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

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- 3 Similarity measure
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# Remote Sensing Images

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





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# Change Detection

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





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### Heterogeneous Sensors

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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.





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### **Difference Image**



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### Sliding window



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### Correlation coefficient

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### Correlation coefficient



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# Mutual information

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

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# Mutual information



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# Optical image

 Affected by additive Gaussian noise

$$\begin{split} I_{\mathsf{Opt}} &= T_{\mathsf{Opt}}(P) + \nu_{\mathcal{N}(0,\sigma^2)} \\ I_{\mathsf{Opt}}|P \sim \mathcal{N}\big[ T_{\mathsf{Opt}}(P), \sigma^2 \big] \end{split}$$

#### where

- T<sub>Opt</sub>(P) is how an object with physical properties P would be ideally seen by an optical sensor
- $\sigma^2$  is associated with the noise variance







[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.

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# SAR image

 Affected by multiplicative speckle noise (with gamma distribution)

$$I_{SAR} = T_{SAR}(P) \times \nu_{\Gamma\left(L,\frac{1}{L}\right)}$$
$$I_{SAR}|P \sim \Gamma\left[L,\frac{T_{SAR}(P)}{L}\right]$$

where

- T<sub>SAR</sub>(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





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# Joint distribution

Independence assumption for the sensor noises

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

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

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# Sliding window

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

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

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

Mixture distribution!

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# Motivation

Parameters of the mixture distribution

 Can be used to derive [T<sub>Opt</sub>(P), T<sub>SAR</sub>(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

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They are not independent





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- For each unchanged window,
   v(P) = [T<sub>Opt</sub>(P), T<sub>SAR</sub>(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





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# Distance to the manifold

### **Unchanged regions**

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



### **Changed regions**

- Pixels belong to different objects
- *P* changes from one image to another

• 
$$\hat{\mathbf{v}} = \left[\hat{T}_{\mathsf{Opt}}(P_1), \hat{T}_{\mathsf{SAR}}(P_2)\right]$$



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# Manifold estimation

- The manifold is a priori unknown
- We must estimate the distance to the manifold
- PDF of v(P)

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- Good distance measure
- Learned using training data from unchanged images



*H*<sub>0</sub> : Absence of change*H*<sub>1</sub> : Presence of change

$$\hat{p}_{oldsymbol{
u}}(\hat{oldsymbol{
u}})^{-1} \mathop{\gtrless}\limits_{H_0}^{H_1} au \ H_0$$

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### Summary

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

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

• Two pixels  $i_{Opt,n}$  and  $i_{SAR,m}$  are not independent



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# Algorithm

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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

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

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Expectation maximization						

### Algorithm

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

$$\begin{split} \mathsf{p}\Big(z_n^{(i)} = k\Big) &= \frac{\mathsf{p}\Big(i_{\mathsf{Opt},n}, i_{\mathsf{SAR},n} \big| \theta^{(i-1)}, z_n = k\Big)}{\sum_{j=1}^{K} \mathsf{p}\Big(i_{\mathsf{Opt},n}, i_{\mathsf{SAR},n} \big| \theta^{(i-1)}, z_n = j\Big)}\\ \theta^{(i)} &= \sum_{n=1}^{N} \log \left[\sum_{j=1}^{K} \mathsf{p}\Big(i_{\mathsf{Opt},n}, i_{\mathsf{SAR},n} \big| \theta^{(i-1)}, z_n = j\Big) \times \mathsf{p}\Big(z_n^{(i)} = j\Big)\right] \end{split}$$

### • The value of K is fixed, or estimated heuristically<sup>[1]</sup>

 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.

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# Results – Synthetic Optical and SAR Images





Synthetic SAR image







Mutual Information

Correlation Coefficient





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Change mask

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#### Results

### Results – Real Optical and SAR Images



before the flooding

the flooding

[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.

Mutual Information





Proposed Method



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### Results – Pléiades Images



Pléiades - May 2012

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Pléiades - Sept. 2013



Change map



Change mask Special thanks to CNES for providing the Pléiades images

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Results

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# Results – Pléiades and Google Earth Images









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#### Homogeneous images



- CC and MI
   Similar performance
- Proposed method Improved performance

#### Heterogeneous images



CC
 Reduced Performance

 Proposed method and MI Performance not affected

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

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$$egin{aligned} &oldsymbol{i}_n |oldsymbol{v}_n \sim \mathcal{F}(oldsymbol{v}_n) \ &oldsymbol{v}_n |oldsymbol{V}' \sim \sum_{k=1}^K w_k \deltaig(oldsymbol{v}_n - oldsymbol{v}'_k) \end{aligned}$$

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

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Prior in the mixture parameters

$$oldsymbol{v}_k^\prime \sim \mathcal{V}_0$$
  
 $oldsymbol{w} \sim \mathsf{Dir}ig(lpha \mathcal{K}^{-1} oldsymbol{u}_{\mathcal{K}}ig)$ 

Now make  $K \to \infty$ 

v<sub>n</sub> will still present clustering behavior

• There are infinite parameters for the prior of  $\boldsymbol{v}_n$ 

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### Bayesian non parametric

Dirichlet Process  $i_n | \mathbf{v}_n \sim \mathcal{F}(\mathbf{v}_n)$  $m{v}_n \sim \mathcal{V}$  $\mathcal{V} \sim \mathsf{DP}(\mathcal{V}_0, \alpha).$ Algorithm For n > 1 $u \sim \text{Uniform}(1, \alpha + n)$ If u < n $\mathbf{v}_n \leftarrow \mathbf{v}_{|\mu|}$ Flse  $m{v}_n\sim\mathcal{V}_0$ 

$$egin{aligned} &oldsymbol{i}_n | z_n \sim \mathcal{F}ig( oldsymbol{v}'_{z_n} ig) \ &oldsymbol{z} \sim \mathsf{CRP}(lpha) \ &oldsymbol{v}'_k \sim \mathcal{V}_0. \end{aligned}$$

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

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### Bayesian non parametric



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### Markov random fields

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

$$\mathsf{p}(z_n|\boldsymbol{z}_{\backslash n})=\mathsf{p}(z_n|\boldsymbol{z}_{\delta(n)})$$

• MRF define the constraints to define a joint distribution p(Z)

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### Markov random fields

We will define out joint distribution as

$$p(z_n | \mathbf{z}_{\setminus n}) \propto \exp \left[ H(z_n | \mathbf{z}_{\setminus n}) \right]$$
$$H(z_n | \mathbf{z}_{\setminus n}) = H_n(z_n) + \sum_{\substack{m \in \delta(n) \\ z_n = z_m}} \omega_{nm} \mathbf{1}_{z_n}(z_m)$$

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

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Results

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# Results – Synthetic Optical and SAR Images





Synthetic SAR image



Mutual Information

BNP



Change mask



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# Results - Real Optical and SAR Images





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AR image during the flooding



Change mask







Mutual Information



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### Results – Pléiades Images



Special thanks to CNES for providing the Pléiades images

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### Results – Pléiades and Google Earth Images



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Google Earth - July 2013



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

Change mask

Introduction 000000000	Image model 0000	Similarity measure	Expectation maximization 0000 00000	Bayesian non parametric 0000000 0000	Conclusions ●00
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### 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

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### Conclusions and Future Work

#### **Future Work**

#### Study the method performance for different image features

- Texture coefficients: Haralick, Gabor, QMF
- Wavelet coefficients
- Gradients

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### Thank you for your attention

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