A New Statistical Model for Multisensor Change Detection

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

TéSA – Supélec-SONDRA – INP/ENSEEIHT – CNES

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Outline

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2. Image Model
3. Similarity Measure
4. Results
5. Conclusions
Motivation

- Monitor urban/rural area evolution
  - Detect new constructions
  - Track changes in agricultural areas
  - Track urban growth

- Coordinate efforts after natural disasters
  - Volcano eruptions
  - Floodings
  - Earthquakes

- Database updating

- Improve the analysis of remote sensing images
  - Find new objects
Introduction – Change Detection for Remote Sensing Images

**Optical Images**
- **Pro**
  - High resolution
  - Easy to interpret
  - Low noise
- **Cons**
  - Needs sunlight
  - Weather dependent

**Radar (SAR) Images**
- **Pro**
  - Can be acquired at night
  - Not occluded by clouds
- **Cons**
  - Lower resolution
  - Speckle noise
  - Interpretation problems
Introduction – Change Detection for Remote Sensing Images

**Usual Change Detection Framework**

- Define a sliding window $W$
- Compute a *similarity measure* on $W$
- Threshold the measure to detect changes

**Statistical Similarity Measures**

- Measure the dependency between pixel intensities
  - Correlation Coefficient
  - Mutual Information
- Others
  - KL-Divergence
Introduction – Change Detection for Remote Sensing Images

Correlation Coefficient (CC)
- Measures linear correlations
  - Only one of many kinds of dependencies!
- Good for homogeneous sensors
- Fails for homogeneous regions
  - Low spatial resolution
Introduction – Change Detection for Remote Sensing Images

**Mutual Information (MI)**
- Measures statistical dependency
- Good for heterogeneous and homogeneous sensors
  - Requires a good estimation of the joint distribution!
- Fails for homogeneous regions
  - Low spatial resolution
Image Model – Optical image for Homogeneous Regions

Sensor Measurements

- Affected by additive Gaussian noise

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

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

where

- \( T_{Opt}(P) \) 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
Image Model – SAR Image for Homogeneous Regions

Sensor Measurements

- Affected by multiplicative speckle noise (with gamma distribution)

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

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

where

- \( T_{SAR}(P) \) 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
Image Model – Joint Distribution for Homogeneous Regions

- 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
Image Model – Heterogeneous Regions

**Sliding window** $W$

- 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!
Similarity Measure – Introduction

Mixture distribution

- Parameters estimation methods
  - Method of moments
  - Expectation Maximization Algorithm
  - Markov Chain Monte Carlo Methods

- Estimates
  - Related to $P$
  - Can be used to derive $[T_{\text{Opt}}(P), T_{\text{SAR}}(P)]$ for each object
**Similarity Measure – Manifold**

**Manifold learning**

- For each unchanged window, $v(P) = [T_{Opt}(P), T_{SAR}(P)]$ can be considered as a point on a manifold.
Similarity Measure – Manifold

**Unchanged regions**
- Pixels belong to the **same** object
- $P$ is the same for both images

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

![Graphs showing TSAR and TOpt](image_url)
**Similarity Measure – Manifold**

**Distance measure between Optical and SAR images**

- PDF of \( \nu(P) \)
- Good distance measure
- Learned using training data from unchanged images

\[
H_0 : \text{Absence of change} \\
H_1 : \text{Presence of change}
\]

\[
\sum_{k=1}^{K} \hat{w}_k \hat{p}_T (\hat{v}_{W,k}) \overset{H_0}{\gtrless} \tau \overset{H_1}{=} \tau
\]

where

- \( \hat{w}_k \) is the estimated \( w_k \)
- \( \hat{v}_{W,k} \) is the estimated vector \( \nu \) for the \( k \)-th component of the window \( W \)
- \( \hat{p}_T \) is the estimated density of \( \nu(P) \)
- \( \tau \) is an application dependent threshold
Similarity Measure – Summary

Using several windows

Manifold Estimation
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 [1]  |  Proposed Method

Performance – ROC

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 mask

Change map

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
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
  - Registration
  - Segmentation
  - Classification
Conclusions and Future Work

Future Work

- Include priors on the sensor parameters: Bayesian methods
- 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