# Fusion of multitemporal and multiresolution remote sensing data and application to natural disasters

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# FUSION OF MULTITEMPORAL AND MULTIRESOLUTION REMOTE SENSING DATA AND APPLICATION TO NATURAL DISASTERS

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## ABSTRACT

In this paper, we propose a novel method to fuse multidate, multiresolution, and multiband remote sensing imagery for multitemporal classification purposes. The proposed method is based on an explicit hierarchical graph-based model that is sufficiently flexible to deal with multisource coregistered time series of images collected at different spatial resolutions. An especially novel element of the proposed approach is the use of multiple quad-trees in cascade, each associated with an image acquired at a different date, with the aim to characterize the temporal correlations associated with distinct images in an input time series. Experimental results are shown with multitemporal and multiresolution Pléiades data[1].

***Index Terms—*** Natural disasters, multiresolution data, supervised classification, hierarchical Markov random fields, maximizer of posterior marginals.

## 1. INTRODUCTION

The capabilities to monitor the Earth surface, and especially urban and built-up areas, from environmental disasters such as floods or earthquakes, and to assess the ground impact and damage of such events play primary roles from multiple social, economic, and human viewpoints. Nowadays, a wide variety of remote sensing images are available, that convey a huge potential for such applications, as they allow a spatially distributed and temporally repetitive view of the monitored area at the desired spatial scales.

In this framework, accurate and time-efficient classification methods are especially important tools to support rapid and reliable assessment of the ground changes and damages induced by a disaster, in particular when an extensive area has been affected. Given the huge amount and variety of data available currently from last-generation very-high resolution (VHR) satellite missions (e.g., Pléiades, COSMO-SkyMed, WorldView-2), the main difficulty is to develop a classifier that can take benefit of multiband, multiresolution, multidate, and possibly multisensor input imagery.

Several approaches to land cover change detection using multitemporal data have been proposed in the literature. In this work, we will focus on multitemporal classification methods; these methods consist of independently or jointly classifying the images in a time series and fusing them in order to map the temporal transitions among land cover classes. Specifically, the proposed method addresses the problem of multitemporal image classification and allows both input data collected at multiple resolutions and additional multiscale features derived through wavelets to be fused. The approach consists of a supervised contextual Bayesian classifier that combines a joint class-conditional statistical model for pixelwise information and a hierarchical Markov random field (MRF) [8] for spatio-temporal [9] and multiresolution contextual information [10]. A non-iterative multitemporal formulation of the maximizer of posterior marginal (MPM) rule [1] is applied and combined with probability density function (PDF) estimators based on copula functions [3] and on the stochastic expectation-maximization (SEM) algorithm [4]. Experimental results are shown with Pléiades data.

## 2. MULTI-DATE HIERARCHICAL MODEL

Given an input time series of remote sensing images acquired at multiple spatial resolutions, a multiscale and multitemporal model is proposed to fuse the related spatial, temporal, and multiresolution information. This model is a hierarchical spatio-temporal and multiresolution MRF integrated in a quad-tree structure presented in Figure 1. The choice of a quad-tree allows to take benefit from its good analytical properties (e.g., causality) and to apply non-iterative classification algorithms such as MPM, which associates, with each spatio-temporal site $s$ in the considered time series, the most probable class label $x_s$, given the entire multitemporal data set $y$ [1]. An especially novel element of the proposed approach is the use of multiple quad-trees in cascade, each associated with one of the images available at each observation date in the considered time series (see Figure 5).

Specifically, for each date, the input images are inserted in the quad-tree structure on the basis of their resolutions,

[1] We would like to thank the French Space Agency (CNES) for providing the data and for partial financial support.

while missing levels of the tree are filled in with wavelet transforms of the images embedded in finer-resolution levels [10].

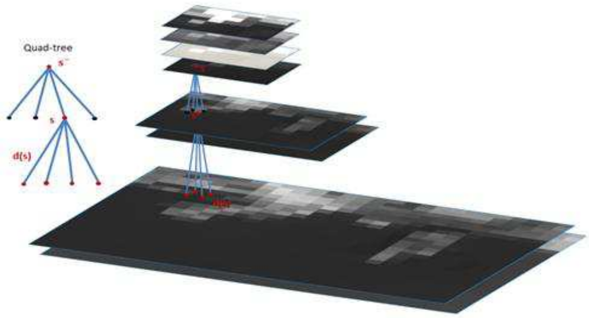



Figure 1: Quad-tree structure

Then, a novel formulation of MPM is proposed for the resulting multitemporal quad-tree. The posterior marginal $p\left(x_s\,|y\right)$ of the class label of each spatio-temporal site $s$ is expressed as a function not only of the posterior marginal $p\left(x_{s^-}\,|y\right)$ of the parent node $s^-$ in the corresponding quad-tree but also of the posterior marginal $p\left(x_{s^=}\,|y\right)$ of the parent node $s^=$ in the quad-tree associated with the previous date, with the aim to characterize the temporal correlations associated, at different scales, with distinct images in the input time series. In particular, we proved that, under mild assumptions:

$$\mathbf{p}\left(\mathbf{x_s}\,|\mathbf{y}\right) = \sum_{x_{s^-},\, x_{s^=}} \left[\frac{p\left(x_s, x_{s^-}, x_{s^=}\,|\, y_{d(s)}\right)}{\sum_{x_s} p\left(x_s, x_{s^-}, x_{s^=}\,|\, y_{d(s)}\right)} .\ \mathbf{p}\left(\mathbf{x_{s^-}}|,\mathbf{y}\right)\mathbf{p}\left(\mathbf{x_{s^=}}|\mathbf{y}\right)\right], \qquad (1)$$

where boldface type highlights the recursively computed posterior marginal. The proposed method extends the single-date technique in [6] through the recursive integration of multitemporal information in the computation of such posteriors as well as the probabilities $p\left(x_s, x_{s^-}, x_{s^=}\,|\, y_{d(s)}\right)$ are made available, where $d(s)$ indicates the set of the descendants of site $s$. This could be computed using:

$$p\left(x_s, x_{s^-}, x_{s^=}\,|\, y_{d(s)}\right) = p\left(x_s\,|\, x_{s^-}, x_{s^=}\right). \frac{p\left(x_{s^-}\,|\, x_{s^=}\right). p\left(x_{s^=}\right)}{p\left(x_s\right)} .\ p\left(x_s\,|\, y_{d(s)}\right) \qquad (2)$$

The proposed hierarchical MRF is achieved by two recursive steps, referred to as "bottom-up" and "top-down" passes (see Figure 5):

- A top-down pass to compute the prior probability $p\left(x_s\right)$ via:

  $$p\left(x_s\right) = \sum_{x_{s^-},\, x_{s^=}} \left[p\left(x_s\,|\, x_{s^-}\right).\ p\left(x_{s^-}\right)\right] \qquad (3)$$

  Where $p\left(x_s\,|\, x_{s^-}\right)$ characterize the relationship across consecutive scales within the same quad-tree, we use the transition probability model proposed by Bouman and Shapiro [2], which favors identity between the class labels of children and parent.

- A bottom-up recursion allows computing the posterior marginal $p\left(x_s\,|\, y_{d(s)}\right)$ using the formulation introduced by Laferte [5] for the single-date case:

  $$p\left(x_s\,|y_{d(s)}\right) \propto p\left(y_s|\, x_s\right). p\left(x_s\right). \prod_{t\in s^+} \sum_{x_t} \left[\frac{p\left(x_t\,|y_{d(t)}\right)}{p(x_t)} .\ p\left(x_t\,|x_s\right)\right] \quad (4)$$

  Where $s^+$ denotes the set of the children of site $s$. This step involves the pixelwise class-conditional PDFs of the image data at each node of each quad-tree (described in Section 3). Then, the probabilities $p\left(x_s, x_{s^-}, x_{s^=}\,|\, y_{d(s)}\right)$ could be computed given the transition probabilities between consecutive scales and consecutive dates:
  - The child-parent transition probability $p\left(x_s\,|\, x_{s^-}, x_{s^=}\right)$ is computed through a new formulation of the transition probability model proposed by Bouman and Shapiro, which favors identity between children and parents in current and previous dates to account for the temporal correlation between images taken over the same area at different times.
  - The transition probabilities between class labels at different dates [9] and at the same level of the quad-tree $p\left(x_{s^-}\,|\, x_{s^=}\right)$ is computed through a specific formulation of the expectation-maximization (EM) algorithm [7].

- A top-down pass allows computing recursively the posterior marginal $p\left(x_s\,|y\right)$ in each level of the quad tree of each date. Classification maps are obtained using modified metropolis dynamics [11] applied to maximize the posterior marginal.

## 3. MULTIVARIATE PDF MODEL

In order to model, for each date, class, and scale level in the multitemporal hierarchical graph, the conditional joint statistics of the input features, first, the corresponding marginal statistics of each feature is estimated; then the joint statistics is modeled using copulas [3]. In particular, given a training set for each date (completely supervised approach), we model the class-conditional marginal PDF corresponding to each class, scale, acquisition time, and (satellite or wavelet) feature using a finite Gaussian mixture. The use of finite mixtures instead of single PDFs offers the possibility to consider heterogeneous distributions, usually reflecting the contributions of the different ground materials in each land cover class. Such class heterogeneity is especially relevant because we deal with VHR images. The parameters of the mixture model are estimated through SEM [4], which is an iterative stochastic parameter estimation technique developed for problems characterized by data incompleteness and approaching, under suitable assumptions, maximum likelihood estimates.

Given the resulting marginal conditional PDF estimates, joint conditional PDF estimates are obtained through copula functions. According to Sklar's theorem [3], an arbitrary joint PDF can be expressed in terms of the corresponding marginal PDFs and of a copula function. In the proposed method, we determine this specific joint PDF for each scale level of each quad-tree in the cascade model, given the aforementioned marginal distributions. To determine the joint PDF and maximize the flexibility of the resulting estimate, we do not predefine a single copula model but we consider a dictionary of three parametric copulas (Clayton, Ali-Mikhail-Haq and Gumbel). To estimate the corresponding parameters and identify the best fitting copula, we use the relationship between the unknown copula parameters and Kendall's $\tau$ (rank statistics) and we choose the best fitting copula according to the highest p-value reported by a Pearson Chi-square goodness-of-fit test [5]. The advantage of using copulas, over the choice of a specific parametric model (e.g., multivariate Gaussian), is that they enable modeling the dependence structure of any type of features. The use of copulas in the joint PDF modeling becomes especially relevant when the dependence between the source features is strong [6].

## 4. RESULTS

Preliminary experiments have been performed with a time series of panchromatic and multispectral Pléiades images acquired over Port-au-Prince (Haiti). Results associated with a set of images acquired on 2011, 2012 and 2013 are shown in this paper (see Figure 2). The finest resolution of the multiresolution pyramid (level 0) is set equal to the finest resolution of the input images (0.5-m panchromatic). Co-registered 2-m multispectral images are integrated in level 2 of the pyramid. Level 1 is filled in through Haar wavelet decomposition of the panchromatic image. Preliminary experiments suggested the Haar transform to be especially effective in the application within the proposed method.Morevoer, both a nonstationary (pixelwise) and a stationary (classwise) versions of EM have been formulated for the estimation of the temporal transition probabilities. Preliminary experiments omitted for brevity pointed out that there was no significant difference in terms of accuracy, whereas the stationary version has remarkably shorter computation time.

Four land cover classes have been considered: urban (red), water (blue), vegetation (green) and bare soil (yellow). A preliminary analysis of the resulting classification maps has suggested that the proposed hierarchical method leads to accurate results (see Figure 3), especially as compared to separate hierarchical classification at each individual date (e.g., [6]). These results suggest the effectiveness of the proposed multitemporal hierarchical model in fusing the temporal, spatial, and multiresolution information associated with the input data (see Figure 2). In particular, one of the main sources of misclassification in the single-date results is the confusion between the "urban" and "soil" classes (see highlighted regions in Figure 2(e)); this misclassification is reduced in the multitemporal classification obtained by the proposed method thanks to the modeling of the temporal relationships among the input multiresolution data. A change map is also presented in Figure 4(c) by comparing the classification maps produced by the developed joint multitemporal classifier (changes are highlighted in black).

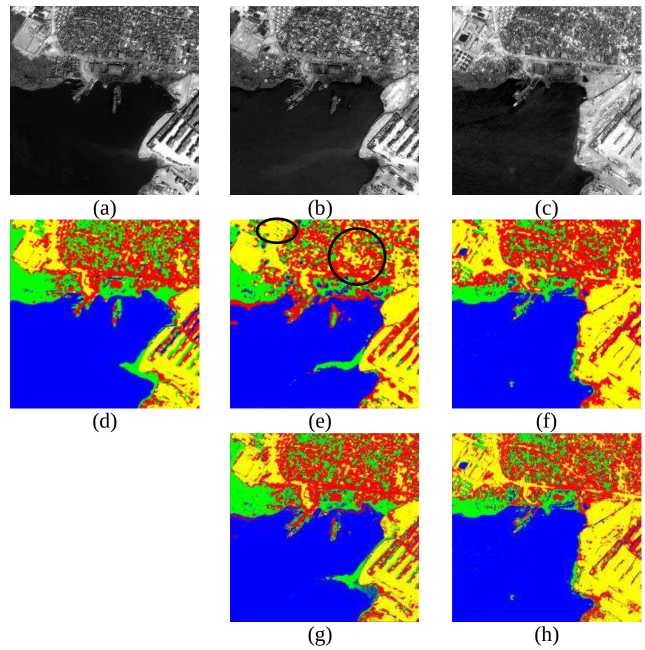
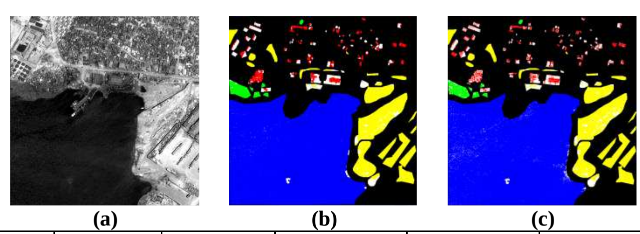
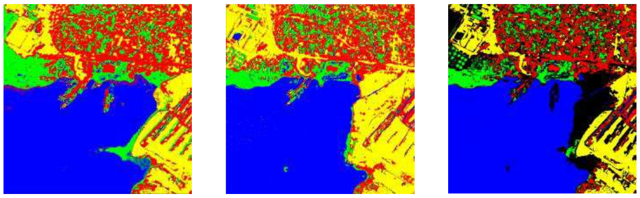



Figure 2: ((a) to (c)) Panchromatic image of Port au Prince (Pléiades, © CNES) for 2011 to 2013 respectively, ((d) to (f)) monotemporal classification maps for 2011 to 2013 respectively, (g) Classification map for 2012, obtained through the proposed cascade method using images acquired in 2011 and 2012, (h) Classification map for 2013, obtained through the proposed cascade method using all multispectral and panchromatic images.




| | Water | Urban | Vegetation | ***Bare Soil*** | Total |
|---|---|---|---|---|---|
| **(b)** | 94.05 % | 71.66 % | 91.69 % | **92.82 %** | **87,55 %** |
| **(c)** | 97,62 % | 67,45 % | 92,59 % | **87.02 %** | **86,17 %** |

Figure 3: Superposition of the obtained classification result and the ground truth made by visual interpretation. (white = classification error and black = no GT available)



(a) (b) (c)

Figure 4: (a) Classification map for 2012, obtained through the proposed cascade method using images acquired in 2011 and 2012, (b) Classification map for 2013, obtained through the proposed cascade method using all images. (c) Change map derived from the classification result of the proposed method.

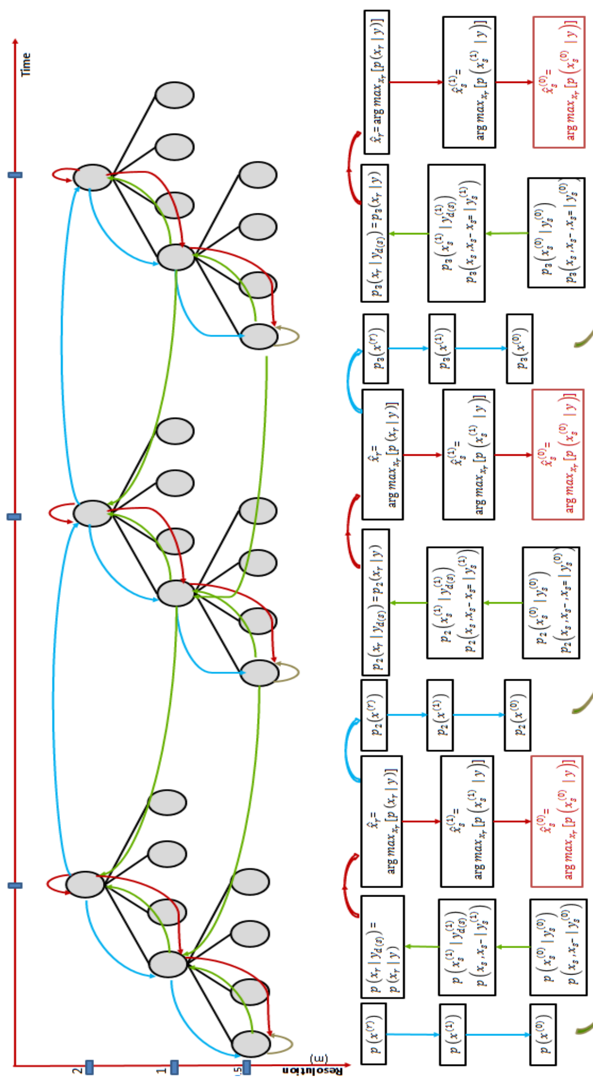


Figure 5: Multidate MPM estimation on the quad-tree: R=2 and three dates.

## 5. CONCLUSIONS

A novel method has been proposed to address the joint classification of multidate, multiband, and multiresolution imagery. It combines a joint statistical model of the considered input images and a hierarchical MRF model for spatio-temporal and multiresolution contextual information, leading to a statistical supervised classification approach. Moreover, a major advantage of the proposed classifier is that it can be extended to the use not only of optical data, but also of synthetic aperture radar (e.g., COSMO-SkyMed) or multisensor data. The extension to the multisensor case will be a major direction of further research.

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