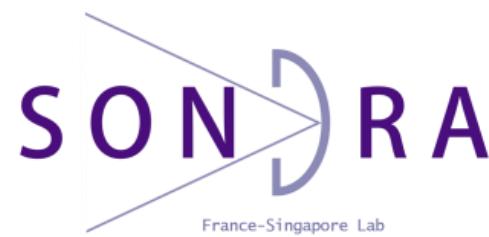


Détection d'anomalies en SAR basée sur les réseaux génératifs

Max MUZEAU, Chengfang REN, Sébastien ANGELIAUME, Mihai DACTU, Jean-Philippe OVARLEZ



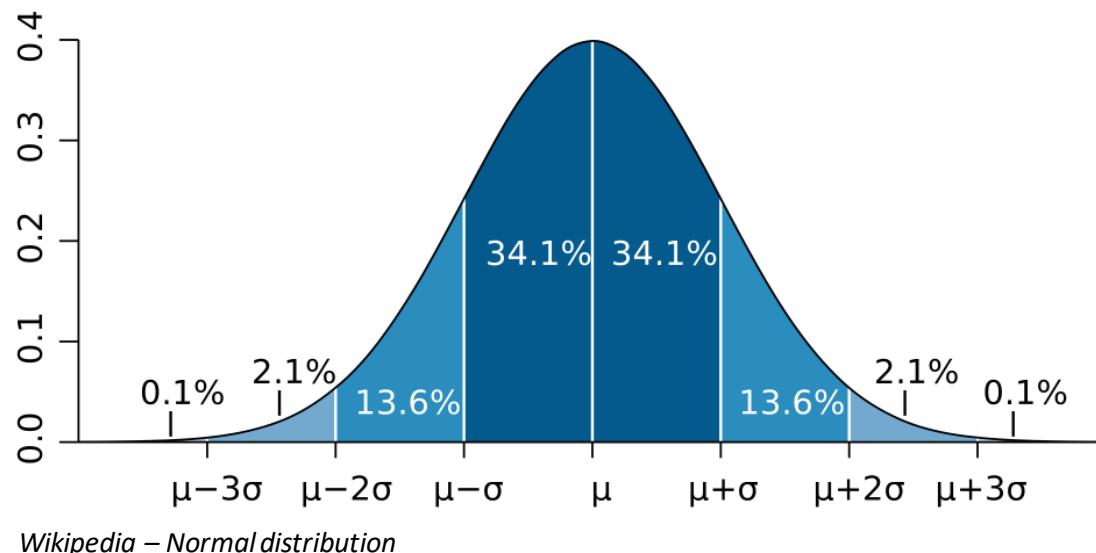
What is an anomaly ?

Context

What is normality ?

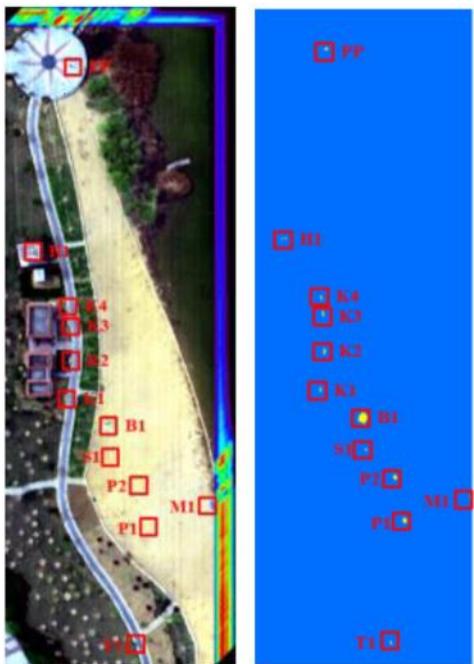
What considerably deviates from it ?

- Point anomaly
- Group anomaly
- Contextual anomaly

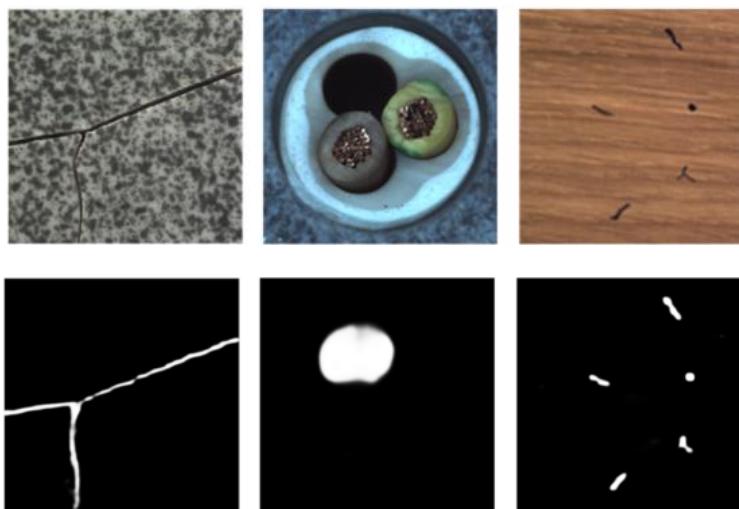


What is an anomaly ?

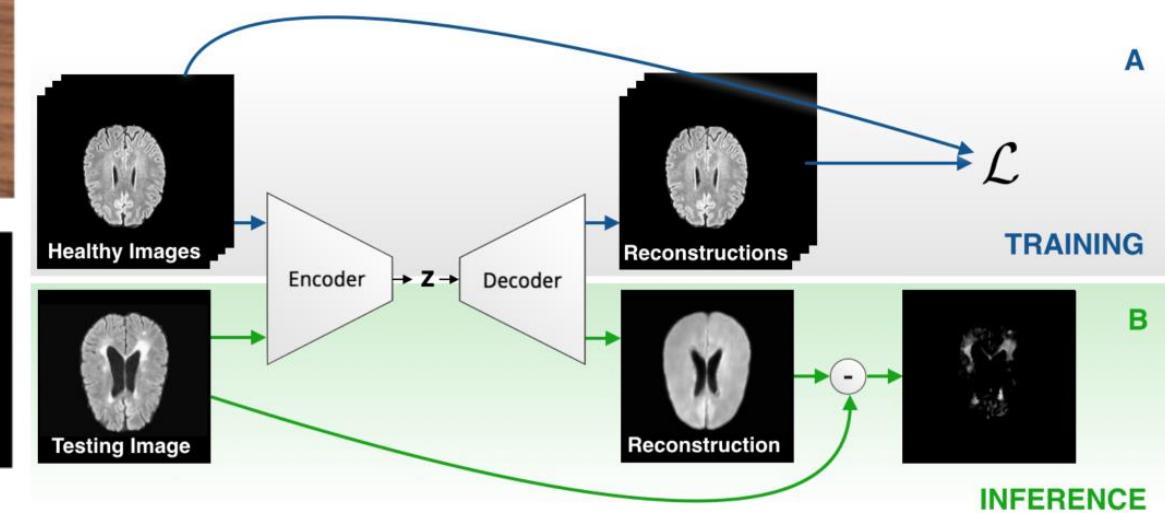
Examples



S. Wang, X. Wang, L. Zhang and Y. Zhong, "Deep Low-Rank Prior for Hyperspectral Anomaly Detection," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1-17, 2022, Art no. 5527017, doi: 10.1109/TGRS.2022.3165833.



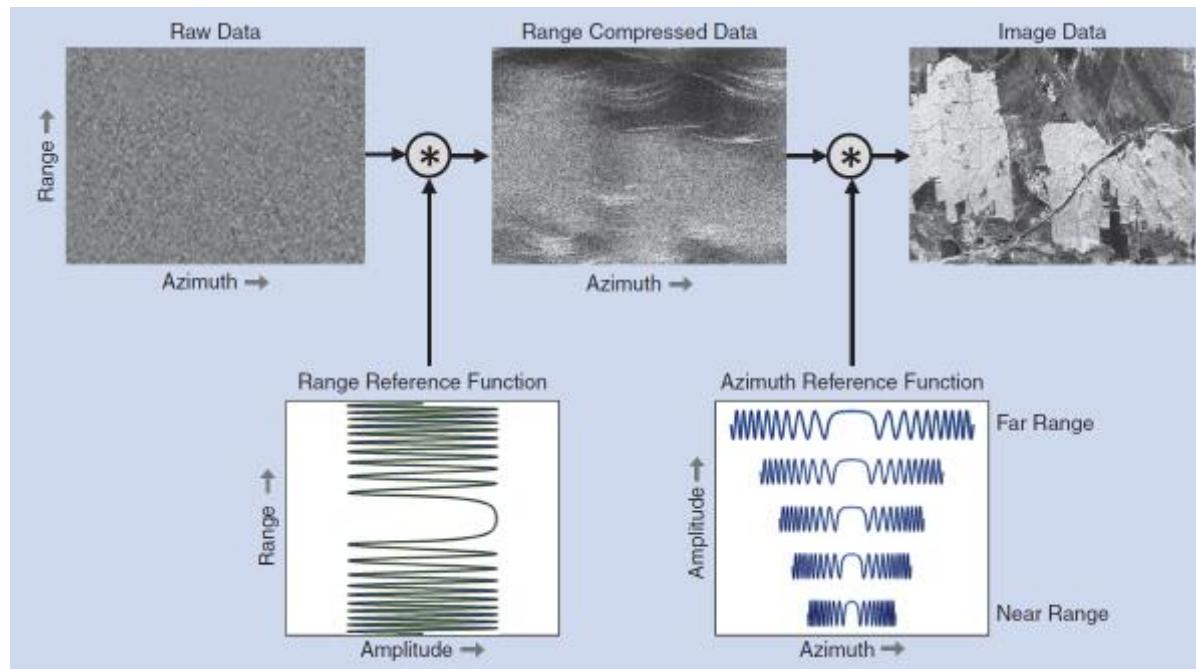
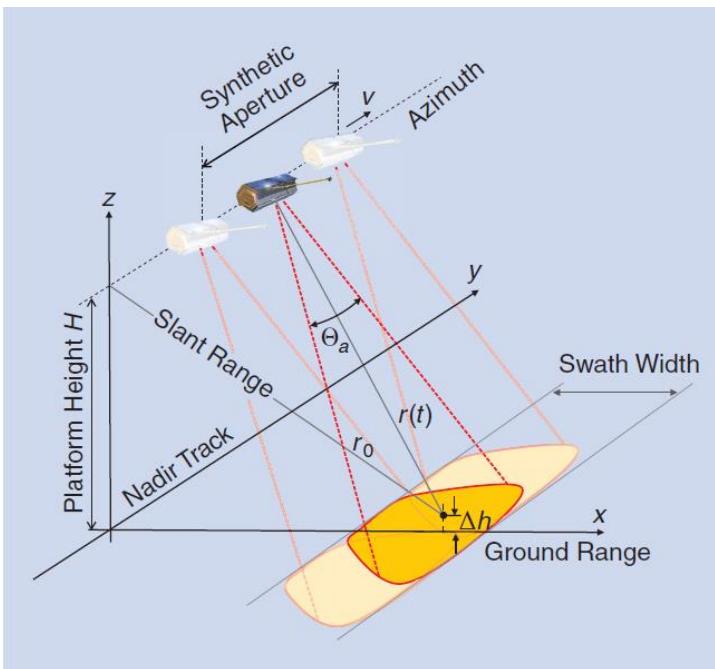
Song, Jouwon & Kong, Kyeongbo & Park, Ye-In & Kim, Seong-Gyun & Kang, Suk-Ju. (2021). *AnoSeg: Anomaly Segmentation Network Using Self-Supervised Learning*.



Baur, Christoph & Denner, Stefan & Wiestler, Benedikt & Albarqouni, Shadi & Navab, Nassir. (2020). *Autoencoders for Unsupervised Anomaly Segmentation in Brain MR Images: A Comparative Study*.

Synthetic aperture radar (SAR)

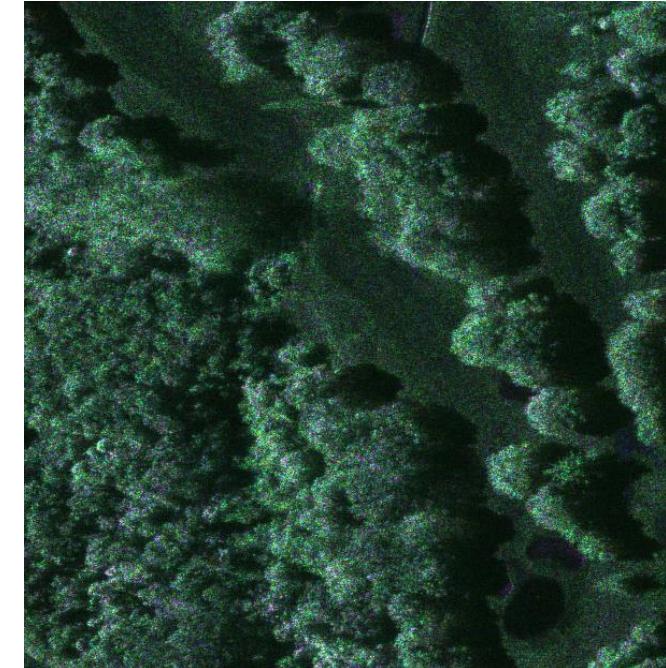
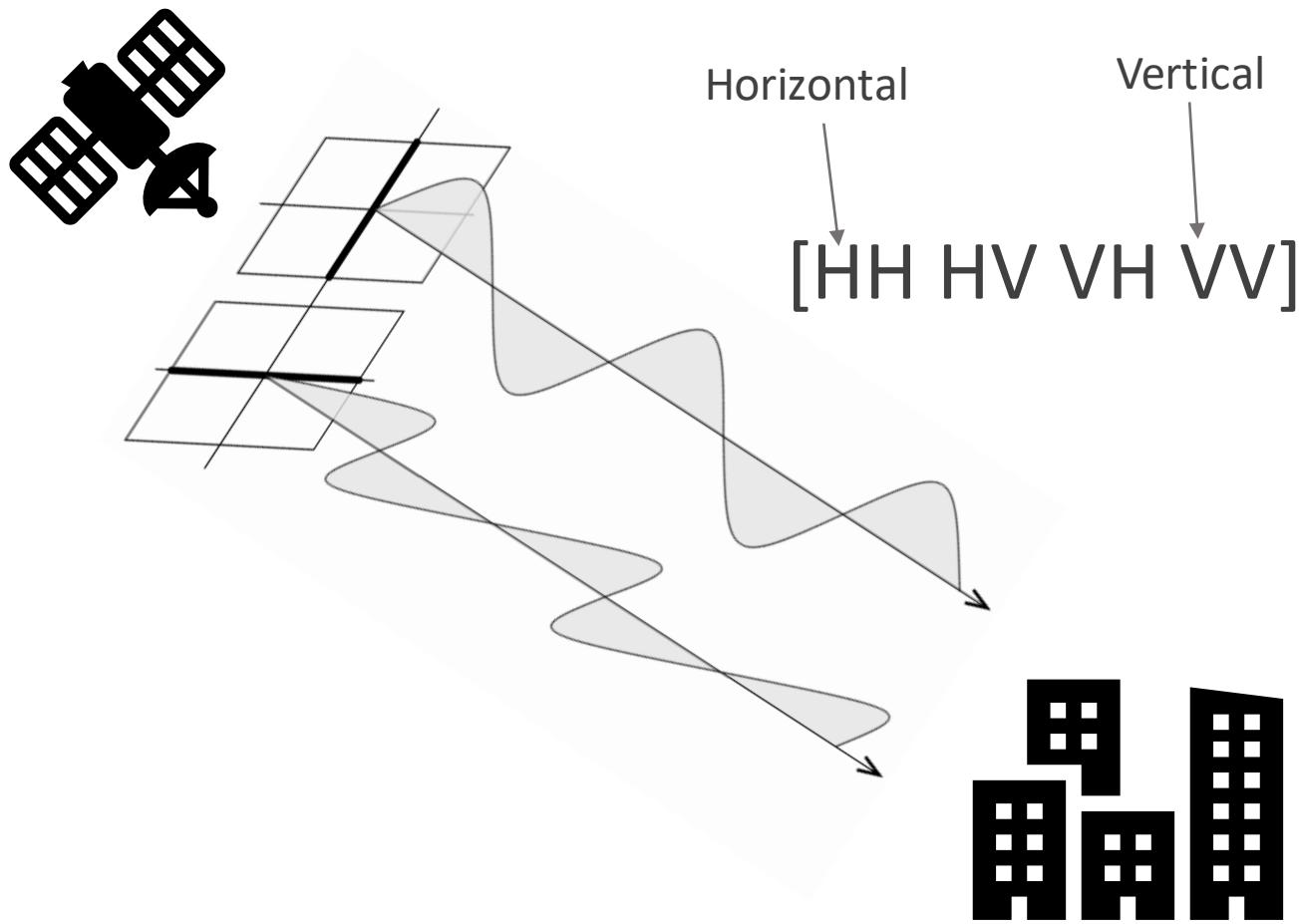
Acquisition



A. Moreira, P. Prats-Iraola, M. Younis, G. Krieger, I. Hajnsek and K. P. Papathanassiou, "A tutorial on synthetic aperture radar," in IEEE Geoscience and Remote Sensing Magazine, vol. 1, no. 1, pp. 6-43, March 2013, doi: 10.1109/MGRS.2013.2248301.

Synthetic aperture radar (SAR)

Polarimetry



Synthetic aperture radar (SAR)

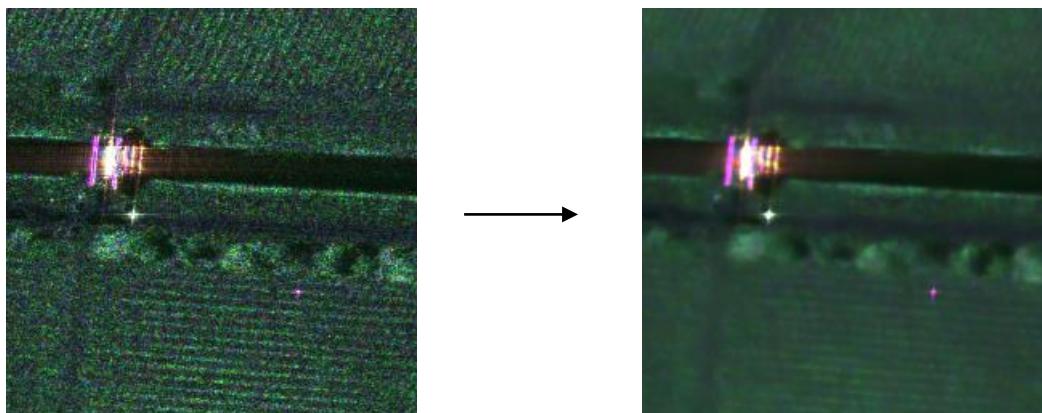
Speckle

$$I = R \times S$$

↑ ↑ ↗
Intensity Reflectivity Speckle

$$p_I(I|R) = \frac{L^L I^{L-1}}{\Gamma(L)R^L} \exp\left(-L\frac{I}{R}\right)$$

- Increase the probability of false alarm (PFA)



Standard statistical approach

Mahalanobis distance

$$d(x) = \sqrt{(x - \mu)^H \Sigma^{-1} (x - \mu)}$$

$$\hat{\Sigma} = \frac{1}{N-1} \sum_{i=1}^N (x_i - \hat{\mu})(x_i - \hat{\mu})^H, \quad \hat{\mu} = \frac{1}{N} \sum_{i=1}^N x_i.$$

- x should follow a normal multivariate distribution
- Not robust to outliers
- Detects edges

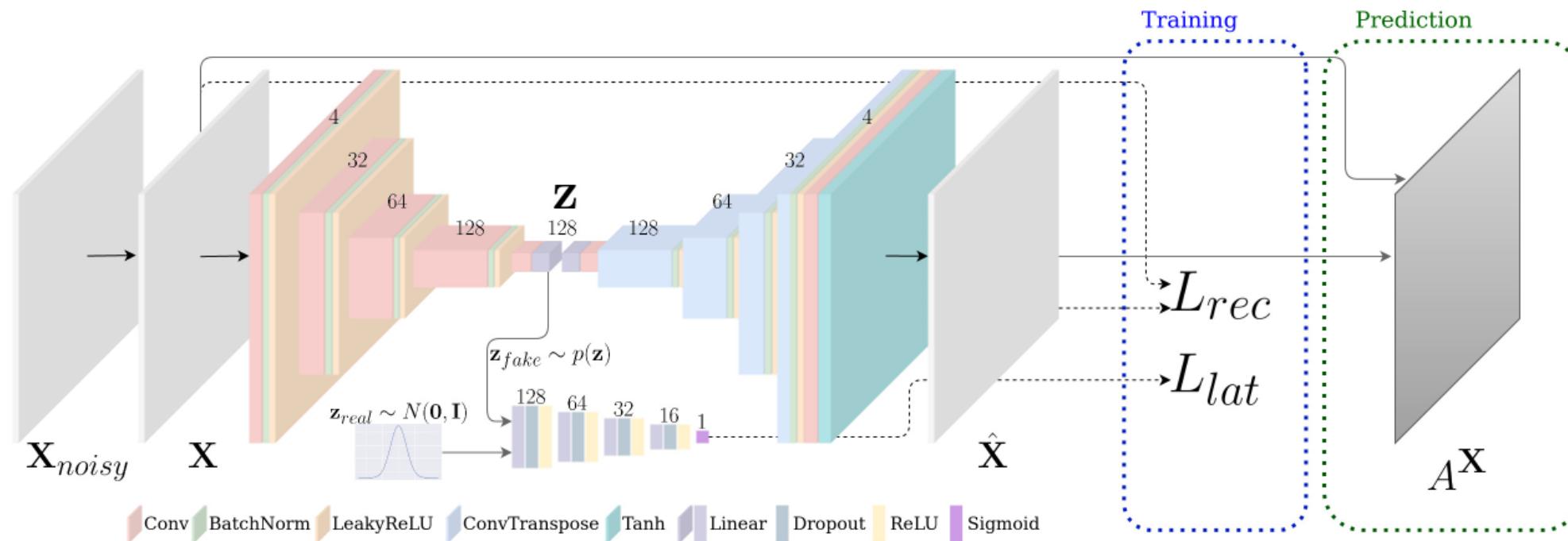
Proposed SAR anomaly detection

Overview

- Deep learning framework combined with a change detection method
- Self-supervised training
- No label
- No a priori

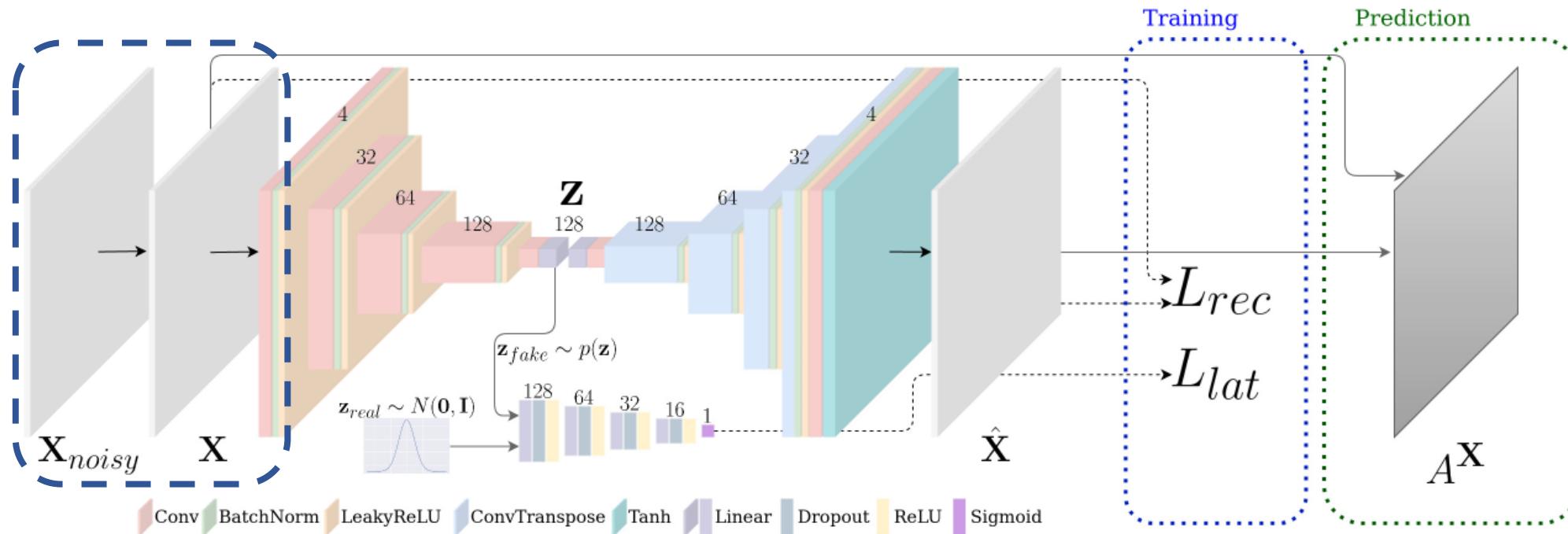
Proposed SAR anomaly detection

Overview



Proposed SAR anomaly detection

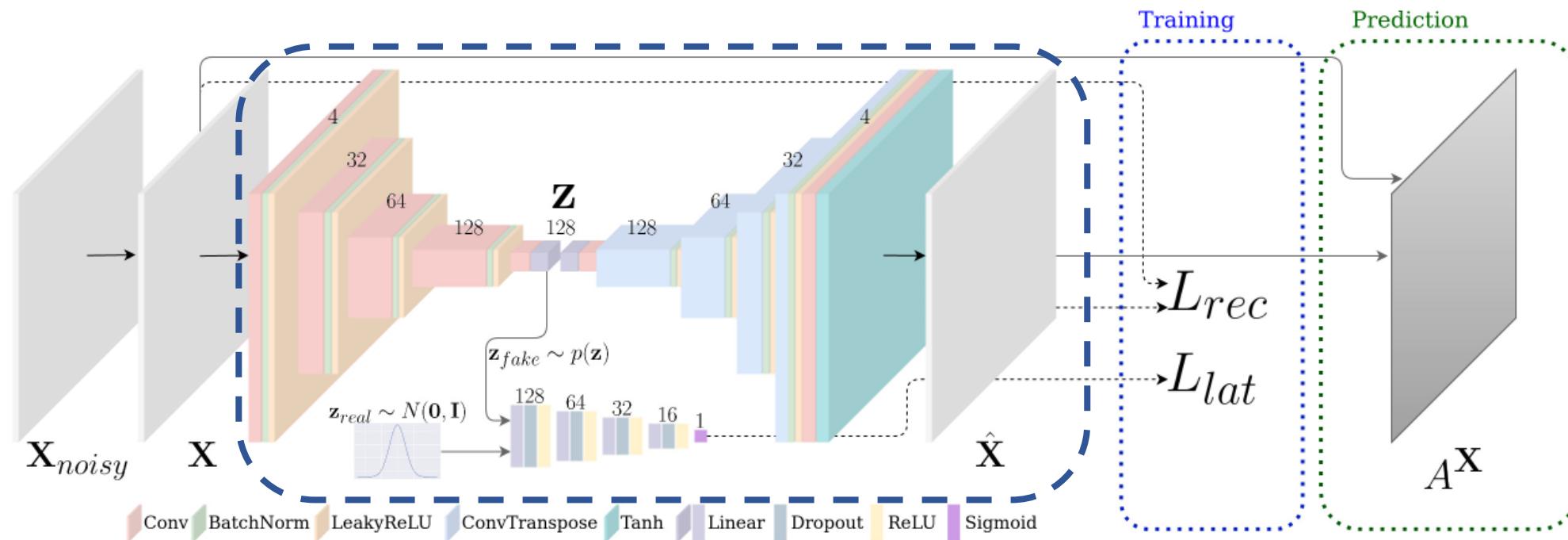
Overview



Despeckling

Proposed SAR anomaly detection

Overview

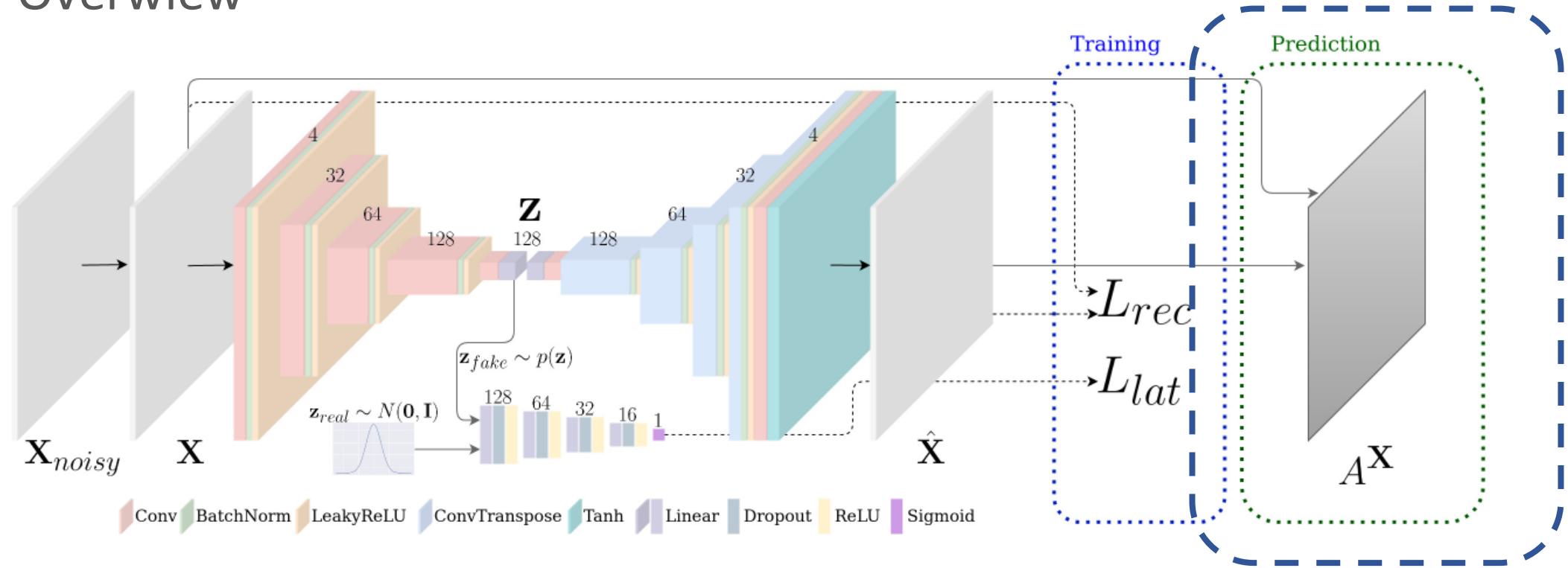


Despeckling

AAE

Proposed SAR anomaly detection

Overview



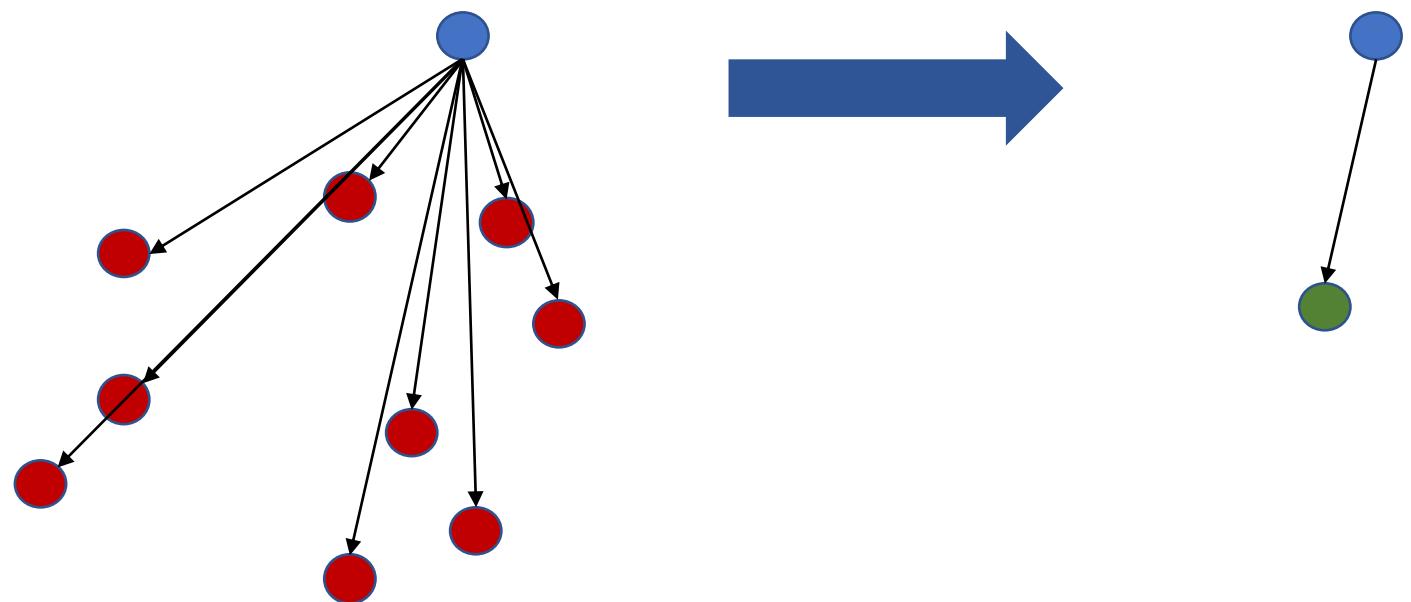
Despeckling

AAE

Change
detection

Proposed SAR anomaly detection

Despeckling



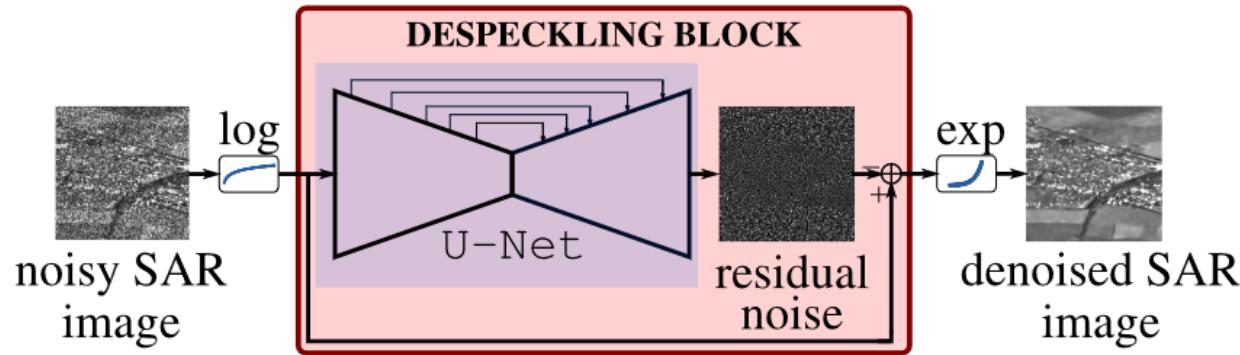
$$\underset{z}{\operatorname{argmin}} \mathbb{E}_y \{ L(z, y) \}$$

$$z = \mathbb{E}_y \{ y \}$$

Proposed SAR anomaly detection

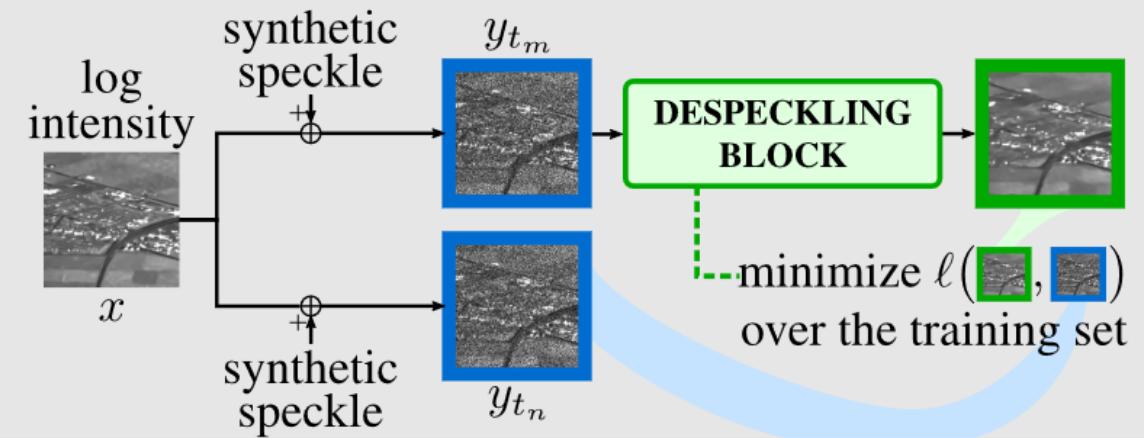
Despeckling

Structure of the despeckling algorithm



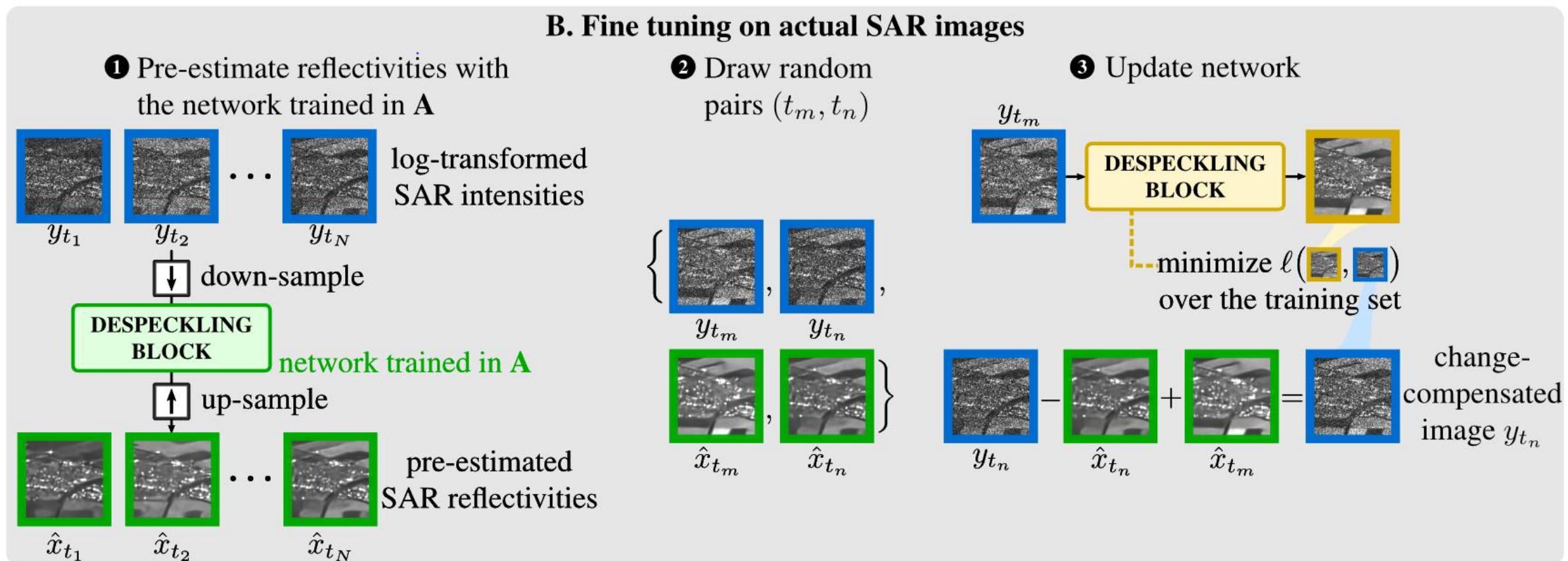
A. Initial training: synthetic speckle realizations

- ① Generate noisy pairs (t_m, t_n) ② Update network from a groundtruth image



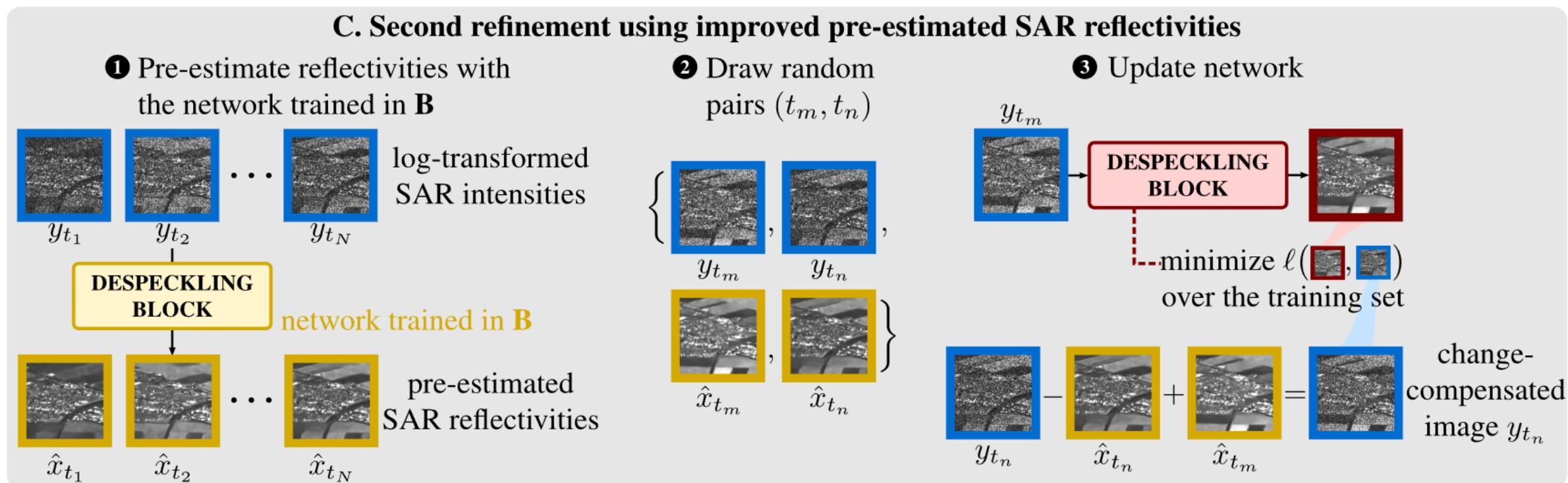
Proposed SAR anomaly detection

Despeckling



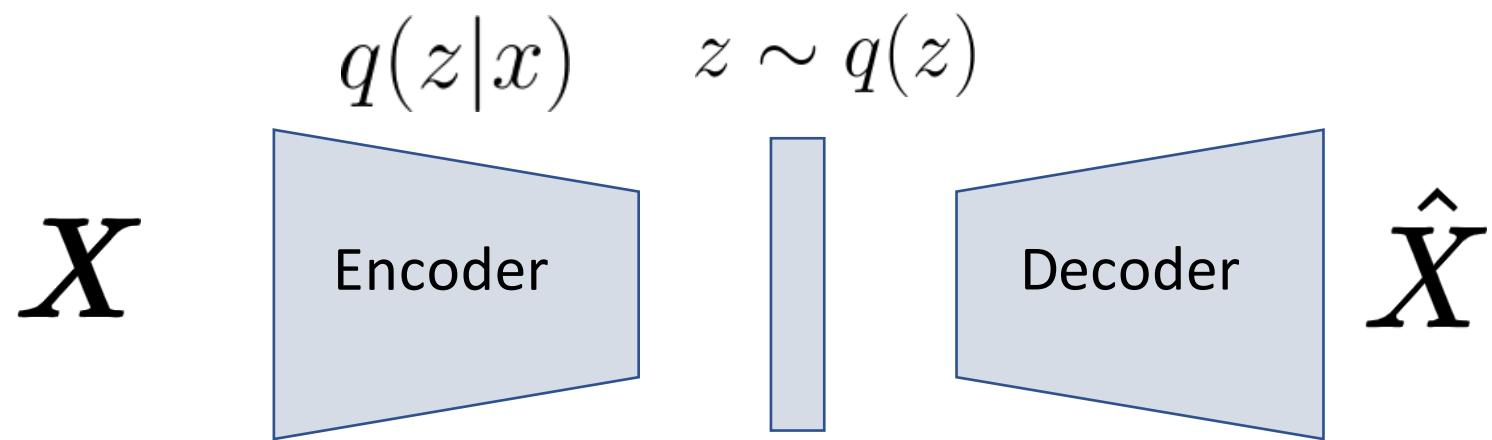
Proposed SAR anomaly detection

Despeckling



Proposed SAR anomaly detection

Autoencoder

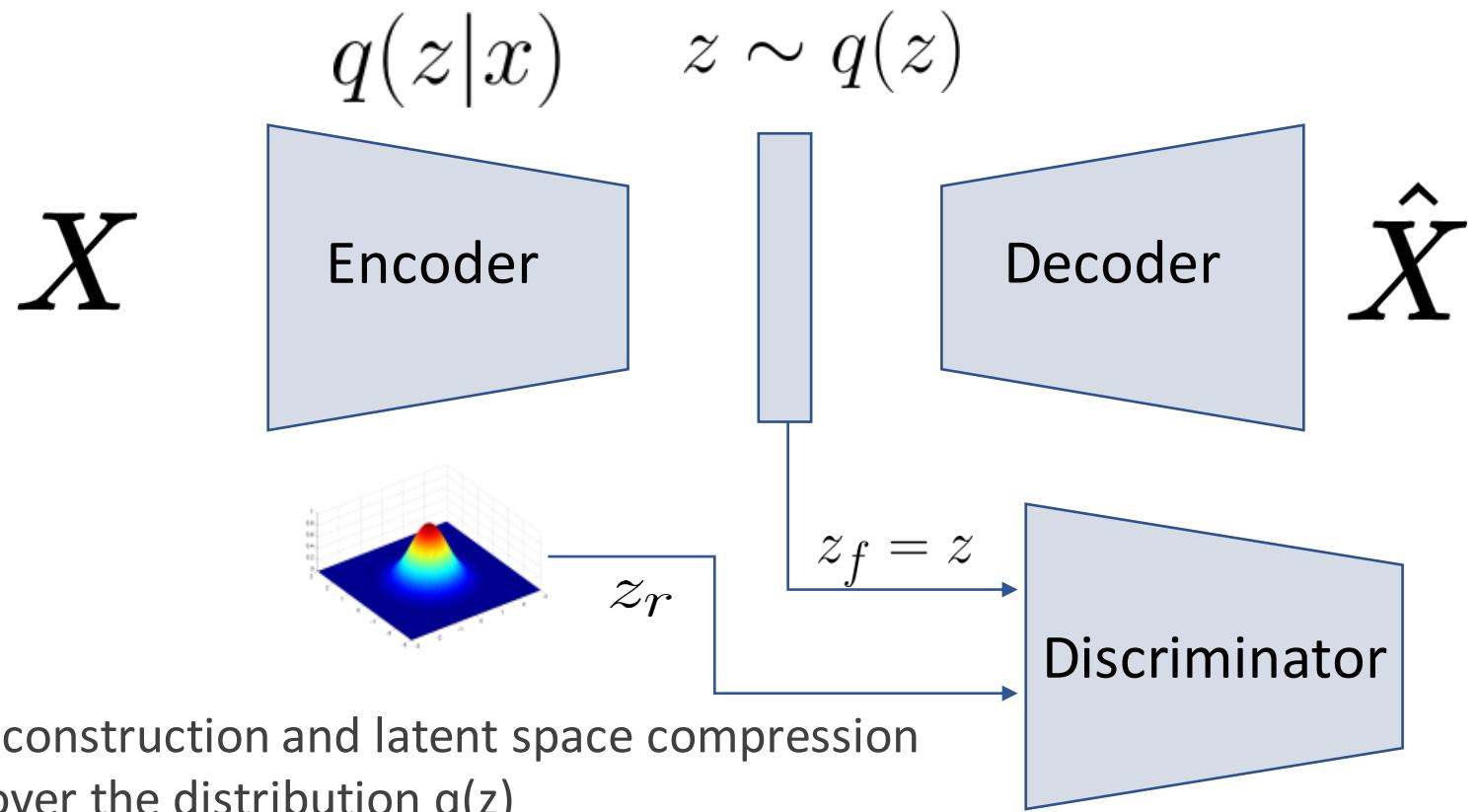


- Compress an image patch in a vector $64 \times 64 \rightarrow 128$
- Only reconstructs frequently seen structures

$$L_{rec} = \frac{1}{h w c} \sum_{i,j,k} \|\mathbf{X}_{i,j,k} - \hat{\mathbf{X}}_{i,j,k}\|_1 .$$

Proposed SAR anomaly detection

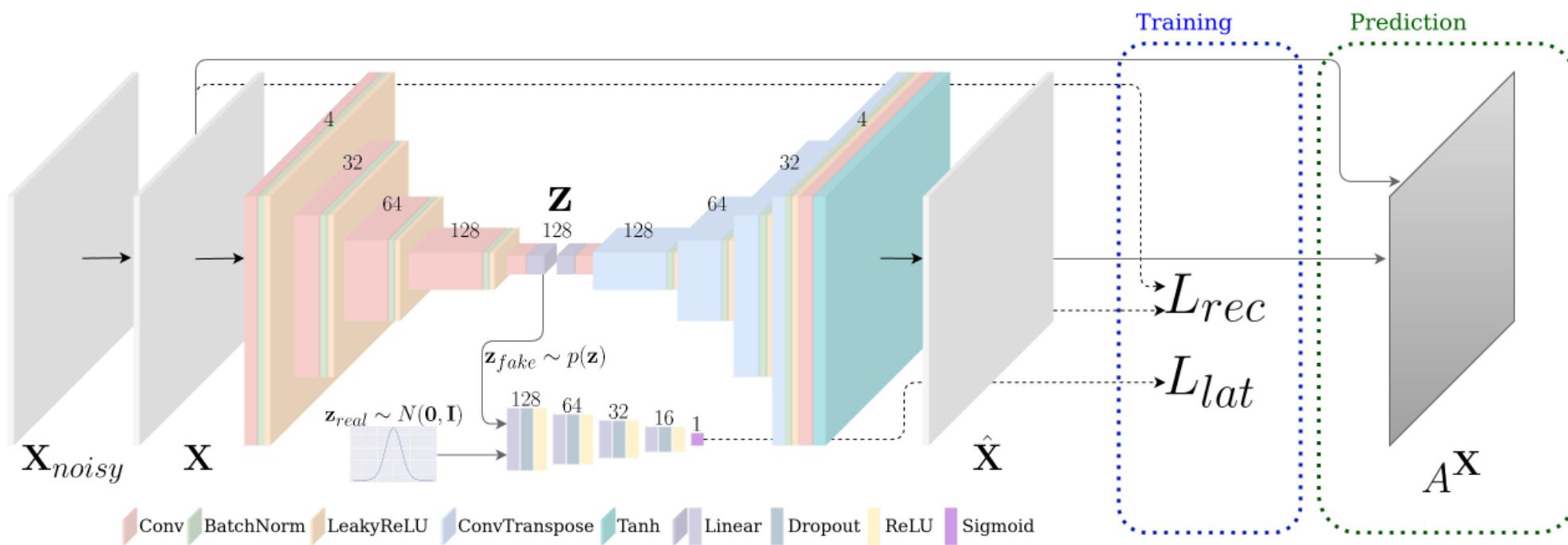
Latent space



$$\min_{\mathcal{E}} \max_{\mathcal{D}_c} L_{lat} \triangleq \mathbb{E}_{\mathbf{z}_{real} \sim N(\mathbf{0}, \mathbf{I})} [\log(\mathcal{D}_c(z_{real}))] + \mathbb{E}_{\mathcal{E}(\mathbf{X}) \sim p(z)} [\log(1 - \mathcal{D}_c(\mathcal{E}(\mathbf{X})))]$$

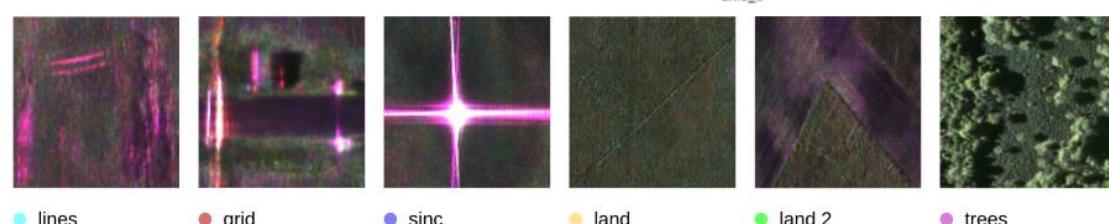
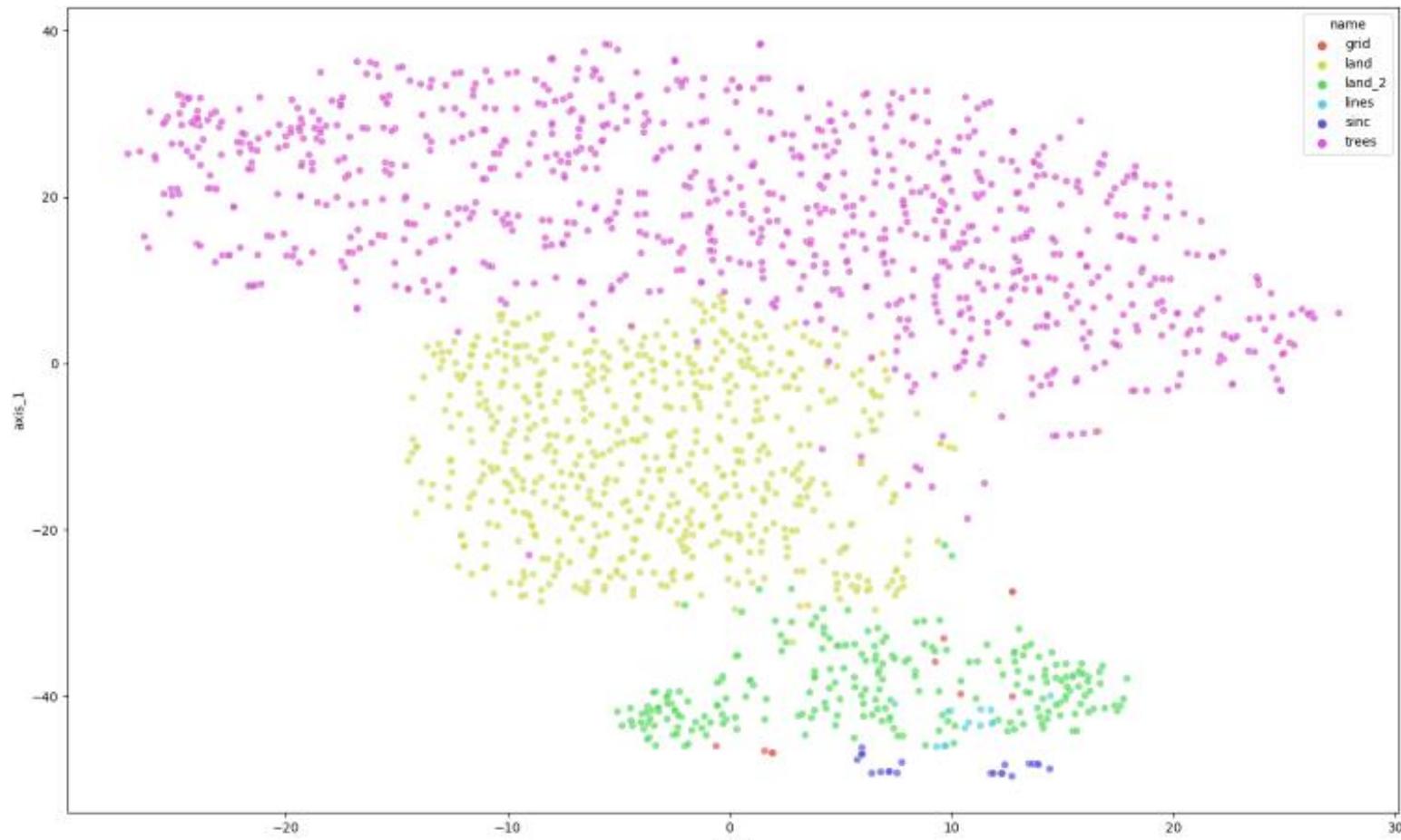
Proposed SAR anomaly detection

Architecture



Proposed SAR anomaly detection

Latent space analysis



Proposed SAR anomaly detection

Change detection

- Covariance estimate for each pixel with a gaussian assumption

$$\hat{\Sigma}_{k,l}^{\mathbf{X}} = \frac{1}{|\mathcal{B}_{k,l}|} \sum_{i,j \in \mathcal{B}_{k,l}} (\mathbf{X}_{i,j} - \hat{\mu}_{k,l}^{\mathbf{X}}) (\mathbf{X}_{i,j} - \hat{\mu}_{k,l}^{\mathbf{X}})^T, \text{ with } \hat{\mu}_{k,l}^{\mathbf{X}} = \frac{1}{|\mathcal{B}_{k,l}|} \sum_{i,j \in \mathcal{B}_{k,l}} \mathbf{X}_{i,j}.$$

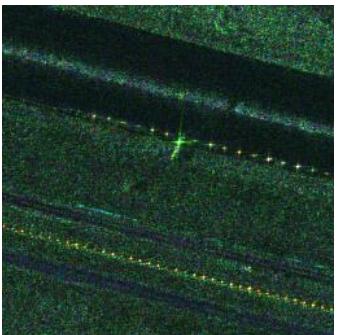
- Euclidian distance between covariance matrices

$$A^{\mathbf{X}}(k, l) = \|\hat{\Sigma}_{k,l}^{\mathbf{X}} - \hat{\Sigma}_{k,l}^{\hat{\mathbf{X}}}\|_F^2$$

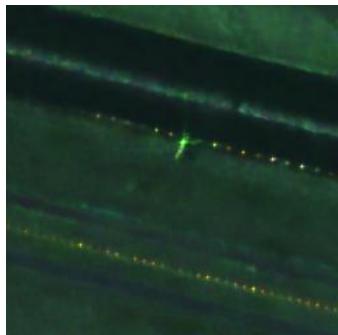
Results and comparison

Noisy vs denoised

X_{noisy}



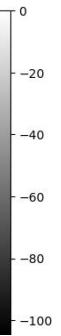
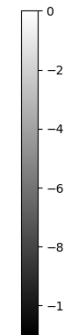
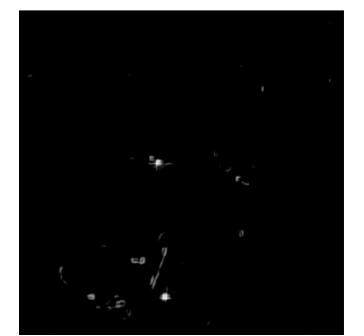
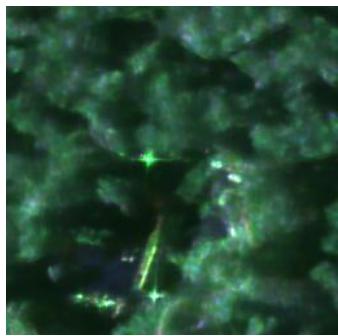
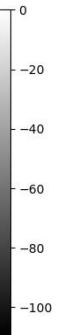
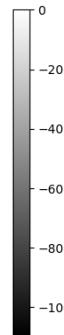
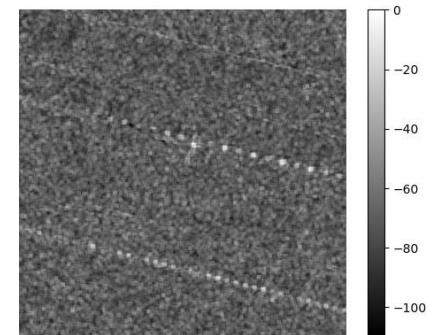
X



A^X

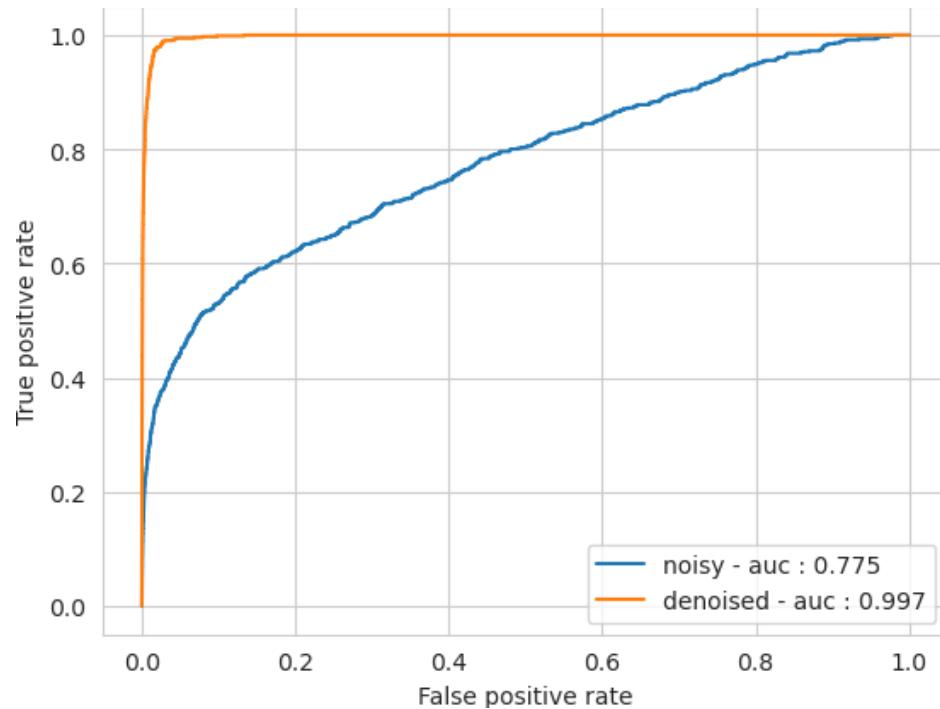
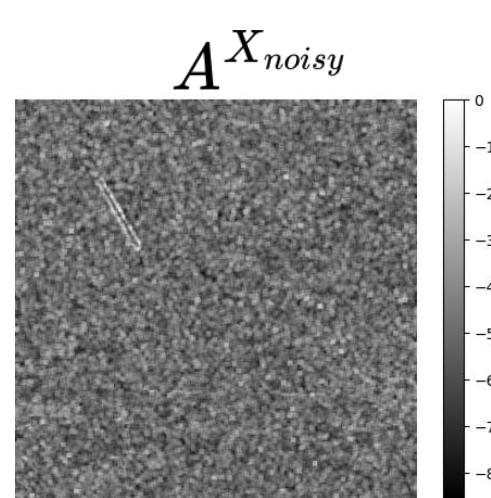
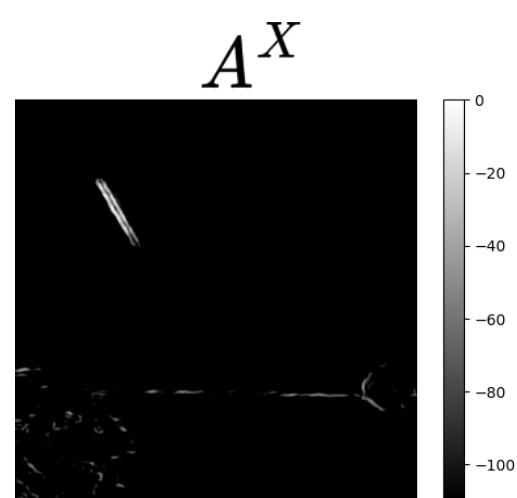
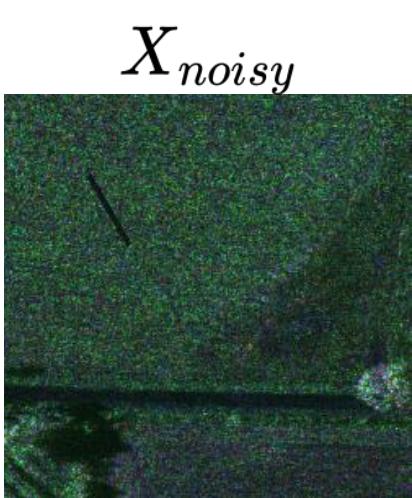


$A^{X_{noisy}}$



Results and comparison

Noisy vs denoised



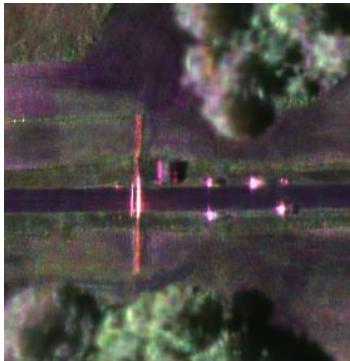
Results and comparison

Comparison with RX detector

X_{noisy}



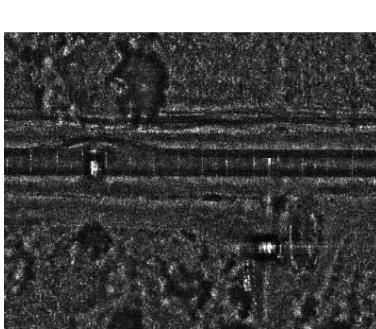
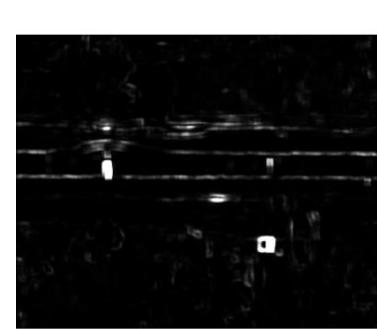
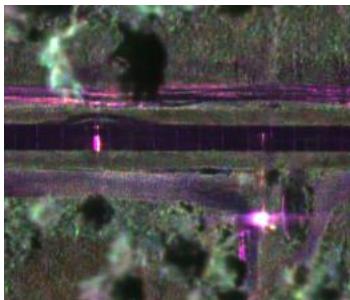
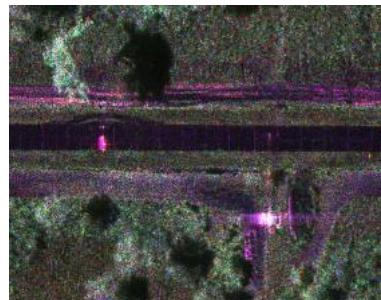
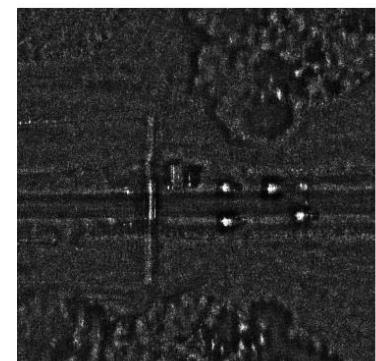
X



A^X



RX



Conclusion and perspectives

- New anomaly detection method for SAR images
- Open new possibilities for deep learning detection methods
- Increase performances with a « pretext task» closer to the goal
- Assert quality with a labeled dataset