New statistical modeling of multi-sensor images with application to change detection

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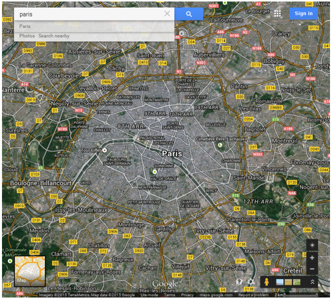
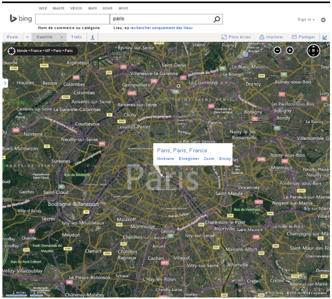
Outline

Remote Sensing Images

Remote sensing images are images of the Earth surface captured from a satellite or an airplane.



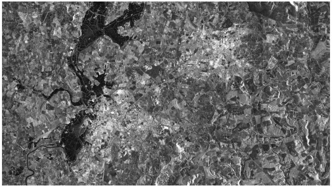


Change Detection

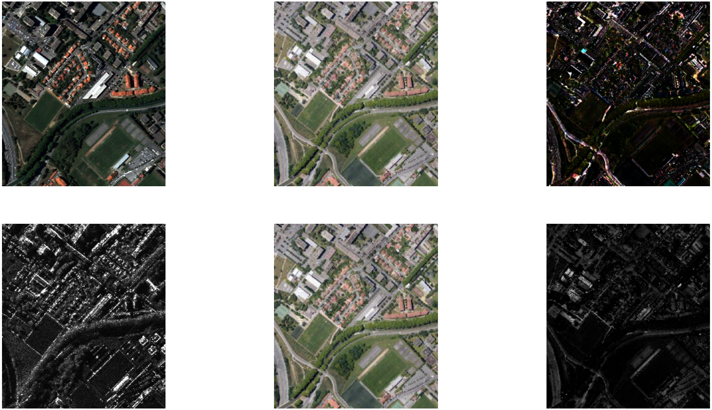
Multitemporal datasets are groups of images acquired at different times. We can detect changes on them!

Heterogeneous Sensors

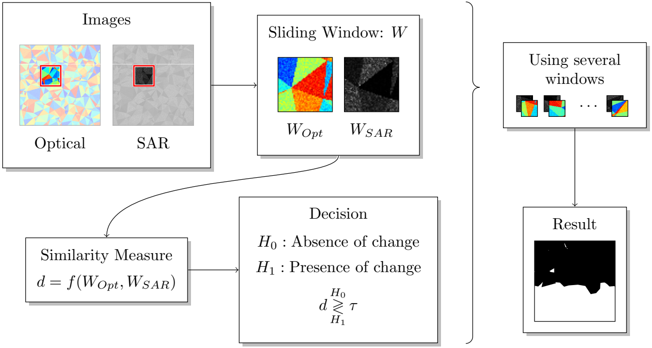
Optical images are not the only kind of images captured.
For instance, SAR images can be captured during the night, or with bad weather conditions.



Difference Image



Sliding window



Correlation coefficient

$$d = f(W_1, W_2) = \left| \frac{\mathrm{E}[(W_1 - \mu_{W_1})(W_2 - \mu_{W_2})]}{\sqrt{\mathrm{E}\left[(W_1 - \mu_{W_1})^2\right]\mathrm{E}\left[(W_2 - \mu_{W_2})^2\right]}} \right|$$

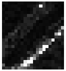
  ✓ no change

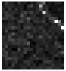
  ✗ change

Correlation coefficient

Mutual information

$$d = f(W_1, W_2) = \sum_{w_1 \in W_1} \sum_{w_2 \in W_2} \mathrm{p}(w_1, w_2) \log \left(\frac{\mathrm{p}(w_1, w_2)}{\mathrm{p}(w_1)\mathrm{p}(w_2)} \right)$$

  ✓ no change

  ✗ change

Mutual information

Optical image

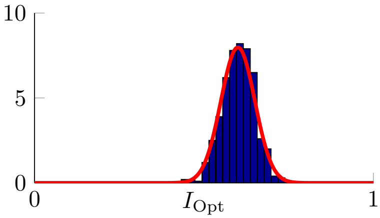
- Affected by additive Gaussian noise

$$I_{\text{Opt}} = T_{\text{Opt}}(P) + \nu_{\mathcal{N}(0,\sigma^2)}$$

$$I_{\text{Opt}}|P \sim \mathcal{N}\left[T_{\text{Opt}}(P), \sigma^2\right]$$

where

- $T_{\text{Opt}}(P)$ is how an object with physical properties P would be ideally seen by an optical sensor
- σ^2 is associated with the noise variance



Histogram of the normalized image

[1] J. Prendes, M. Chabert, F. Pascal, A. Giros, and J.-Y. Tourneret, "A new multivariate statistical model for change detection in images acquired by homogeneous and heterogeneous sensors," IEEE Trans. Image Process., vol. 24, no. 3, pp. 799–812, March 2015.

SAR image

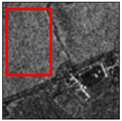
- Affected by multiplicative speckle noise (with gamma distribution)

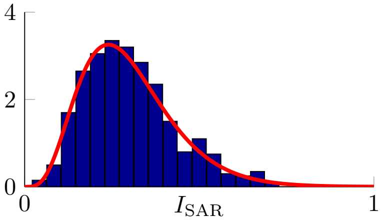
$$I_{\text{SAR}} = T_{\text{SAR}}(P) \times \nu_{\Gamma(L, \frac{1}{L})}$$

$$I_{\text{SAR}} | P \sim \Gamma\left[L, \frac{T_{\text{SAR}}(P)}{L}\right]$$

where

- $T_{\text{SAR}}(P)$ is how an object with physical properties P would be ideally seen by a SAR sensor
- L is the number of looks of the SAR sensor





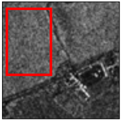
Histogram of the normalized image

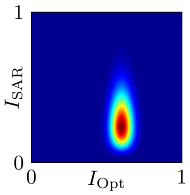
Joint distribution

- Independence assumption for the sensor noises

$$p(I_{\mathrm{Opt}}, I_{\mathrm{SAR}} | P) = p(I_{\mathrm{Opt}} | P) \times p(I_{\mathrm{SAR}} | P)$$

- *Conclusion*
  Statistical dependency (CC, MI) is not always an appropriate similarity measure





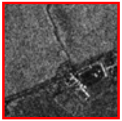
Sliding window

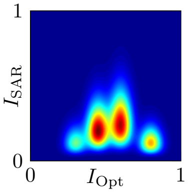
- Usually includes a finite number of objects, K
- Different values of P for each object

$$\Pr(P = P_k | W) = w_k$$

$$\mathrm{p}(I_{\mathrm{Opt}}, I_{\mathrm{SAR}} | W) = \sum_{k=1}^{K} w_k \mathrm{p}(I_{\mathrm{Opt}}, I_{\mathrm{SAR}} | P_k)$$

- Mixture distribution!





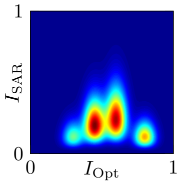
Motivation

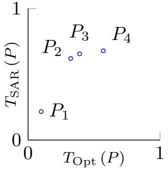
Parameters of the mixture distribution

- Can be used to derive $[T_{\text{Opt}}(P), T_{\text{SAR}}(P)]$ for each object

$$I_{\text{Opt}}|P \sim \mathcal{N}\left[T_{\text{Opt}}(P), \sigma^2\right]$$
$$I_{\text{SAR}}|P \sim \Gamma\left[L, \frac{T_{\text{SAR}}(P)}{L}\right]$$

- Related to P
- They are not independent

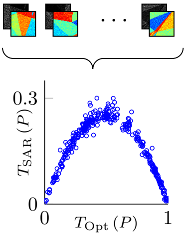




Manifold

- For each unchanged window, $v(P) = [T_{\text{Opt}}(P), T_{\text{SAR}}(P)]$ can be considered as a point on a manifold
- The manifold is parametric on P
- Estimating $v(P)$ from pixels with different values of P will trace the manifold

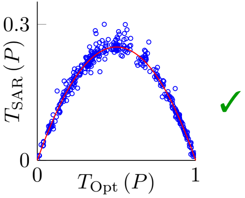
Several unchanged windows



Distance to the manifold

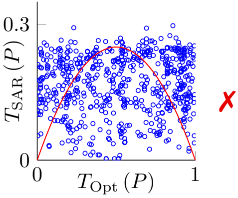
Unchanged regions

- Pixels belong to the same object
- P is the same for both images
- $\hat{v} = \left[\hat{T}_{\text{Opt}}(P), \hat{T}_{\text{SAR}}(P)\right]$



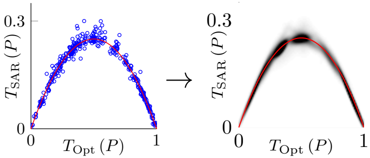
Changed regions

- Pixels belong to different objects
- P changes from one image to another
- $\hat{v} = \left[\hat{T}_{\text{Opt}}(P_1), \hat{T}_{\text{SAR}}(P_2)\right]$



Manifold estimation

- The manifold is *a priori* unknown
- We must estimate the distance to the manifold
- PDF of $v(P)$
  - Good distance measure
  - Learned using training data from unchanged images

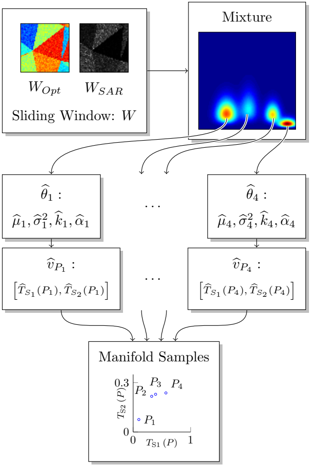


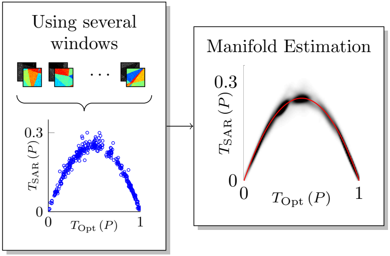
H_0 : Absence of change

H_1 : Presence of change

$$\hat{p}_{\mathbf{v}}(\hat{\mathbf{v}})^{-1} \underset{H_0}{\overset{H_1}{\gtrless}} \tau$$

Summary


Mixture
W_{Opt}
W_{SAR}
Sliding Window: W
$\widehat{\theta}_1$:
$\widehat{\mu}_1, \widehat{\sigma}_1^2, \widehat{k}_1, \widehat{\alpha}_1$
...
$\widehat{\theta}_4$:
$\widehat{\mu}_4, \widehat{\sigma}_4^2, \widehat{k}_4, \widehat{\alpha}_4$
$\widehat{v}_{P_1}$:
$[\widehat{T}_{S_1}(P_1), \widehat{T}_{S_2}(P_1)]$
...
$\widehat{v}_{P_4}$:
$[\widehat{T}_{S_1}(P_4), \widehat{T}_{S_2}(P_4)]$
Manifold Samples
0.3
0
$T_{S2}(P)$
P_1
P_2
P_3
P_4
0
$T_{S1}(P)$
1

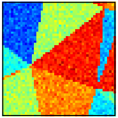

Using several windows
...
0.3
0
$T_{SAR}(P)$
0
$T_{Opt}(P)$
1
Manifold Estimation
0.3
0
$T_{SAR}(P)$
0
$T_{Opt}(P)$
1

Motivation

- To estimate $v(P)$ we must estimate the mixture parameters θ
- We can use a maximum likelihood estimator

$$\theta = \arg\max_{\theta} p(I_{\text{Opt}}, I_{\text{SAR}} | \theta)$$

- Two pixels $i_{\text{Opt},n}$ and $i_{\text{SAR},m}$ are not independent



Algorithm

- The class labels Z make the pixels independent

$$p(I_{\text{Opt}}, I_{\text{SAR}}|\theta, Z) = \prod_{n=1}^{N} p(i_{\text{Opt},n}, i_{\text{SAR},n}|\theta, z_n)$$

where we have N pixels in the window

- Now we also have to estimate Z

$$\theta = \arg\max_{\theta} p(I_{\text{Opt}}, I_{\text{SAR}}|\theta, Z)$$
$$= \sum_{n=1}^{N} \log\left[p(i_{\text{Opt},n}, i_{\text{SAR},n}|\theta, z_n)\right]$$

- Z can take N^K different values

Algorithm

- Iterative algorithm, estimate $\theta^{(i)}$ using $\theta^{(i-1)}$

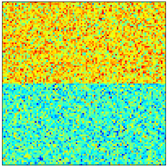
$$\mathrm{p}\left(z_n^{(i)} = k\right) = \frac{\mathrm{p}\left(i_{\mathrm{Opt},n}, i_{\mathrm{SAR},n} \middle| \theta^{(i-1)}, z_n = k\right)}{\sum_{j=1}^{K} \mathrm{p}\left(i_{\mathrm{Opt},n}, i_{\mathrm{SAR},n} \middle| \theta^{(i-1)}, z_n = j\right)}$$

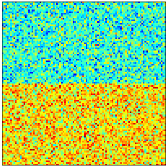
$$\theta^{(i)} = \sum_{n=1}^{N} \log\left[\sum_{j=1}^{K} \mathrm{p}\left(i_{\mathrm{Opt},n}, i_{\mathrm{SAR},n} \middle| \theta^{(i-1)}, z_n = j\right) \times \mathrm{p}\left(z_n^{(i)} = j\right)\right]$$

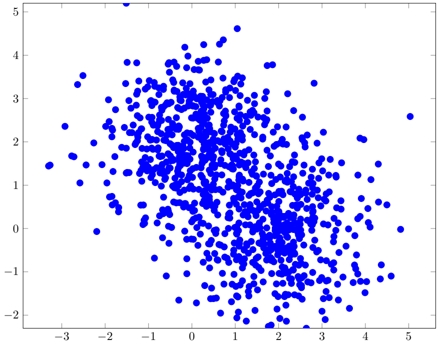
- The value of K is fixed, or estimated heuristically[1]

[1] M. A. T. Figueiredo and A. K. Jain, “Unsupervised learning of finite mixture models,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 3, pp. 381–396, March 2002.

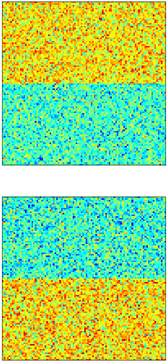
Example

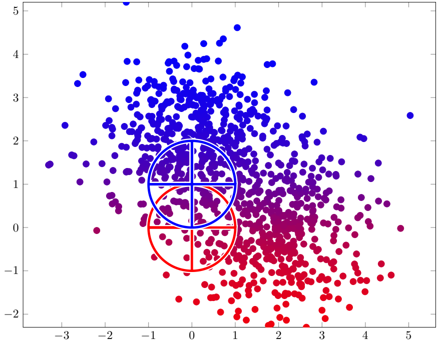




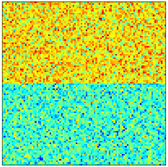


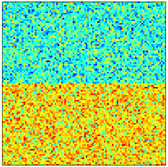
Example

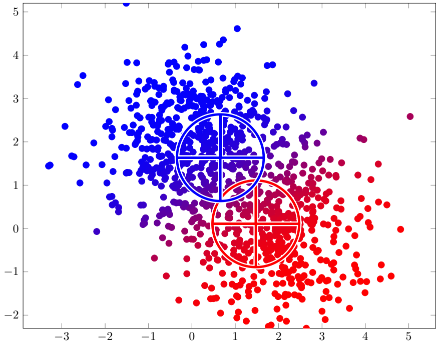




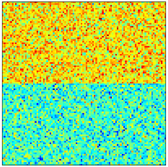
Example

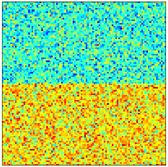


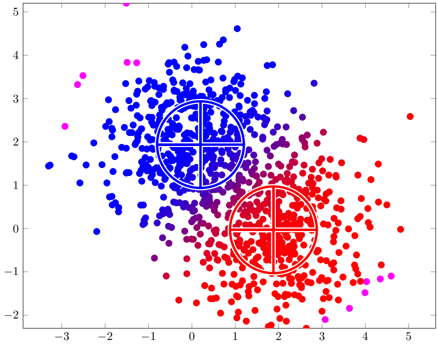




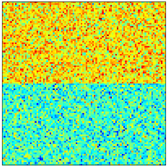
Example

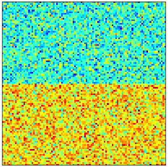


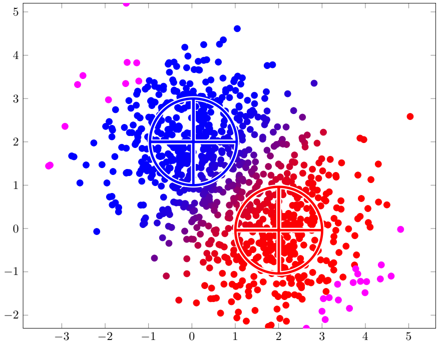




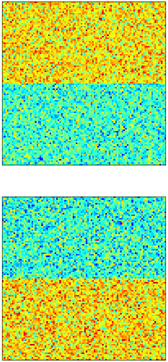
Example

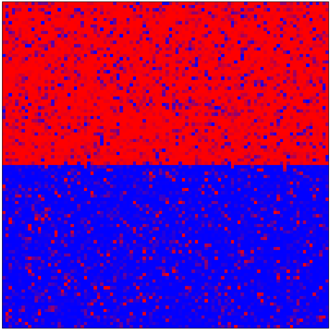




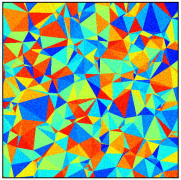


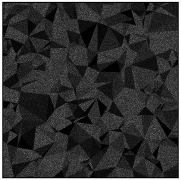
Example



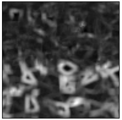


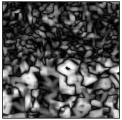
Results – Synthetic Optical and SAR Images

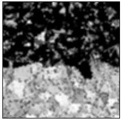

Synthetic optical image

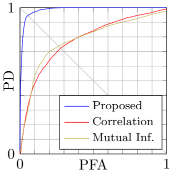

Synthetic SAR image


Change mask


Mutual Information


Correlation Coefficient

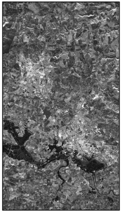

Proposed Method

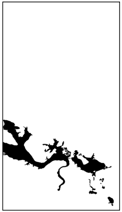


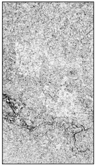
Performance – ROC

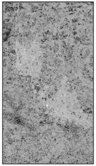
Results – Real Optical and SAR Images


Optical image before the flooding

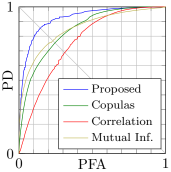

SAR image during the flooding


Change mask


Mutual Information


Conditional Copulas [2]

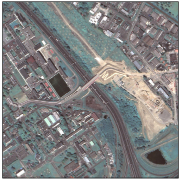

Proposed Method



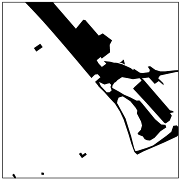
Performance – ROC

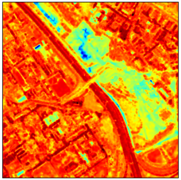
[2] G. Mercier, G. Moser, and S. B. Serpico, "Conditional copulas for change detection in heterogeneous remote sensing images," IEEE Trans. Geosci. and Remote Sensing, vol. 46, no. 5, pp. 1428–1441, May 2008.

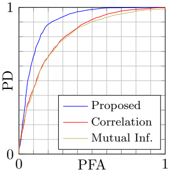
Results – Pléiades Images


Pléiades – May 2012


Pléiades – Sept. 2013


Change mask

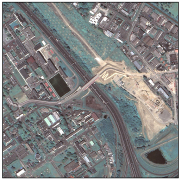

Change map



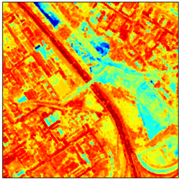
Performance – ROC

Special thanks to CNES for providing the Pléiades images

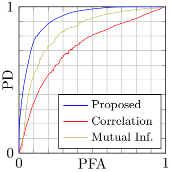
Results – Pléiades and Google Earth Images


Pléiades – May 2012


Google Earth – July 2013


Change map

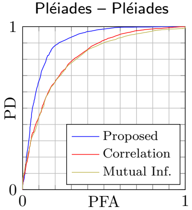

Change mask



Performance – ROC

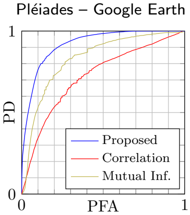
Results

Homogeneous images



- *CC and MI*
  Similar performance
- *Proposed method*
  Improved performance

Heterogeneous images



- *CC*
  Reduced Performance
- *Proposed method and MI*
  Performance not affected

Motivation

- Introduce a Bayesian framework into the labels: K is not fixed
- Classic mixture model

$$\boldsymbol{i}_n \big| \boldsymbol{v}_n \sim \mathcal{F}(\boldsymbol{v}_n)$$

$$\boldsymbol{v}_n \big| \boldsymbol{V}' \sim \sum_{k=1}^{K} w_k \delta\left(\boldsymbol{v}_n - \boldsymbol{v}'_k\right)$$

$\boldsymbol{i}_n = \left[i_{\mathrm{Opt},n}, i_{\mathrm{SAR},n}\right]$, and $\mathcal{F}$ is a distribution family which is application dependent, i.e., a bivariate Normal-Gamma distribution.

Motivation

- Prior in the mixture parameters

$$\boldsymbol{v}'_k \sim \mathcal{V}_0$$
$$\boldsymbol{w} \sim \mathrm{Dir}\left(\alpha K^{-1} \boldsymbol{u}_K\right)$$

- Now make $K \to \infty$
  - $\boldsymbol{v}_n$ will still present clustering behavior
  - There are infinite parameters for the prior of $\boldsymbol{v}_n$

Bayesian non parametric

- Dirichlet Process

$$\begin{aligned} \boldsymbol{i}_n | \boldsymbol{v}_n &\sim \mathcal{F}(\boldsymbol{v}_n) \\ \boldsymbol{v}_n &\sim \mathcal{V} \\ \mathcal{V} &\sim \mathrm{DP}(\mathcal{V}_0, \alpha). \end{aligned}$$

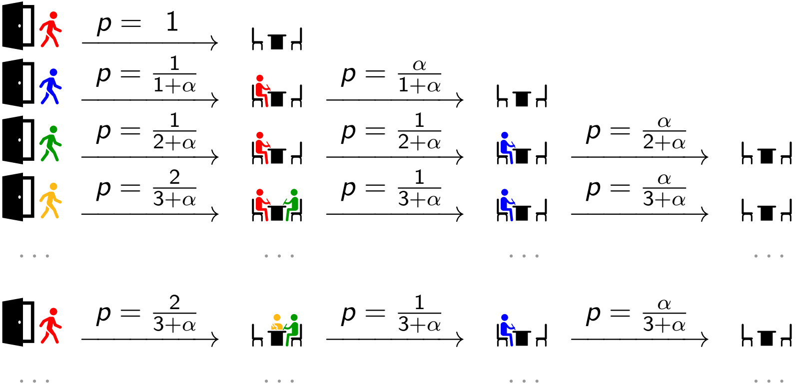
$$\begin{aligned} \boldsymbol{i}_n | z_n &\sim \mathcal{F}(\boldsymbol{v}'_{z_n}) \\ \boldsymbol{z} &\sim \mathrm{CRP}(\alpha) \\ \boldsymbol{v}'_k &\sim \mathcal{V}_0. \end{aligned}$$

- Algorithm

For $n \geq 1$
  $u \sim \mathrm{Uniform}(1, \alpha + n)$
  If $u < n$
    $\boldsymbol{v}_n \leftarrow \boldsymbol{v}_{\lfloor u \rfloor}$
  Else
    $\boldsymbol{v}_n \sim \mathcal{V}_0$

Allows to sample the finite $\boldsymbol{v}_n$ from α and $\mathcal{V}_0$ skipping the infinite parameters

Bayesian non parametric



Markov random fields

- Markov random fields are a common tool to capture spatial correlation
- We would like to define

$$\mathrm{p}\left(z_n \middle| \boldsymbol{z}_{\setminus n}\right) = \mathrm{p}\left(z_n \middle| \boldsymbol{z}_{\delta(n)}\right)$$

- MRF define the constraints to define a joint distribution $\mathrm{p}(Z)$

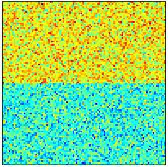
Markov random fields

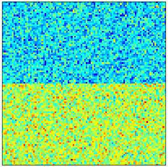
- We will define out joint distribution as

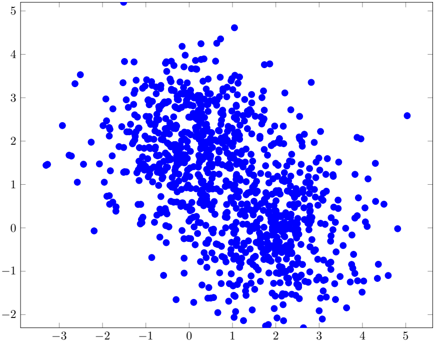
$$
\begin{aligned}
\mathrm{p}\left(z_n \middle| \boldsymbol{z}_{\backslash n}\right) &\propto \exp\left[H\left(z_n \middle| \boldsymbol{z}_{\backslash n}\right)\right] \\
H\left(z_n \middle| \boldsymbol{z}_{\backslash n}\right) &= H_n(z_n) + \sum_{m \in \delta(n)} \omega_{nm} \mathbf{1}_{z_n}(z_m) \\
&= H_n(z_n) + \sum_{\substack{m \in \delta(n) \\ z_n = z_m}} \omega_{nm}
\end{aligned}
$$

- The trick is to take $H_n(z_n) = \log \mathrm{p}(z_n | I_n, \boldsymbol{V})$

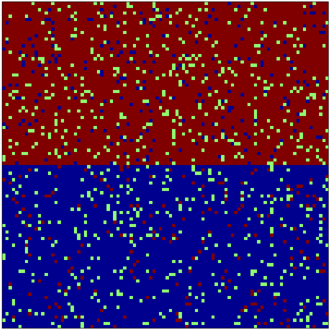
Example

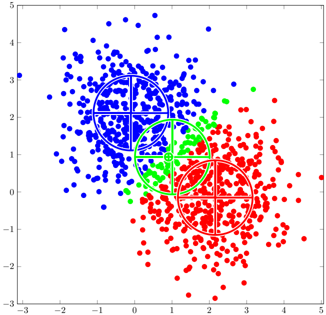




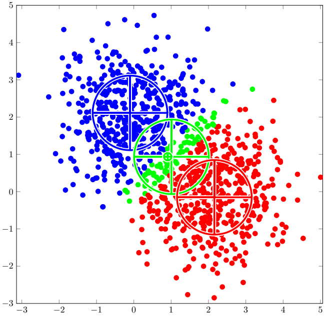


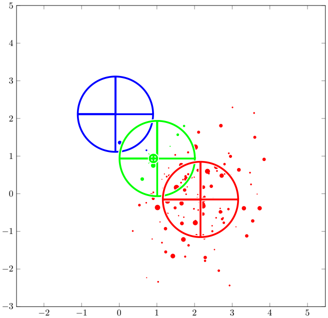
Example



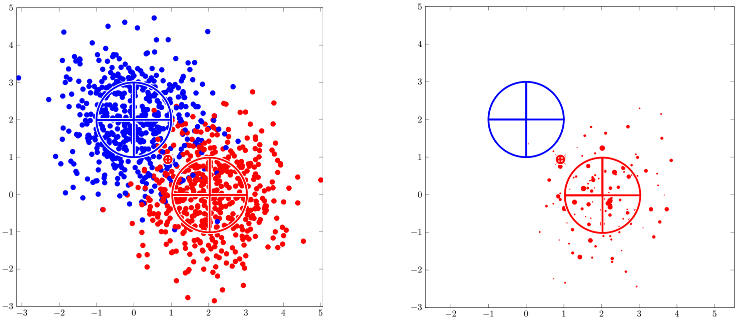


Example

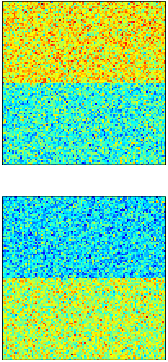


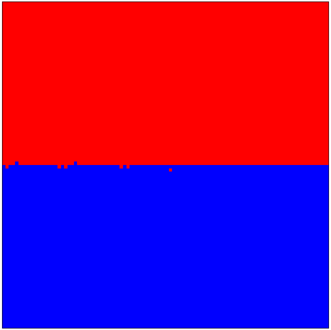


Example

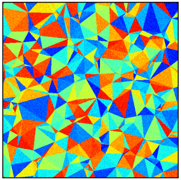


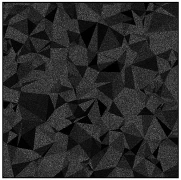
Example



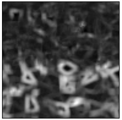


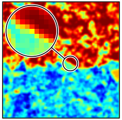
Results – Synthetic Optical and SAR Images

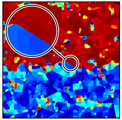

Synthetic optical image

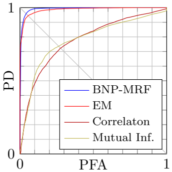

Synthetic SAR image


Change mask


Mutual Information


EM

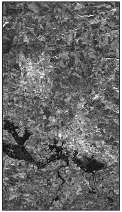

BNP

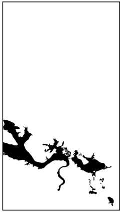


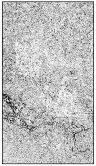
Performance – ROC

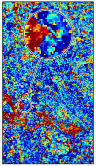
Results – Real Optical and SAR Images

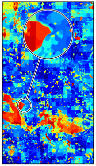

Optical image before the flooding

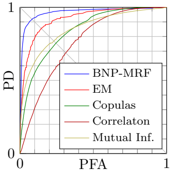

SAR image during the flooding


Change mask


Mutual Information

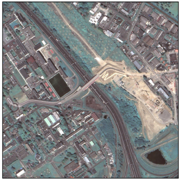

EM


BNP

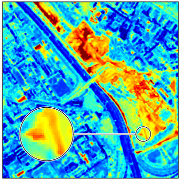


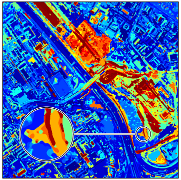
Performance – ROC

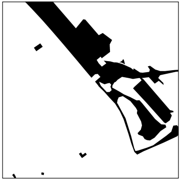
Results – Pléiades Images

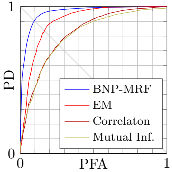

Pléiades – May 2012


Pléiades – Sept. 2013


EM


BNP

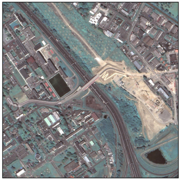

Change mask



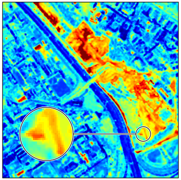
Performance – ROC

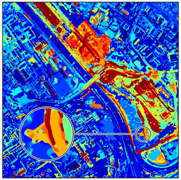
Special thanks to CNES for providing the Pléiades images

Results – Pléiades and Google Earth Images

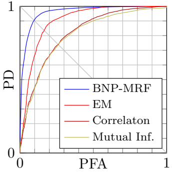

Pléiades – May 2012


Google Earth – July 2013


EM


BNP


Change mask



Performance – ROC

Conclusions and Future Work

Conclusions

- New statistical model to describe multi-channel images
  - Analyze the joint behavior of the channels to detect changes, in contrast with channel by channel analysis
  - e.g., Pléiades multi-spectral and panchromatic images
- New similarity measure showing encouraging results for homogeneous and heterogeneous sensors
  - Pléiades – Pléiades
  - Pléiades – SAR
  - Pléiades – Other VHR instument
- Interesting for many applications
  - Change detection
  - Classification
  - Registration – using the similarity measure to measure miss-registration

Conclusions and Future Work

Future Work

- Study the method performance for different image features
  - Texture coefficients: Haralick, Gabor, QMF
  - Wavelet coefficients
  - Gradients

Thank you for your attention

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