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

Jorge PRENDES

Marie CHABERT, Frédéric PASCAL, Alain GIROS, Jean-Yves TOURNERET

June 15, 2015 – TéSA
Outline

1. Introduction
2. Image model
3. Similarity measure
4. Expectation maximization
5. Bayesian non parametric
6. Conclusions
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

Images
Optical  SAR

Similarity Measure
\[ d = f(W_{Opt}, W_{SAR}) \]

Sliding Window: \( W \)
\[ W_{Opt} \quad W_{SAR} \]

Decision
\[ H_0 : \text{Absence of change} \]
\[ H_1 : \text{Presence of change} \]
\[ d \geq \tau \]

Using several windows

Result
Correlation coefficient

\[ d = f(W_1, W_2) = \frac{\mathbb{E}[(W_1 - \mu_{W_1})(W_2 - \mu_{W_2})]}{\sqrt{\mathbb{E}[(W_1 - \mu_{W_1})^2]\mathbb{E}[(W_2 - \mu_{W_2})^2]}} \]

- ✔ no change
- ✗ change
Correlation coefficient
Mutual information

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

- ![Image](image1.png)
  - no change

- ![Image](image2.png)
  - change
Mutual information

- Image model
- Similarity measure
- Expectation maximization
- Bayesian non parametric
- Conclusions

Introduction

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

Optical image

- Affected by additive Gaussian noise

\[ I_{\text{Opt}} = T_{\text{Opt}}(P) + \nu \mathcal{N}(0, \sigma^2) \]

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

where

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

Histogram of the normalized image

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

\[ p(I_{\text{Opt}}, I_{\text{SAR}} | P) = p(I_{\text{Opt}} | P) \times p(I_{\text{SAR}} | P) \]

- 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

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

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

- Mixture distribution!
Motivation

Parameters of the mixture distribution

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

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

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

- Related to \( P \)
- They are not independent
For each unchanged window, $v(P) = [T_{Opt}(P), T_{SAR}(P)]$ 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.
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
- $\hat{v} = \left[ \hat{T}_{\text{Opt}}(P_1), \hat{T}_{\text{SAR}}(P_2) \right]$

\[
\begin{align*}
T_{\text{SAR}}(P) &\quad 0.3 \\
T_{\text{Opt}}(P) &\quad 0 \quad 0.3 \\
\checkmark &\quad 1
\end{align*}
\]

\[
\begin{align*}
T_{\text{SAR}}(P) &\quad 0.3 \\
T_{\text{Opt}}(P) &\quad 0 \quad 0.3 \\
\times &\quad 1
\end{align*}
\]
Manifold estimation

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

$$H_0 : \text{Absence of change}$$
$$H_1 : \text{Presence of change}$$

$$\hat{p}_\nu(\hat{\nu})^{-1} \begin{cases} H_1 \\ \geq \tau \\ H_0 \end{cases}$$
Summary

Manifold Samples

Using several windows

Manifold Estimation
Motivation

- To estimate $\nu(P)$ we must estimate the mixture parameters $\theta$
- 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
The class labels $Z$ make the pixels independent

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

where we have $N$ pixels in the window

Now we also have to estimate $Z$

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

$$= \sum_{n=1}^{N} \log [p(i_{Opt,n}, i_{SAR,n}|\theta, z_n)]$$

$Z$ can take $N^K$ different values
Algorithm

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

\[
p(z_n^{(i)} = k) = \frac{p(i_{\text{Opt},n}, i_{\text{SAR},n} \mid \theta^{(i-1)}, z_n = k)}{\sum_{j=1}^{K} p(i_{\text{Opt},n}, i_{\text{SAR},n} \mid \theta^{(i-1)}, z_n = j)}
\]

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

- The value of $K$ is fixed, or estimated heuristically\(^1\)

Expectation maximization

Example
Example
Example
Example
Example

![Diagram](image-url)
Example
Results – Synthetic Optical and SAR Images
Results – Real Optical and SAR Images

Results

Results – Pléiades Images

Special thanks to CNES for providing the Pléiades images
Results – Pléiades and Google Earth Images

Pléiades – May 2012

Google Earth – July 2013

Change map

Performance – ROC

J. Prendes

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

\[
i_n | \mathbf{v}_n \sim \mathcal{F}(\mathbf{v}_n)
\]

\[
\mathbf{v}_n | \mathbf{V}' \sim \sum_{k=1}^{K} w_k \delta(\mathbf{v}_n - \mathbf{v}_k')
\]

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

- Prior in the mixture parameters

\[ \mathbf{v}'_k \sim \mathcal{V}_0 \]
\[ \mathbf{w} \sim \text{Dir}(\alpha K^{-1} \mathbf{u}_K) \]

- Now make \( K \to \infty \)
  - \( \mathbf{v}_n \) will still present clustering behavior
  - There are infinite parameters for the prior of \( \mathbf{v}_n \)
Bayesian non parametric

- Dirichlet Process
  \[ i_n | v_n \sim F(v_n) \]
  \[ v_n \sim \mathcal{V} \]
  \[ \mathcal{V} \sim \text{DP}(\mathcal{V}_0, \alpha). \]

- Algorithm
  For \( n \geq 1 \)
  \[ u \sim \text{Uniform}(1, \alpha + n) \]
  If \( u < n \)
  \[ v_n \leftarrow v_{[u]} \]
  Else
  \[ v_n \sim \mathcal{V}_0 \]

\[ i_n | z_n \sim F(v'_{z_n}) \]
\[ z \sim \text{CRP}(\alpha) \]
\[ v'_k \sim \mathcal{V}_0. \]

Allows to sample the finite \( v_n \) from \( \alpha \) and \( \mathcal{V}_0 \) skipping the infinite parameters.
Bayesian non parametric

\[ p = \frac{1}{1+\alpha} \rightarrow \frac{1}{2+\alpha} \rightarrow \frac{2}{3+\alpha} \rightarrow \cdots \]

\[ p = \frac{\alpha}{1+\alpha} \rightarrow \frac{1}{2+\alpha} \rightarrow \frac{1}{3+\alpha} \rightarrow \cdots \]

\[ p = \frac{\alpha}{2+\alpha} \rightarrow \frac{\alpha}{3+\alpha} \rightarrow \cdots \]

\[ p = \frac{2}{3+\alpha} \rightarrow \frac{1}{3+\alpha} \rightarrow \frac{\alpha}{3+\alpha} \rightarrow \cdots \]
Markov random fields

- Markov random fields are a common tool to capture spatial correlation
- We would like to define
  \[ p(z_n|z_{\delta(n)}) = p(z_n|z_{\delta(n)}) \]
- MRF define the constraints to define a joint distribution \( p(Z) \)
We will define our joint distribution as

\[ p(z_n | z_{\backslash n}) \propto \exp \left[ H(z_n | z_{\backslash n}) \right] \]

\[ H(z_n | z_{\backslash n}) = H_n(z_n) + \sum_{m \in \delta(n)} \omega_{nm} 1_{z_n}(z_m) \]

\[ = H_n(z_n) + \sum_{m \in \delta(n)} \omega_{nm} \quad \text{for} \quad z_n = z_m \]

The trick is to take \( H_n(z_n) = \log p(z_n | I_n, V) \)
Bayesian non parametric

Example
Example
Example

![Graph 1](image1.png)

![Graph 2](image2.png)
Example
**Example**

<table>
<thead>
<tr>
<th>Bayesian non parametric</th>
</tr>
</thead>
</table>

- Image model
- Similarity measure
- Expectation maximization
- Conclusions

![Example Image](image-url)
## Results – Synthetic Optical and SAR Images

<table>
<thead>
<tr>
<th>Synthetic optical image</th>
<th>Synthetic SAR image</th>
<th>Change mask</th>
<th>Mutual Information</th>
<th>EM</th>
<th>BNP</th>
</tr>
</thead>
</table>

Performance – ROC

![ROC curve](image)

**J. Prendes**

**TeSA – Supélec-SONDRA – INP/ENSEEIHT – CNES**

New statistical modeling of multi-sensor images with application to change detection
Results – Real Optical and SAR Images

Optical image before the flooding

SAR image during the flooding

Change mask

Mutual Information

EM

BNP

Performance – ROC

J. Prendes
Results – Pléiades Images

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

J. Prendes TéSA – Supélec-SONDRA – INP/ENSEEIHT – CNES
New statistical modeling of multi-sensor images with application to change detection
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 instrument

- 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

Jorge Prendes
jorge.prendes@tesa.prd.fr