A Multivariate Statistical Model for Multiple Images Acquired by Homogeneous or Heterogeneous Sensors

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Outline

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Introduction

Motivation: Change detection on remote sensing images

- **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

- **Improve the analysis of remote sensing images**
  - Find new objects

- **Different type of sensors: Optical, SAR, Hyperspectral, etc.**

Joint analysis of heterogeneous sensors!
Introduction

Change Detection Framework
- Sliding window $W$
- **Similarity measure** on $W$
- Threshold

Statistical Similarity Measures
- Dependency between pixel intensities
  - **Correlation Coefficient**
    Linear dependency, Fails on homogeneous areas
  - **Mutual Information**
    Requires pdf estimation, Fails on homogeneous areas

Objective: Similarity measure for homogeneous and heterogeneous sensors based on a statistical model
Image Model – Optical image for Homogeneous Regions

Optical Sensor

- 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
Radar Sensor

- Affected by multiplicative speckle noise (with gamma distribution)

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

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

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
Image Model – Generic Image for Homogeneous Regions

**Generic Model:** Sensor $S$

$$I_S|P = f_S[T_S(P), \nu_S]$$

**Optical Image**

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

$$T_{Opt}(P) = \mu_P$$

**SAR Image**

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

$$T_{SAR}(P) = \alpha_P \times \theta_P$$
Image Model – Joint Distribution for Homogeneous Regions

- Independence assumption for the sensor noises

\[ p(I_{S1}, I_{S2} \mid P) = p(I_{S1} \mid P) \times p(I_{S2} \mid P) \]

- **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

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

$$
p(I_{S1}, I_{S2} | W) = \sum_{k=1}^{K} w_k p(I_{S1}, I_{S2} | P_k)
$$

- Mixture distribution!
Image Model – Mixture Distribution

Mixture Distribution

\[ p(I_{S1}, I_{S2} | W) = \sum_{k=1}^{K} w_k p(I_{S1}, I_{S2} | P_k) \]

Parameter Estimation

- Expectation Maximization
- Iteratively Algorithm
  - Estimate class prob. \( \pi_{n,k}^{(i)} \)
  - Maximize parameters \( \theta_k^{(i)} \)
  - Repeat

- Selection of the number of classes [1]

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**Similarity Measure – Introduction**

**Mixture distribution**
- Parameter Estimates
  - Related to $P$
  - Can be used to derive $[T_{S1}(P), T_{S2}(P), \ldots]$ for each object
- Example:
  - $T_{Opt}(P_k) = \mu_k$
  - $T_{SAR}(P_k) = L \times \theta_k$
**Similarity Measure – Manifold**

**Main assumption**
- For each unchanged window, \( v(P) = [T_{S1}(P), T_{S2}(P), \ldots] \) can be considered as a point on a manifold.

**Manifold**
- Describes the joint behavior of the different images.
- Belongs to a \( D \)-dimensional space.
  - \( D \): Number of combined channels.
**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

![Graph showing TSAR(P) vs T_{Opt}(P) for unchanged and changed regions](image_url)
**Similarity Measure – Manifold**

**Distance measure between Optical and SAR images**

PDF of $v(P)$

- Good distance measure
- Learned using training data from unchanged images
- Learning strategies
  - Histogram
  - Parzen windows
  - Mixture models

$H_0: \text{Absence of change}$

$H_1: \text{Presence of change}$

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

where

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

Using several windows

Manifold Estimation

\[ W_{Opt} \quad W_{SAR} \]

Sliding Window: \( W \)

\[ \hat{\mu}_1, \hat{\sigma}_1^2, \hat{k}_1, \hat{\alpha}_1 \]

\[ \hat{\theta}_1 : \]

\[ \hat{\nu}_{P_1} : [\hat{T}_{S1}(P_1), \hat{T}_{S2}(P_1)] \]

Manifold Samples

\[ T_{S1}(P) \quad T_{S2}(P) \]

\[ 0 \quad 0.3 \quad P_1 \quad P_2 \quad P_3 \quad P_4 \]

\[ T_{Opt}(P) \quad 1 \]

\[ 0 \quad 0 \quad T_{S1}(P) \]

...
Results – Synthetic Optical and SAR Images

Synthetic optical image

Synthetic SAR image

Change mask

Performance – ROC
Results – Real Optical and SAR Images

Results – Pléiades Images

Pléiades – May 2012

Pléiades – Sept. 2013

Change mask

Manifold Projection

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

Manifold Projection

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 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
- New similarity measure showing encouraging results for homogeneous and heterogeneous sensors
- Interesting for many applications
  - Change detection
  - Registration
  - Segmentation
  - Classification
Conclusions and Future Work

Future Work

- **Model validation** on larger datasets.
- **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

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