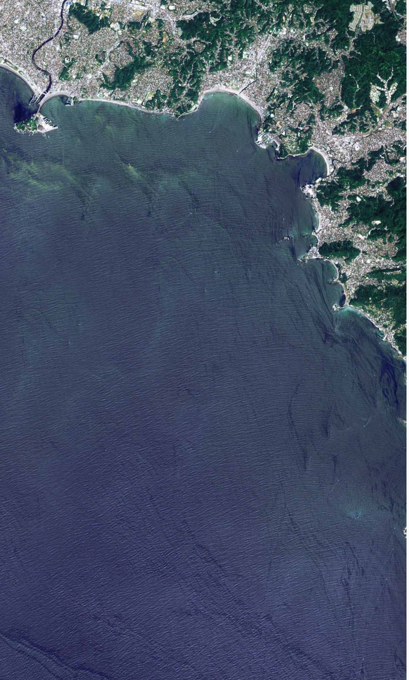

Robust low-rank change detection for SAR image time series

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Tuesday, July 30

SONDRA Université Paris Nanterre LISTIC ONERA

Contents of the presentation

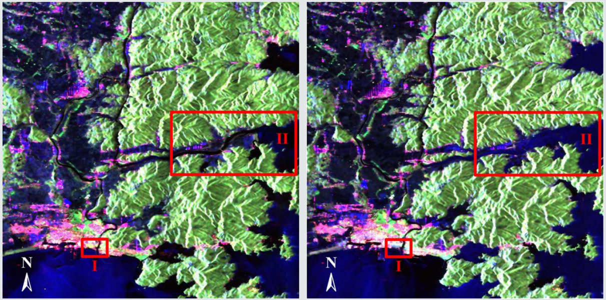
Sources available at:

- **Slides:** *https://ammarmian.github.io/igarss_slides_2019.pdf*
- **Code:** *https://github.com/AmmarMian/Robust-Low-Rank-CD*

Motivations

Change detection

Monitoring natural disasters:



PolSAR images of Ishinomaki and Onagawa areas [Sato et al., 2012], Nov.2010 (left), Apr.2011 (right).

Problems to consider

Huge increase in the number of available acquisitions:

- Sentinel-1: 12 days repeat cycle, since 2014
- TerraSAR-X: 11 days repeat cycle, since 2007
- UAVSAR, ...

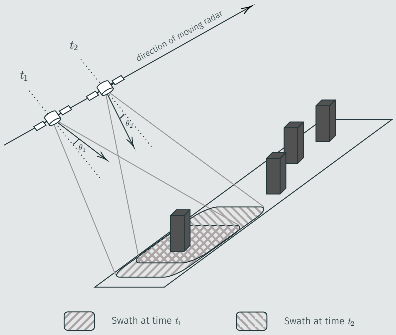
Detect changes

- Massive amount of data $\longrightarrow$ Automatic process
- Unlabeled data $\longrightarrow$ Unsupervised detection

Data

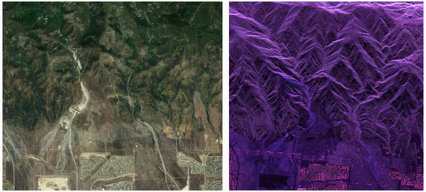
Synthetic aperture radar (SAR)

Principle of SAR



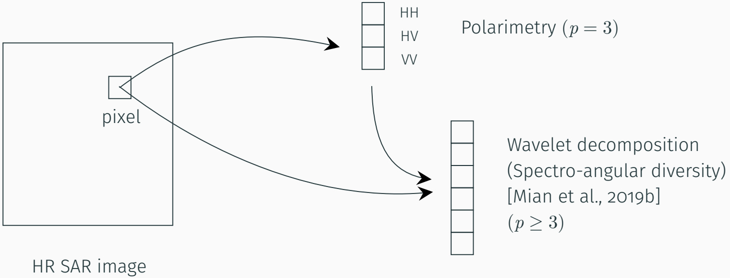
Advantages:

- All weather and illumination conditions (active technology)
- Very high-resolution (sub-meter) imaging



Comparison of optical and image

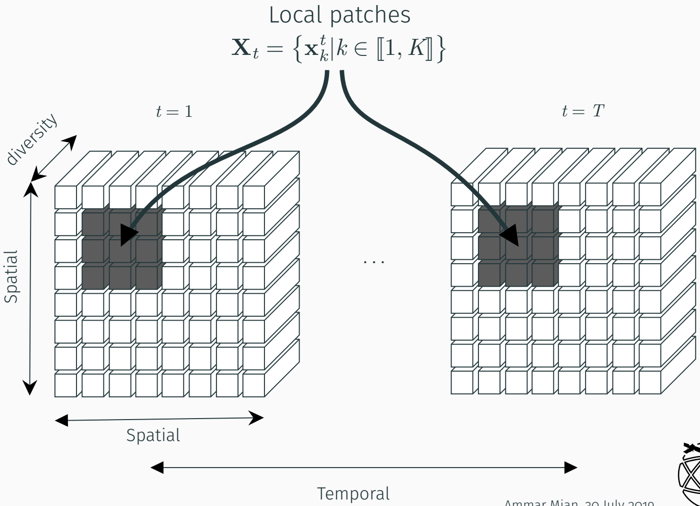
Multivariate data: natural or pre-processing



Feature selection

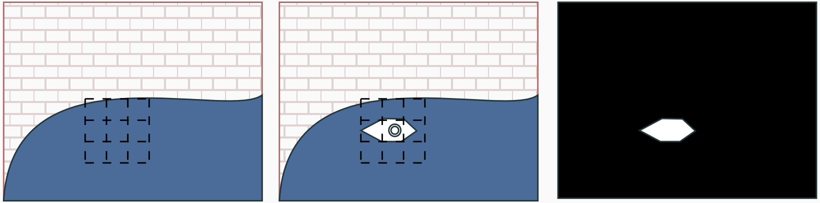
- Leverage **diversity** to improve the detection
- Requires to process **multivariate** pixels

SAR image time series representation



Change detection (CD) problem (T=2)

For each patch, decide if a change occured between $\mathbf{X}_1$ and $\mathbf{X}_2$.



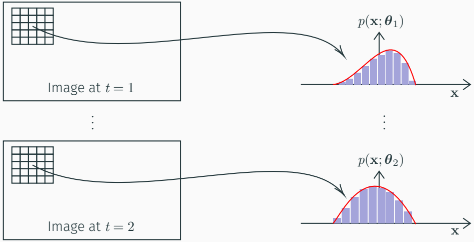
$t = 1$ $t = 2$ Ideal CD map

Statistical detection framework

- Can handle the multivariate aspect of the data
- Can account for physical modelling of the data/noise
- Strong theoretical guarantees from statistical litterature

Statistical framework

Parametric change detection



Parametric probability model:

$$\mathbf{X}_t \sim \mathcal{L}(\mathbf{X}_t; \boldsymbol{\theta}_t).$$

Change detection $\longrightarrow$ Hypothesis test:

$$\begin{cases} \mathrm{H}_0 : & \boldsymbol{\theta}_1 = \boldsymbol{\theta}_2 \quad (\textit{no change}) \\ \mathrm{H}_1 : & \boldsymbol{\theta}_1 \neq \boldsymbol{\theta}_2 \quad (\textit{change}) \end{cases}.$$

Generalized likelihood ratio test (GLRT)

Statistical decision test derived as:

$$\frac{\underset{\boldsymbol{\theta}_1,\boldsymbol{\theta}_2}{\max} \quad \mathcal{L}\left(\{\mathbf{X}_1,\mathbf{X}_2\}\,;\,\{\boldsymbol{\theta}_1,\boldsymbol{\theta}_2\}\right)}{\underset{\boldsymbol{\theta}_0}{\max} \quad \mathcal{L}\left(\{\mathbf{X}_1,\mathbf{X}_2\}\,;\,\boldsymbol{\theta}_0\right)} \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \lambda_{\mathrm{GLRT}}.$$

Problems

- Specify $\mathcal{L}$ and $\boldsymbol{\theta}$ to model the data
  - Good fit
  - Robust to a large class of distributions and outliers
- Handy model to compute the ratio efficiently (closed form or optimization)

Seminal work [Conradsen et al., 2003]

Gaussian model

Assuming $\mathbf{x} \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \boldsymbol{\Sigma})$:

$$\boldsymbol{\theta} = \boldsymbol{\Sigma}$$

$$\mathcal{L}(\mathbf{X}; \boldsymbol{\Sigma}) \propto |\boldsymbol{\Sigma}|^{-K} \mathrm{etr}\left\{-\mathbf{X}^{\mathrm{H}}\boldsymbol{\Sigma}^{-1}\mathbf{X}\right\}.$$

Detection test:

$$\begin{cases} \mathrm{H}_0: & \boldsymbol{\Sigma}_1 = \boldsymbol{\Sigma}_2 \quad (\textit{no change}) \\ \mathrm{H}_1: & \boldsymbol{\Sigma}_1 \neq \boldsymbol{\Sigma}_2 \quad (\textit{change}) \end{cases}.$$

Corresponding GLRT[a]

$$\hat{\Lambda}_{\mathrm{G}} = \frac{\left|\frac{1}{2}\left(\hat{\boldsymbol{\Sigma}}_1 + \hat{\boldsymbol{\Sigma}}_2\right)\right|^2}{\left|\hat{\boldsymbol{\Sigma}}_1\right|\left|\hat{\boldsymbol{\Sigma}}_2\right|} \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \lambda,$$

where

$$\forall t, \hat{\boldsymbol{\Sigma}}_t = \mathbf{X}_t\mathbf{X}_t^{\mathrm{H}}/K.$$

[a] Other Gaussian/Covariance methods [Ciuonzo et al., 2017, Nascimento et al., 2019].

Non-Gaussian models in CD [Mian et al., 2019a]

Robust model: Compound-Gaussian distributions

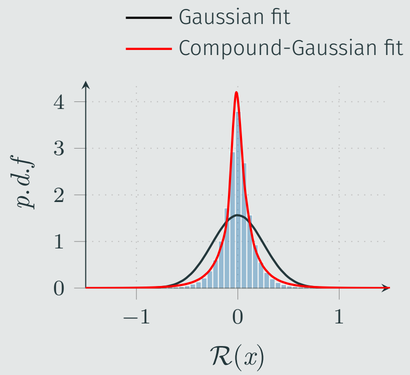
Assuming $\mathbf{x}_k \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \tau_k \boldsymbol{\Sigma})$.

$$\boldsymbol{\theta} = \{\boldsymbol{\Sigma}, \{\tau_k\}\}$$

$$\mathcal{L}(\mathbf{X}; \boldsymbol{\Sigma}, \{\tau_k\}) \propto \prod_{k=1}^{K} |\tau_k \boldsymbol{\Sigma}|^{-1} \exp\left\{-\frac{\mathbf{x}_k{}^{\mathrm{H}} \boldsymbol{\Sigma}^{-1} \mathbf{x}_k}{\tau_k}\right\}.$$

Corresponding GLRTs in [Mian et al., 2019a].

Histogram of UAVSAR data (HH)



Structured covariance models in CD [Ben Abdallah et al., 2019]

Low-rank structured covariance

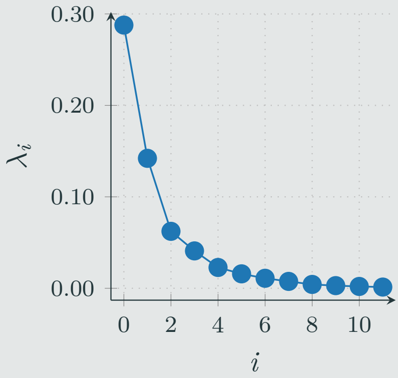
Assuming $\mathbf{x} \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \mathbf{\Sigma}_R + \sigma^2\mathbf{I})$.

$\boldsymbol{\theta} = \mathbf{\Sigma}_R$, with $\mathrm{rank}(\mathbf{\Sigma}_R) = R$

$$\mathcal{L}(\mathbf{X}; \mathbf{\Sigma}_R) \propto |\mathbf{\Sigma}_R + \sigma^2\mathbf{I}|^{-K}\mathrm{etr}\left\{-\mathbf{X}^{\mathrm{H}}(\mathbf{\Sigma}_R + \sigma^2\mathbf{I})^{-1}\mathbf{X}\right\}$$

Corresponding GLRTs in [Ben Abdallah et al., 2019].

Spectrum of UAVSAR data (wavelets)



IGARSS 2019

Proposed Approach

Proposed CD test

Low-rank Compound-Gaussian model

Assuming $\mathbf{x}_k \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \tau_k(\mathbf{\Sigma}_R + \sigma^2\mathbf{I}))$.

$$\boldsymbol{\theta} = \{\mathbf{\Sigma}_R, \{\tau_k\}\} \text{ with } \mathrm{rank}(\mathbf{\Sigma}_R) = R$$

$$\mathcal{L}(\mathbf{X}; \mathbf{\Sigma}, \{\tau_k\}) \propto \prod_{k=1}^{K} |\tau_k(\mathbf{\Sigma}_R + \sigma^2\mathbf{I})|^{-1} \exp\left\{-\frac{{\mathbf{x}_k}^{\mathrm{H}}(\mathbf{\Sigma}_R + \sigma^2\mathbf{I})^{-1}\mathbf{x}_k}{\tau_k}\right\}.$$

Recalling our problems

- Specify $\mathcal{L}$ and $\boldsymbol{\theta}$ to model the data ($\checkmark$)
- Compute the ratio efficiently (**?**)

Proposed block coordinate descent (BCD) algorithms

Algorithm 1 BCD for MLEs under H_1

Input: $\{\mathbf{x}_k^t\}$ with $t \in \{1, 2\}$

repeat

$$\tau_k^t = \left((\mathbf{x}_k^t)^H \boldsymbol{\Sigma}_t^{-1} \mathbf{x}_k^t \right) / p$$

$$\boldsymbol{\Sigma}_t = \mathcal{T}\left\{ \frac{1}{K} \sum_{k=1}^{K} \frac{\mathbf{x}_k^t (\mathbf{x}_k^t)^H}{\tau_k^t} \right\}$$

until convergence

Output: $\left\{ \hat{\boldsymbol{\Sigma}}_t, \{\hat{\tau}_k^t\} \right\}$

Algorithm 2 BCD for MLE under H_0

Input: $\{\mathbf{x}_k^1, \mathbf{x}_k^2\}$

repeat

$$\tau_k^0 = \left((\mathbf{x}_k^1)^H \boldsymbol{\Sigma}_0^{-1} \mathbf{x}_k^1 + (\mathbf{x}_k^2)^H \boldsymbol{\Sigma}_0^{-1} \mathbf{x}_k^2 \right) / 2p$$

$$\boldsymbol{\Sigma}_0 = \mathcal{T}\left\{ \frac{1}{K} \sum_{k=1}^{K} \frac{\mathbf{x}_k^1 (\mathbf{x}_k^1)^H + \mathbf{x}_k^2 (\mathbf{x}_k^2)^H}{2\tau_k^0} \right\}$$

until convergence

Output: $\left\{ \hat{\boldsymbol{\Sigma}}_0, \{\hat{\tau}_k^0\} \right\}$

Low-rank Compound-Gaussian GLRT

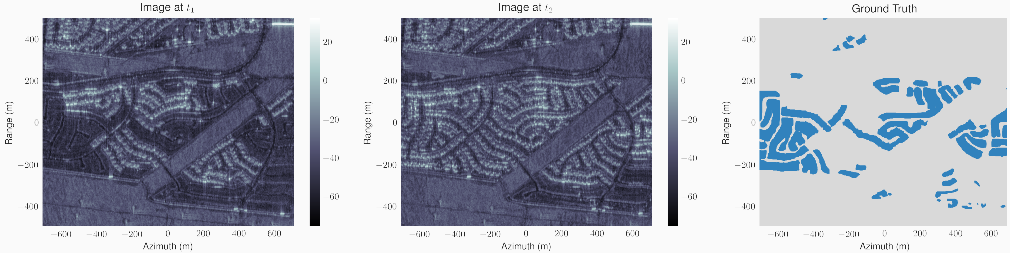
$$\frac{\mathcal{L}_{\mathrm{H}_1}\left(\{\mathbf{X}_1, \mathbf{X}_2\} \,;\, \left\{ \hat{\boldsymbol{\Sigma}}_1, \hat{\boldsymbol{\Sigma}}_2, \{\hat{\tau}_k^1\}, \{\hat{\tau}_k^2\} \right\} \right)}{\mathcal{L}_{\mathrm{H}_0}\left(\{\mathbf{X}_1, \mathbf{X}_2\} \,;\, \left\{ \hat{\boldsymbol{\Sigma}}_0, \{\hat{\tau}_k^0\} \right\} \right)} \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \lambda_{\mathrm{GLRT}}.$$

Experimental results

Dataset

Description

- Polarimetric data $\longrightarrow$ wavelet decomp. [Mian et al., 2017] $\longrightarrow$ $p = 12$ dim. pixels
- Image size: 2360px×600px
- Resolution: 1.67 m (Range) and 0.60 m (Azimuth)
- CD ground truth from [Nascimento et al., 2019]



Recall of the considered CD methods

Gaussian

$$\mathbf{x} \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \boldsymbol{\Sigma})$$
$$\boldsymbol{\theta} = \boldsymbol{\Sigma}$$

Low-rank Gaussian

$$\mathbf{x} \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \boldsymbol{\Sigma}_R + \sigma^2\mathbf{I})$$
$$\boldsymbol{\theta} = \boldsymbol{\Sigma}_R, \text{ with } \mathrm{rank}(\boldsymbol{\Sigma}_R) = R$$

Compound-Gaussian

$$\mathbf{x}_k \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \tau_k\boldsymbol{\Sigma})$$
$$\boldsymbol{\theta} = \{\boldsymbol{\Sigma}, \{\tau_k\}\}$$

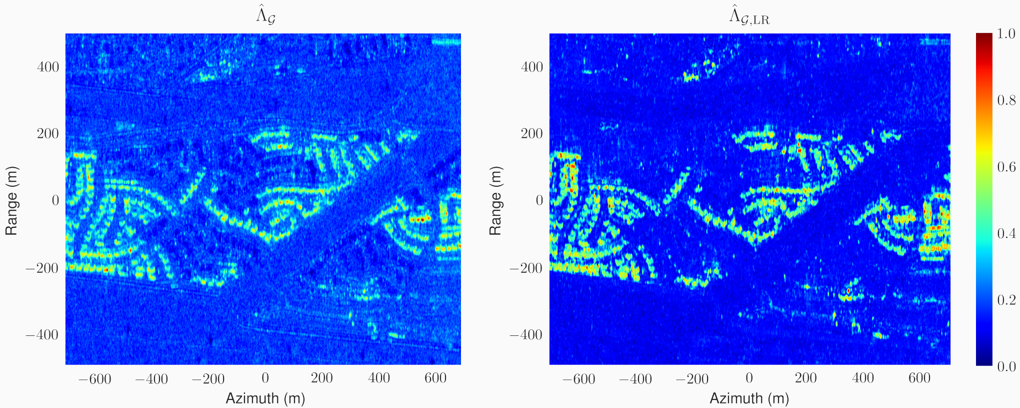
Low-rank Compound-Gaussian

$$\mathbf{x}_k \sim \mathbb{C}\mathcal{N}(\mathbf{0}_p, \tau_k(\boldsymbol{\Sigma}_R + \sigma^2\mathbf{I}))$$
$$\boldsymbol{\theta} = \{\boldsymbol{\Sigma}_R, \{\tau_k\}\}, \text{ with } \mathrm{rank}(\boldsymbol{\Sigma}_R) = R$$

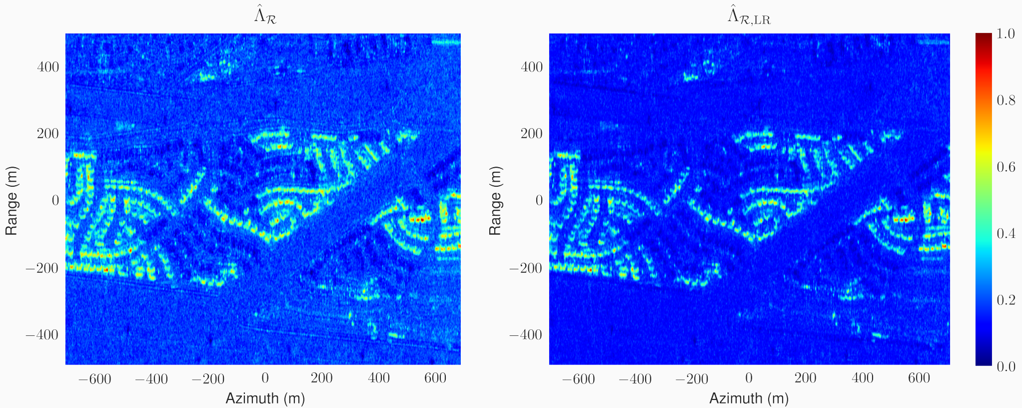
Side parameters

- Rank R and noise floor σ^2 estimated on the whole datacube

Results with a 5×5 sliding windows: Gaussian detectors



Results with a 5×5 sliding windows: Robust detectors



Performance curves

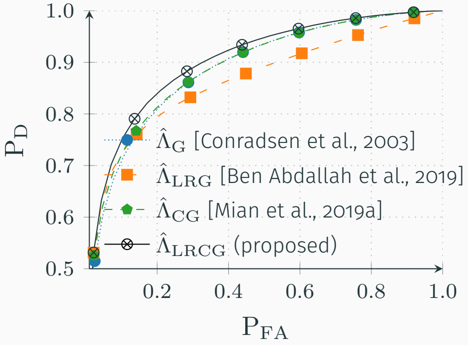


Figure 2: Probability of detection $\mathrm{P_D}$ versus probability of false alarm $\mathrm{P_{FA}}$ with $(p = 12, N = 25, R = 3)$

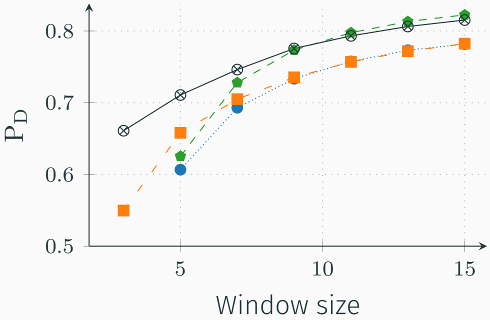


Figure 3: $\mathrm{P_D}$ versus the size of window at $\mathrm{P_{FA}} = 5\%$ with $(p = 12, R = 3)$

Thanks for your attention !

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Impact of rank estimation

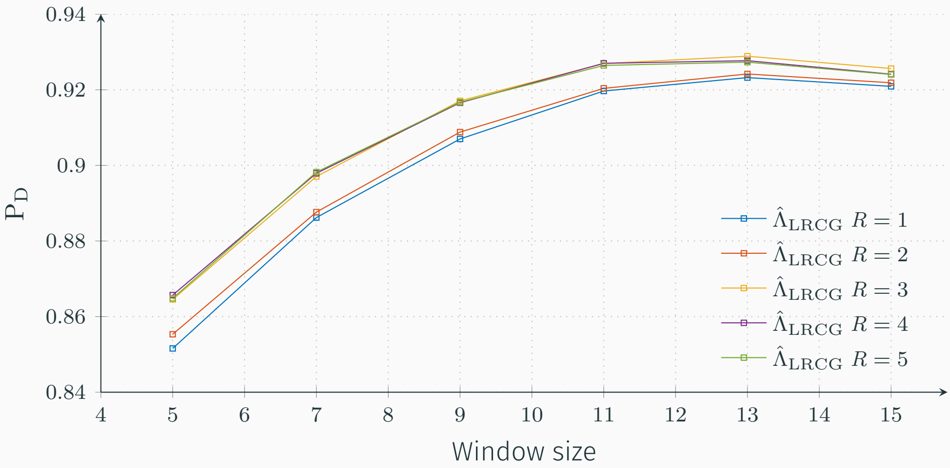
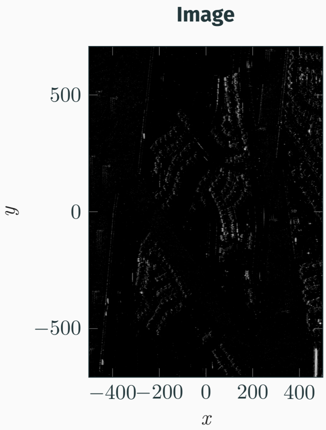
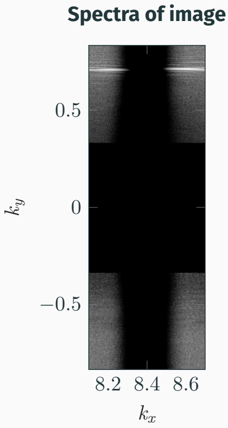


Figure 4: $\mathrm{P_D}$ versus the size of window at $\mathrm{P_{FA}} = 10\%$

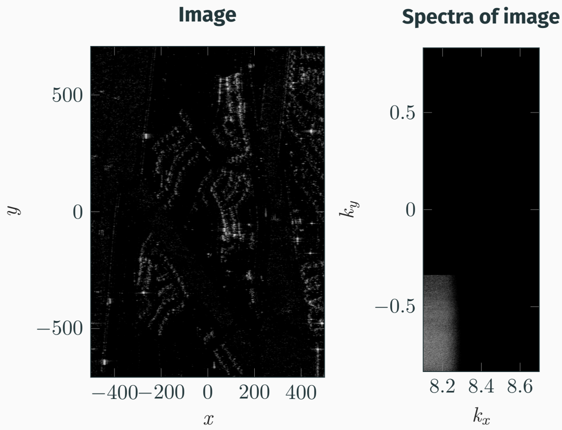
Wavelet decomposition pre-processing





As studied in [Mian et al., 2017], it is possible to increase detection performance by increasing data diversity using wavelet decomposition.
→ By doing a 2×2 decomposition, we obtain vectors of dimension $p = 12$.

Wavelet decomposition pre-processing



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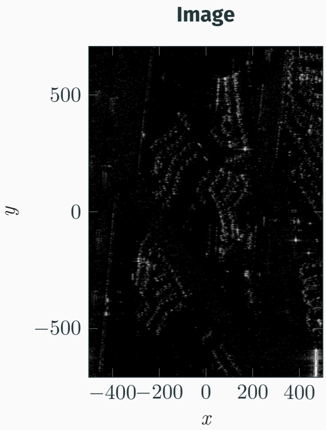

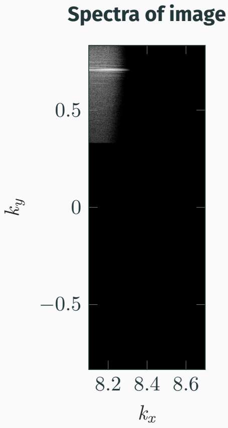

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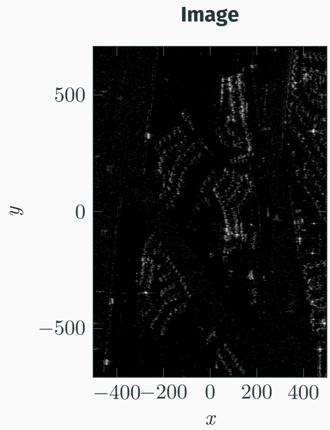

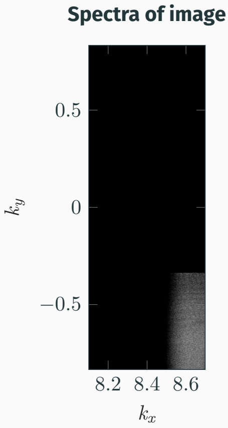

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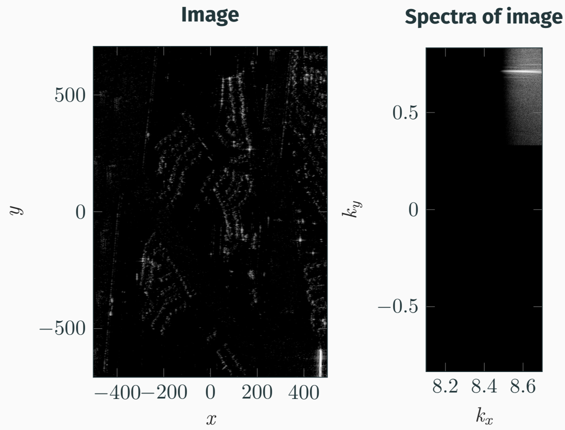

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