Hierarchical joint classification models for multi-resolution, multi-temporal and multi-sensor remote sensing images. Application to natural disasters

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Publications available on https://team.inria.fr/ayin/publications-hal/
Introduction and Background

Remote sensing and applications

Remote sensing has extensive applications:

- Mineral exploration
- Weather prediction
- Risk management
- Precision agriculture
- Infrastructure management
- Urban mapping
Introduction and Background

Remote sensing and applications

The proliferation of data gives rise to the increasing complexity of RS data, As well as to the diversity and higher dimensionality characteristic of the data.

Complementary informations
Introduction and Background

Remote sensing data

Scattering intensity has a strong dependence on the size of the particles.

Valuable spatial information from different sensors.

Visible Pléiades

X-band Cosmoskymed

C-band RADARSAT 2

L-band ALOS PALSAR
Introduction and Background

Focus on image classification as part of risk management

Earthquake in Nepal (2015)
Introduction to the Research Activity

Focus of the talk

Due to the **huge number** and the (short) **revisit** time of high resolution satellites

Huge amount of satellite images can be acquired at different resolutions

valuable spatio-temporal information.

Problem Statement

develop methods to explore such huge data

- Multiresolution information
- Multitemporal information
- Multisensor information
Introduction to the Research Activity

Objectives

- Joint classification of coregistered mono-/multi-band, multi-resolution and/or multi-sensor (SAR, optical) acquisitions into $M$ classes.
- Hierarchical graph: use multi-resolution data.
- Flexible enough and sufficiently robust to different types of images at different dates and/or from different sensors.

Key points

- Focus on multi-resolution and multi-temporal optical images
- Extension to multi-sensor images (SAR+ optical) and multi-frequency SAR

Proposed methods

Three novel hierarchical methods have been proposed to fuse multi-date, multi-resolution, multi-band and multi-sensor remote sensing imagery for multi-temporal classification purposes. Experimentally validated with challenging multi-modal imagery from Haiti test sites.
Hierarchical Markov Models on quad-trees

Proposed method 1: Multi-temporal Hierarchical Markov Model

Proposed method 2: Multi-sensor Hierarchical Markov Model

Proposed method 3: Contextual Hierarchical Markov Model

Conclusion and Perspectives
Hierarchical Markov Model on quad-trees

General presentation: Hierarchical method

- **Classification**: Estimate the labels $X$ at the finest resolution given all the observations.

- **Quad-tree structure**: causality that allows to use a non-iterative algorithm.

- **MPM (Marginal Posterior Mode) criterion**: penalizes the errors according to their number and the scale at which they occur.
Hierarchical Markov Model on quad-trees

Causality

- Define an **order** over the set of sites $S$. In such a way, we characterize the **past** of a site $s(i, j)$.
- For instance:
• Images are organized **according to their resolutions** in a pyramid structure
Hierarchical Markov Model on quad-trees

Quad-tree structure

Operators on the quad-tree:
- $\delta$: the backward shift
- $\alpha$: the interchange operator at the same scale
- $\beta$: the forward shift

$\mathbf{s^-} = \delta(\mathbf{s})$
$\mathbf{s^+} = \beta(\mathbf{s})$
$\mathbf{d}(\mathbf{s}) = \mathbf{s^+} \cup (\mathbf{s^+})^+ \cup ((\mathbf{s^+})^+)^+ \cup ...$

Missing levels might appear

To coarser scales
To finer scales

wavelets

Quad-tree structure and Hierarchical Markov Model on quad-trees.
These probabilities are calculated through a MPM algorithm which runs in two passes on a quad tree, referred to as “bottom-up” and “top-down” passes.
Hierarchical Markov Model on quad-trees

Global scheme
Hierarchical Markov Model on quad-trees

Two neighboring sites at a given scale may not have the same parent.

A **boundary** is more likely to appear than when they are linked to the same parent node.
## Contents

1. Hierarchical Markov Models on quad-trees
2. **Proposed method 1**: Multi-temporal Hierarchical Markov Model
3. Proposed method 2: Multi-sensor Hierarchical Markov Model
4. Proposed method 3: Contextual Hierarchical Markov Model
5. Conclusion and Perspectives
Multi-temporal Hierarchical Markov Model

Novel hierarchical cascade structure
These probabilities are calculated through a MPM algorithm which runs in two passes on a quad-tree, referred to as “bottom-up” and “top-down” passes.

\[ \hat{x}_s = \text{arg max}_{x_s \in \omega} P(x_s | y) \]

\[
p(x_s | y) = \sum_{x_{s^-}, x_s=} \left[ \frac{p(x_s, x_{s^-}, x_s= | y_{d(s)})}{\sum_{x_s} p(x_s, x_{s^-}, x_s= | y_{d(s)})} \right] \cdot p(x_{s^-} | y) \cdot p(x_s= | y)
\]

Calculate recursively the posterior marginal \( p(x_s | y) \) while the probabilities \( p(x_s, x_{s^-}, x_s= | y_{d(s)}) \) are made available.

1. Prior
2. Posterior marginal
3. Transition Probabilities over scale and time
4. These probabilities are calculated through a MPM algorithm which runs in two passes on a quad-tree, referred to as “bottom-up” and “top-down” passes.

Multi-temporal Hierarchical Markov Model

Time $t=0$: single-time MPM

- Classification is performed at time $t=0$ using a single-date MPM
- A case-specific initialization strategy is applied that makes use of a spatial MRF model
Top-down

Prior

\[ p(x_s) = \sum_{x_{s-}} \left[ p(x_s | x_{s-}) \cdot p(x_{s-}) \right] \]

Transition Probabilities over scale*

\[ p(x_s | x_{s-}) = \begin{cases} 
\theta & \text{if } x_s = x_{s-} \\
1 - \theta & \text{if } x_s \neq x_{s-}
\end{cases} \]

Transition Probabilities over scale and time

\[ p(x_s | x_{s-}, x_{s=}) = \begin{cases} 
\theta & \text{if } x_s = (x_{s-} = x_{s=}) \\
\phi & \text{if } x_s = (x_{s-} \neq x_{s=}) \\
1 - \theta & \frac{1}{M - 1} & \text{if } x_s \neq (x_{s-} = x_{s=}) \\
1 - 2\phi & \frac{1}{M - 2} & \text{if } x_s \neq (x_{s-} \neq x_{s=})
\end{cases} \]

Multi-temporal Hierarchical Markov Model

Time $t = 1$: bottom-up pass

Initialisation: $p(x_s | y_s) \propto p(y_s | x_s). p(x_s)$

Bottom-up

$2$

Posterior marginal [4]

$p(x_s | y_d(s)) \propto p(y_s | x_s). p(x_s). \prod_{u \in S^+} \sum_{x_u} \left[ \frac{p(x_u | y_d(u))}{p(x_u)} \cdot p(x_u | x_s) \right]$

Likelihood term estimated using Gaussian mixture (SEM to estimate the parameters)

Bottom-up

$2$

$\mathbb{P}(x^{(r)})$

$p_2(x_r | y_d(s)) = p_2(x_r | y)$

$p_2(x^{(1)})$

$p_2(x_s^{(0)} | y_s^{(0)})$

$p_2(x_s^{(1)} | y_d(s))$

$p_2(x_s^{(0)}, x_s^{(0)} | y_s^{(0)})$

$p_2(x_s, x_s^{(0)} | y_s^{(0)})$

$p_2(x_s, x_s^{(0)} | y_s^{(0)})$
Need to maximize the posterior probability at each scale.

Several techniques are used in the literature (Metropolis dynamics, ICM, Graph-cut ...)

Tool: modified Metropolis dynamics.

Experimental results

Data sets

Port au Prince
Pléiades ©CNES (2011), distribution
Airbus DS

Port au Prince
Pléiades ©CNES (2012), distribution
Airbus DS

Port au Prince
Pléiades ©CNES (2013), distribution
Airbus DS

Port au Prince
©GeoEye (2009),

Port au Prince
©GeoEye (2010),
Experimental results

(a) Pléiades image (2013)  (b) Ground Truth  (c) Single scale method (MPM criterion)
(d) Single scale method (MAP criterion)  

(e) Multi-temporal single scale  (f) The proposed method  (g) KNN-MRF method
(h) Kmeans

<table>
<thead>
<tr>
<th></th>
<th>urban</th>
<th>water</th>
<th>vegetation</th>
<th>bare soil</th>
<th>containers</th>
<th>overall</th>
<th>computation time</th>
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<tbody>
<tr>
<td>Proposed method</td>
<td>81.62%</td>
<td>100%</td>
<td>90.69%</td>
<td>92.82%</td>
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<td>Single scale method using MPM criterion</td>
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<td>88.62%</td>
<td>72.59%</td>
<td>86.02%</td>
<td>57.02%</td>
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<td>Single scale method using MAP criterion</td>
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<td>100%</td>
<td>81.90%</td>
<td>87.02%</td>
<td>73.21%</td>
<td>79.65%</td>
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<td>Multitemporal single-scale method</td>
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<td>100%</td>
<td>86.33%</td>
<td>87.61%</td>
<td>69.61%</td>
<td>84.83%</td>
<td>=1 hour</td>
</tr>
<tr>
<td>K-NN + MRF</td>
<td>96.84%</td>
<td>92.42%</td>
<td>47.15%</td>
<td>71.83%</td>
<td>16.75%</td>
<td>64.99%</td>
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<tr>
<td>K-means</td>
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<td>98.63%</td>
<td>59.18%</td>
<td>91.66%</td>
<td>29.42%</td>
<td>58.25%</td>
<td>20s</td>
</tr>
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Table 1. Results obtained using the Pléiades dataset: class accuracies (producer’s accuracies), overall accuracy, and computation time.

Experiments were conducted using one (1600x1000) image at level 0, one (800x500) image at level 1 and four (400x250) images at level 2 on an Intel i7 quad-core (2.4 GHz) 8-GB-RAM 64-bit Linux system.
Experiments were conducted using one (1600x800) image at level 0, one (800x400) image at level 1 and one (400x250) image at level 2 on an Intel i7 quad-core (2.4 GHz) 8-GB-RAM 64-bit Linux system.
Experimental results

✓ **Blocky artifacts**

(a) blocky artefacts using the method with a single quad-tree (MPM criterion)
(b) reduction of these blocky artefacts using the proposed method.

✓ **Computation time**

- **classification step**
- **PDF estimation step**
The measurement in SAR and optical bands are very different from each other.

How to address the problem of SAR + optical PDF modeling?

1. First, estimate the marginal class-conditional statistics of each SAR/optical channel separately via distinct finite mixtures.
2. Then, model the joint PDF through **multivariate statistics**.

Multi-sensor Hierarchical Markov Model

Using Gaussian mixture

Using generalized Gamma distribution

Optical data

SAR data

Joint PDF

multivariate statistics
Multi-sensor Hierarchical Markov Models

The First proposed method: highlight the synergy between two SAR sensors

Proposed Multi-sensor Quad-tree (case 1)
Experimental results on multi-sensor data (case 1).

(a) Pleiades, (b) CSK, (c) RS2

two datasets acquired over Port-au-Prince (Haiti) using:
- a panchromatic Pléiades acquisition at 0.5m resolution (Pléiades, © CNES distribution Airbus DS, 2011), shown in Figures 1(a) and 2(a).
- a CSK image (© ASI, 2011), X band, HH polarization, Spotlight mode (1m pixel spacing), geocoded, single-look, shown in Figures 1(b) and 2(b).
- a RS2 image (© CSA, 2011), C band, HH polarization, Ultra-Fine mode (1.56 m pixel spacing), geocoded, single-look, shown in Figures 1(c) and 2(c).
Experimental results on multi-sensor data (case 1).

<table>
<thead>
<tr>
<th>Water</th>
<th>Urban</th>
<th>Vegetation</th>
<th>Bare Soil</th>
<th>containers</th>
<th>Overall accuracy</th>
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<tr>
<td>(a) Only Pléiades</td>
<td>100 %</td>
<td>61.66 %</td>
<td>81.69 %</td>
<td>82.82 %</td>
<td>56.72%</td>
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<tr>
<td>(b) Pléiades + CSK</td>
<td>100%</td>
<td>44.32%</td>
<td>83.54%</td>
<td>74.75%</td>
<td>49.12%</td>
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<tr>
<td>(c) Pléiades + RS2</td>
<td>92.56%</td>
<td>44.85%</td>
<td>79.85%</td>
<td>78.62%</td>
<td>42.15%</td>
</tr>
<tr>
<td>(d) Pléiades +CSK+RS2</td>
<td>90.79%</td>
<td>91.45 %</td>
<td>82.59 %</td>
<td>81.02 %</td>
<td>54.85%</td>
</tr>
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</table>
Multi-sensor Hierarchical Markov Models

The second proposed method: SAR/optical fusion (cascade method)

Proposed Multi-sensor Quad-tree (case 2)
Experimental results on multi-sensor data (case 2).

(a) One channel from the optical image (© GeoEye),
(b) SAR image (© ASI),
(c) hierarchical MRF-based classification obtained from the optical image,
(d) hierarchical MRF-based classification obtained for the SAR image,
(e) hierarchical MRF-based classification obtained by the proposed cascade method.
Contextual multi-scale classification on quad-tree

Markov Mesh Random Field (MMRF)

The past of the site $s(i, j)$ $pa(s_{i,j})$
Contextual multi-scale classification on quad-tree

Markov Mesh Random Field (MMRF)

Causal neighborhood $\partial(s_{i,j})$

\[
p(x_{s_{i,j}} | x_{pa(s_{i,j})}) = p(x_{s_{i,j}} | x_{\partial(s_{i,j})}) \quad (1)
\]

(1) is abbreviated to:

\[
p(x_s | x_{pa(s)}) = p(x_s | x_{\partial(s)})
\]
Hierarchical Markov Model on quad-tree

Combined Structure (MMRF and quad-tree)

Multi-temporal MPM inference

Again, when the causality property holds, non-iterative classification algorithms can be applied.

\[
\hat{x}_s = \arg \max_{x_s \in \omega} P(x_s | y)
\]

\[
p(x_s | y) = \sum_{x_{s^{-}}, x_{\partial(s)}} \left[ \frac{p(x_s, x_{s^{-}}, x_{\partial(s)} | y_{d(s)})}{\sum_{x_s} p(x_s, x_{s^{-}}, x_{\partial(s)} | y_{d(s)})} \right] \cdot p(x_{s^{-}} | y) \prod_{\tilde{s} \in \partial(s)} p(x_{\tilde{s}} | y)
\]

Calculate recursively the posterior marginal \( p(x_s | y) \) while the probabilities \( p(x_s, x_{s^{-}}, x_{\partial(s)} | y_{d(s)}) \) are made available.

1. **Prior**
2. **Posterior marginal**
3. **Transition Probabilities over scale**
4. **Contextual Probabilities**
Experimental results

classification maps of optical (Pléiades) image (a) using the original method proposed in [Laferté et al., 2000] (b), the proposed method (c) and method in [Voisin et al., 2014] (d).

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<td>method in [Voisin et al., 2014]</td>
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<td>86</td>
<td>92</td>
<td>87</td>
<td>154 seconds</td>
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5. Conclusion and Perspectives
Conclusions

- **Methodology:**
  A family of novel techniques, framed in the methodological area of hierarchical Markov random field models, has been developed and endowed with efficient decision (MPM) and parameter estimation algorithms.

- **Application:**
  - The developed methods have been experimentally validated with complex optical multispectral, X-band SAR, and C-band SAR imagery taken from the Haiti sites.
  - The challenging problem of the classification of remote sensing images associated jointly with multiple resolutions, sensors, frequencies, and times has been addressed.

- **Results:**
  Experimental results and comparison with the state of the art suggests the effectiveness of the proposed approaches in fusing multiple information sources for classification purposes.
Perspectives

- Look for an automatic selection of the **wavelet operator**.
- Propose a **new hierarchical model** in order to use a **different number of classes** at each level of the pyramid.
- Incorporate **semantic information** on class meaning at different spatial resolutions.
- Circumvent the drawback of MMRF (**corner dependency**) by using more sophisticated techniques (**QMRF, SMMRF**).
- Further optimize applicability to large data sets through **parallel processing**.
## Publications

### Peer-reviewed papers for international conferences:


### Peer-reviewed journals:


- I. Hedhli, G. Moser, J. Zerubia, Nouvelle méthode en cascade pour la classification hiérarchique multi-temporelle ou multi-capteur d’image satellitaires haute résolution La Revue Française de Photogrammétrie et de Télédétection (under revision)
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- The Italian Space Agency (ASI, Italy) for providing the COSMO-SkyMed images

- The Canadian Space Agency (CSA, Canada) for providing the RADARSAT-2 images

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