,l}$ denotes the Sample Covariance Matrix of *boxcar* $\mathcal{B}_{k,l}$, computed with the Sample Mean Vector $\hat{\boldsymbol{\mu}}_{k,l}$:

$$\hat{\boldsymbol{\Sigma}}_{k,l}^{\mathcal{X}} = \frac{1}{|\mathcal{B}_{k,l}|}\sum_{i,j\in\mathcal{B}_{k,l}} \left(\mathcal{X}_{i,j} - \hat{\boldsymbol{\mu}}_{k,l}^{\mathcal{X}}\right)\left(\mathcal{X}_{i,j} - \hat{\boldsymbol{\mu}}_{k,l}^{\mathcal{X}}\right)^T ,$$

Anomaly map:



References

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