SAR anomaly detection based on generative networks

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1 Abstract

Anomaly detection is a fundamental topic in image processing. Studied in many fields such as medical imaging (1), video (2), hyperspectral imaging (3) and in our case, Synthetic Aperture Radar (SAR) imagery (4), as the availability of such data has greatly increased in recent years following the launch of numerous satellites such as TerraSAR-X and Sentinel. Even if the data are now massively available, the lack of annotation of the data remains a crucial problem for the use of supervised algorithms. Moreover, the number of anomalous areas is much lower than the number of normal areas, which makes supervised training even more complex. In this context, the use of unsupervised algorithms is generally preferred, among which one of the most used is the Reed-Xiaoli detector (5). Recently, many works are based on deep neural networks, mainly thanks to autoencoders and GANs (6; 7). They allow to strongly reduce the size of the input data while preserving the information. Their use allows moreover not to reconstruct the abnormal zones at the output of the decoder. Some authors have applied these algorithms for SAR imaging (8; 4), without addressing the problem of speckle noise, which however strongly increases the difficulty (9).

The proposed method anomaly detection method for SAR imagery is based on deep learning. It does not require ground truth of anomalies, which addresses a recurrent problem in remote sensing: the lack of labeled data to train neural networks. The proposed model combines an adversarial autoencoder followed by a statistical change detector based on the covariance matrix, results are showed Fig. 2 A despeckling step is first performed using the deep learning framework (10), which allows to filter the speckle noise and to significantly improve the detection performances. Results of the despackling step are showed Fig. 1.

References

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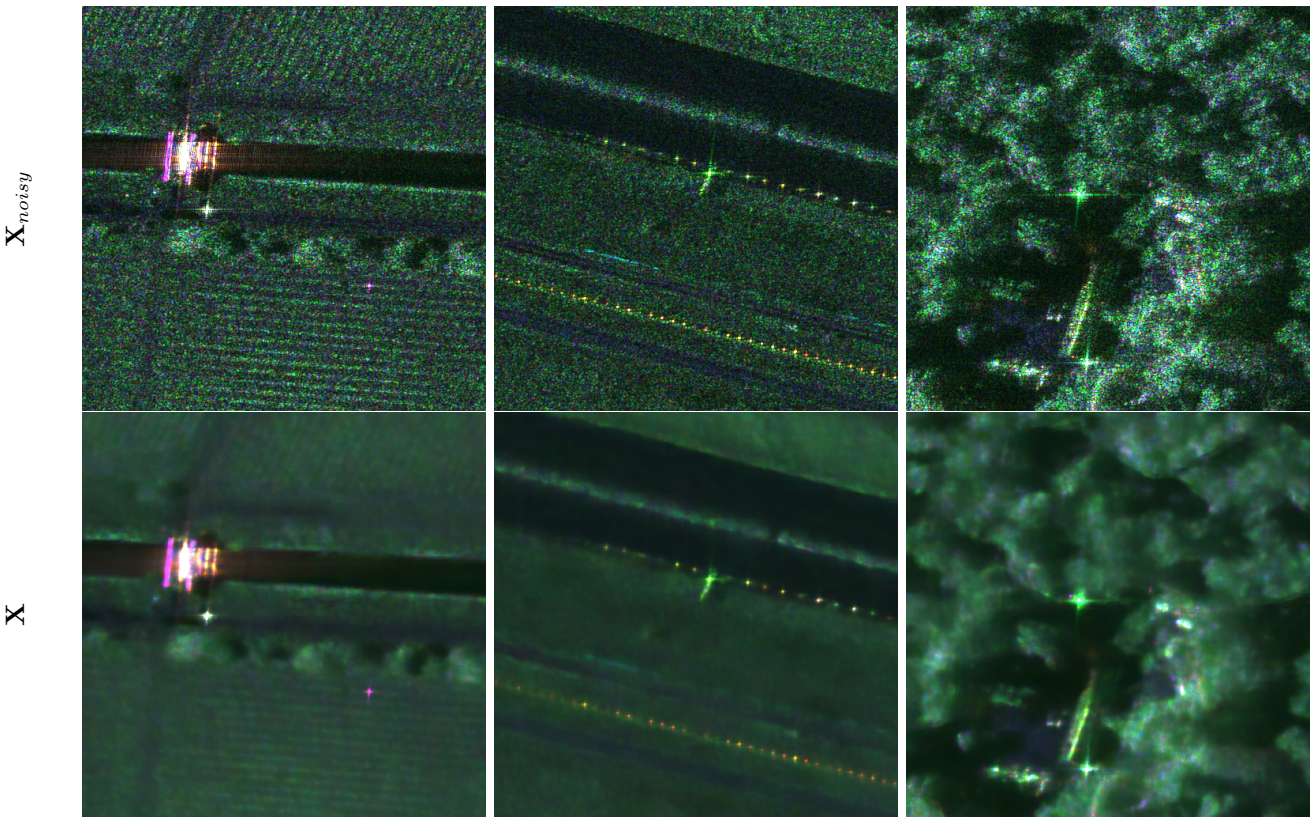

Figure 1: Images SAR avec *speckle* (haut) et image après débruitage (bas)

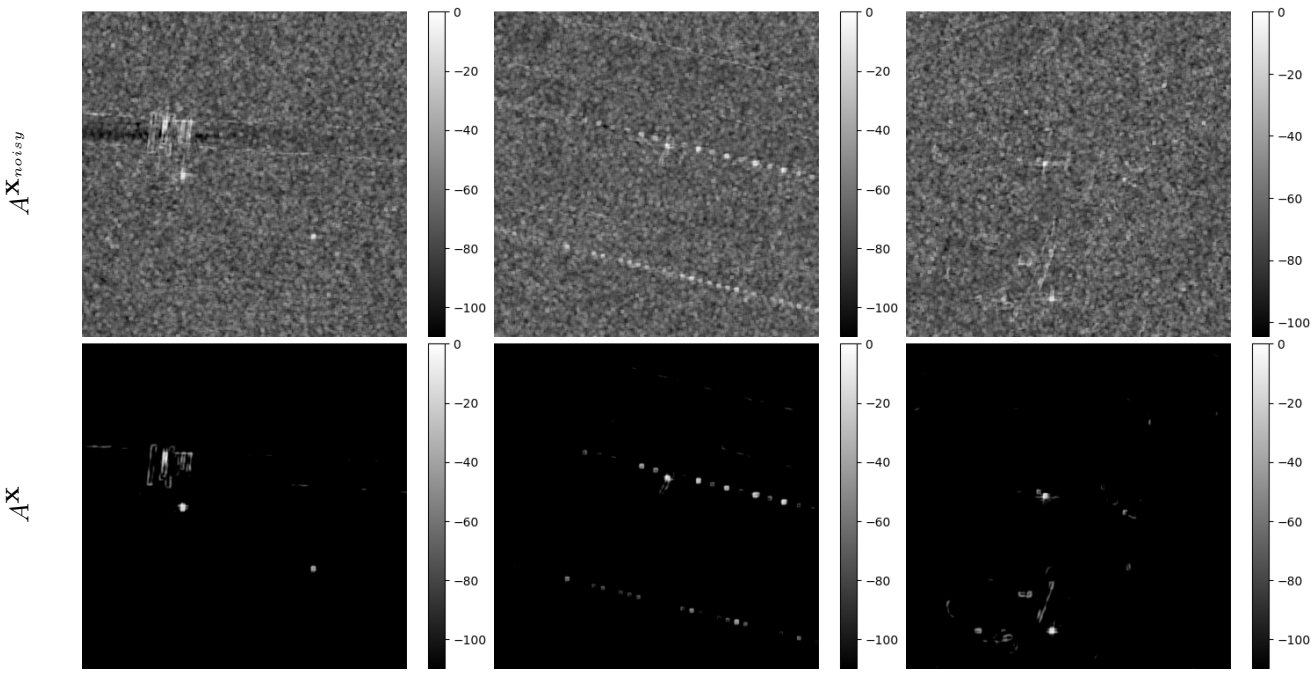

Figure 2: Détection de changement entre $\mathbf{X}_{noisy}$ et $\hat{\mathbf{X}}_{noisy}$ (haut) et détection de changement entre $\mathbf{X}$ et $\hat{\mathbf{X}}$ (bas)