# A GRAPH-CUT-BASED METHOD FOR SPATIO-TEMPORAL SEGMENTATION OF FIRE FROM SATELLITE OBSERVATIONS

*Yuliya Tarabalka*[1], *Guillaume Charpiat*[2]

INRIA Sophia-Antipolis Méditerranée, AYIN[1] and STARS[2] teams,
2004 route des Lucioles, 06902 Sophia Antipolis, France
e-mail: yuliya.tarabalka@inria.fr

**ABSTRACT**

We propose a new method based on graph cuts for the segmentation of burned areas in time series of satellite images. The method consists in rewriting a segmentation problem as a (s, t)-min-cut on the spatio-temporal image graph and computing this minimal cut. As burned areas grow in time, we *introduce growth constraint in graph cuts* by using directed infinite links connecting pixels at the same spatial locations in successive image frames. This method guarantees to find the globally optimal segmentation satisfying the growth constraint in small time complexity. Experimental results on a set of MODIS measurements over the Northern Australia demonstrated that the new approach succeeded in combining both spatial and temporal information for accurate segmentation of burned areas.

***Index Terms*—** Segmentation, fire mapping, graph cut, spatio-temporal graph, MODIS.

## 1. INTRODUCTION

Biomass burning has a significant impact on the Earth's climate system. Therefore, a frequent and accurate fire scar mapping is important for fire prevention and management. Satellite-based remote sensors acquire data for the continuous monitoring of fires at both regional and global scales. Thus, there is a need to develop methods for automated mapping of burned areas. While most of the existing techniques for mapping fire scars analyze temporal evolution of each pixel in an image scene (*pixelwise* methods) [1], recent studies have demonstrated the advantage of using spatial contextual classification for accurate fire classification [2, 3]. Both works [2, 3] map fires from the Moderate Resolution Imaging Spectroradiometer (MODIS) observations, using change detection approach. Giglio *et al.* [3] exploit the closest fixed pixel's neighborhood for refining fire classification. Lewis [2] segment and analyze change detection maps between two consecutive time moments to accurately delineate fire scars. Manual post-processing is needed to correct classification errors, which are a consequence of either a cloud cover, or low contrast between burned and unburned areas.

In this paper, we propose a new method based on graph cuts for joint segmentation of growing burned areas in time series of images. Graph cut is an optimization tool, which can be used to compute the globally optimal binary segmentation of images by rewriting a segmentation problem as a (s, t)-min-cut on the image grid and by finding this minimal cut [4, 5] in small time complexity. We propose to segment simultaneously a time series of $T$ images, in order to exploit time coherency information not available for a single image. Because burned areas grow in time, we introduce *directed infinite links* between pixels at the same spatial locations in successive images (see Fig. 1), which impose fire *growth constraint* in graph cuts. By minimizing an energy computed on the resulting spatio-temporal graph of the image sequence, the proposed method yields a *globally optimal segmentation*. We demonstrate the performance of the proposed approach on a 40-day time series of MODIS measurements.

The outline of the paper is as follows. In the next section, the data set used for experiments is described. Section 3 introduces the proposed segmentation method. Experimental results are discussed in Section 4. Finally, conclusions are drawn in Section 5.

## 2. DATA SET

In this study, we analyzed forty days of Terra MODIS atmospherically-corrected Level 2G daily surface reflectance measurements over the tropical savannas in the Northern Australia ("MOD09GA" product, tile h31v10), acquired in September-October 2011 (days 244-283). Wildfires in this region of Australia are frequent and extensive. Because of the vast areas affected and low population density, remote sensed mapping is a critical tool for dealing with fires effectively. We used MODIS band 5 (1.240 $\mu$m) 500-m land surface reflectance data as they provide the highest burned-unburned separability and are largely insensitive to smoke aerosols [1]. We extracted for segmentation a subset of $T = 40$ images with spatial dimensions $W \times H = 400 \times 400$ pixels. Fig. 2(a) shows three images from the considered set.

We used MODIS Collection 5.1 Direct Broadcast Monthly

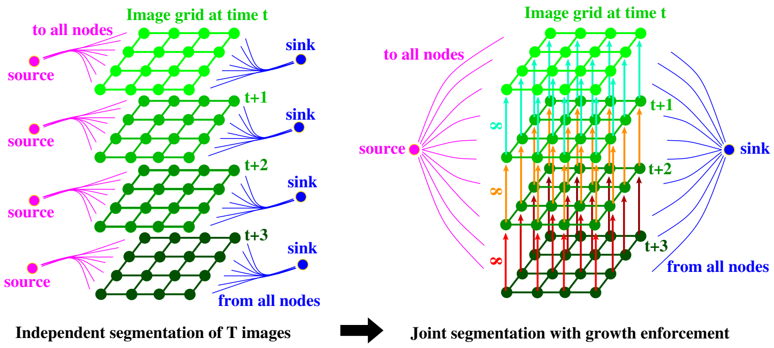



**Fig. 1**. Enforcing shape growth in an image sequence.

Burned Area Product (MCD64A1) [3] for learning and testing the proposed method: to create an initial histogram of burned areas and compare fire maps, respectively. The MCD64A1 product contains fire classification maps obtained by applying the approach from [3] on the Terra and Aqua MODIS daily surface reflectance data, where each pixel is associated with either an estimated day of burn, or an unburned flag, or an unmapped flag due to insufficient data.

## 3. PROPOSED METHOD

The objective is to compute $T$ segmentation maps $L^t$ with $t \in [1, T]$, of size $W \times H$, where each pixel $(x, y)$ has label $L^t_{(x,y)} = 1$ if at time $t$ it belongs to a burned area, and 0 otherwise. Segmentation maps can be globally optimally found by mapping each image $I(t)$ of the time series onto a graph (see Fig. 1(left)), and by minimizing a submodular energy of the form:

$$E^t(L) = \sum_{\text{pixels } i} V_i^t(L_i^t) + \sum_{i \sim j} W_{i,j}^t(L_i^t, L_j^t), \qquad (1)$$

where $L$ is the binary labelling function to be found ($L_i^t$ is the label of pixel $i$ at time $t$), individual potentials $V_i^t(L_i^t)$ are any binary real-valued functions expressing a penalty for a pixel $i$ to have a label $L_i^t$ , $i \sim j$ denotes a pair of neighboring pixels (any neighborhood system can be used), and $W_{i,j}^t(L_i^t, L_j^t)$ are interaction terms between neighboring pixels expressing spatial coherency. We refer the reader to [5] for details on a min-cut efficient algorithm for energy minimization.

Object (in our case, fire) growth in a sequence of images $I(t)$ can be expressed as the property that if a pixel belongs to the foreground object at time $t_1$, then it belongs to the foreground object for all times $t > t_1$. Otherwise said, if the background has a label 0 and the foreground object has a label 1, and if the foreground object can only grow, a pair of pixels $((x, y, t), (x, y, t + 1))$, sharing the same location and immediately successive in time, cannot have the pair of labels (1,0). We propose to enforce object growth by setting directed infinite links from all pixels to their immediate predecessor in time. A directed infinite link between two pixels expresses precisely the constraint that this pair of pixels cannot have the pair of labels (0,1).

Given $T$ images $I(t), t \in [1, T]$, and as many associated segmentation criteria $E^t$, we transform the problem of segmenting independently each image $I(t)$ according to its criterion $E^t$, into a joint segmentation of all images together, by enforcing the object growth constraint with directed infinite links (see Fig. 1). Thus, instead of computing graph cut $T$ times independently on planar grids of the size $W \times H$, we apply graph cut once to a 3D grid $W \times H \times T$, consisting of the same nodes and edges, but with additional directed infinite links in time. The criterion to be minimized is then $E = \sum_t E^t$ under the constraint of shape growth. As this problem is binary and submodular, graph cut can be applied to find its globally optimal solution.

The proposed segmentation method for days $[t_1, t_T]$ consists of the following steps:

*Initialization:* $k := 0$. The initial burned training mask $R_k^B$ is built using the MCD64A1 product by selecting the pixels burned during the days $[t_1 - D, t_1 - 1]$. This mask can also be created based on ground observations of the considered area on the day $(t_1 - 1)$.

1. The unburned training mask $R_k^U$ is built by dilating $R_k^B$ with a disk of radius $r$ [6] and selecting the complementary of the resulting image.

2. For a subset of $T'$ images $t = [t_1 + kT', t_1 + (k+1)T' - 1]$, intensity histograms of the MODIS band 5 for burned $p^t(I|B)$ and unburned $p^t(I|U)$ areas are computed, using the masks $R_k^B$ and $R_k^U$, respectively. If the data for some pixels are missing (MODIS does not provide 100% daytime coverage of the terrestrial surface each day, see Fig. 2(a)), these pixels are not considered when computing histograms.

3. For the images $[t_1 + kT', t_1 + (k+1)T' - 1]$, individual potentials and interaction terms between neighboring pixels (see Eq. 1) are computed, assuming equal priors $p^t(B) =$

$p^t(U) = 1/2$:

$$V_i^t(1) = -ln[p^t(B|I_i^t)] = -ln\left[\frac{p^t(I_i^t|B)}{p^t(I_i^t|B)+p^t(I_i^t|U)}\right], \tag{2}$$

$$V_i^t(0) = -ln[p^t(U|I_i^t)] = -ln\left[\frac{p^t(I_i^t|U)}{p^t(I_i^t|B)+p^t(I_i^t|U)}\right], \tag{3}$$

$$W_{i,j}^t \ = \ \delta_{L_i\neq L_j}\ \beta\ \exp\left[-\frac{(I_i^t-I_j^t)^2}{2\sigma^2}\right], \tag{4}$$

where $\sigma$ is a standard deviation of $I^t$, $\beta$ is a parameter that controls the importance of the spatial interaction energy term. If data $I_i^t$ is missing for pixel $i$ at time $t$, we set $V_i^t(1) = V_i^t(0) = 0$ (no prior).

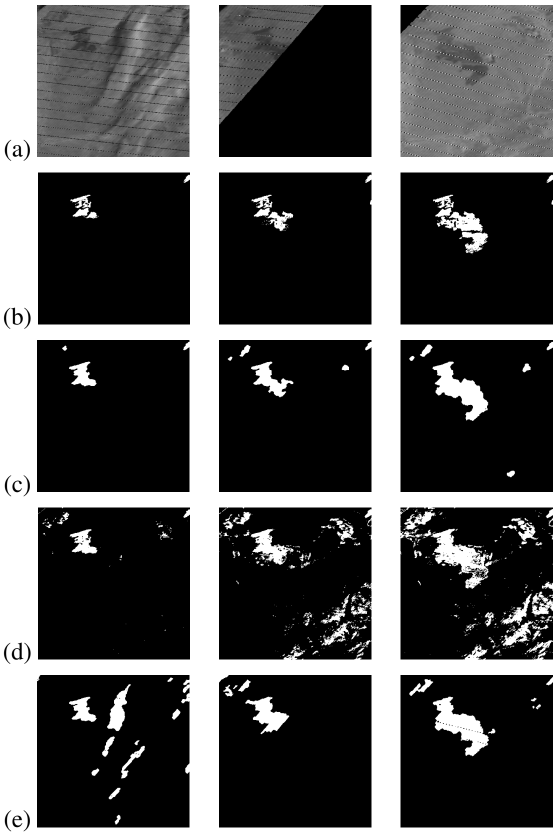



**Fig. 2**. (a) MODIS band 5 images for three days in September-October 2011: 251, 265 and 279, respectively. (b) Maps from the MCD64A1 product of areas burned during the days 213-251, 213-265 and 213-279, respectively (white pixels = burned areas). (c-e) Segmentation maps for images (a) computed by: (c) the proposed spatio-temporal method; (d) graph cut with temporal constraints, but no spatial interactions; (e) graph cut with spatial interactions, but no temporal constraints.

4. The graph-cut optimization is applied on a joint graph of the images $[t_1, t_1 + (k+1)T' - 1]$, yielding $(k+1)T'$ segmentation maps.

5. If the whole set of $T$ images is segmented, exit the algorithm. Otherwise: $k := k+1$. The segmentation map $L^{t_1+kT'-3}$ is used as the new burned training mask $R_k^B$. Go to step 1.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

We applied the proposed method to the set of forty MODIS images described in Section 2. The parameters were empirically set as $D = 31$, $r = 20$, $\beta = 2$ and $T' = 20$.

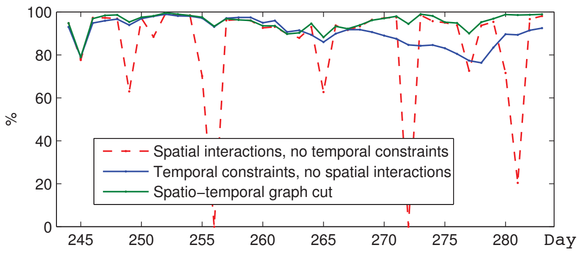
Fig. 2(c) shows the obtained segmentation maps for three days, chosen every two weeks: days 251, 265 and 279, respectively. The obtained results are compared with the maps from the MCD64A1 product of areas estimated as burned during the days [213 - current day] (see Fig. 2(b)). It can be seen that the proposed method succeeds in detecting burned areas in the the image scene, and yields comparable contours of fire regions. The graph-cut-based segmentation maps contain more burned pixels when compared to the MCD64A1 maps. However, it must be noted that the MCD64A1 maps used for comparison consider as *burned areas* only pixels burned in the period [day 213 - current day], *i.e* from August 1 to current day. Therefore, the areas burned before August and not recovered yet are not delineated in the considered MCD64A1 maps, but are detectable by the proposed approach. It is thus expectable to detect a higher number of burned pixels by the proposed approach. On the other hand, *false burned* pixels may be detected by the proposed method due to the imposed spatial interactions. By changing a value of the parameter $\beta$, one can choose the importance of spatial coherency.

In order to demonstrate significance of spatial interactions and proposed temporal constraints, we show in Fig. 2(d) the segmentation maps obtained by applying the same graph-cut-based method, but with no spatial interactions, *i.e.* $W_{i,j}^t = 0$. Fig. 2(e) depicts results of the graph cut segmentation with spatial interactions, but no temporal constraints (see Fig. 1(left)). It can be seen that in both cases mapping results are less accurate than those obtained by optimization on a spatio-temporal graph. Spatial energy term helps to accurately segment images with low contrast between burned/unburned areas. Temporal constraints are especially useful when data is missing.

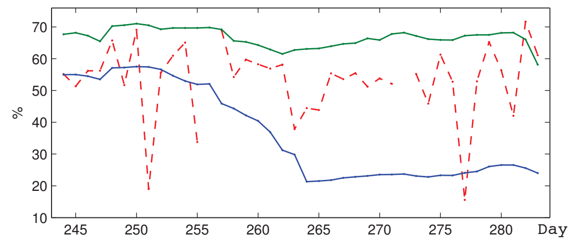
Fig. 3(a) illustrates a graph of the percentage of pixels which are identified as burned by the proposed method among all the pixels estimated as burned in the period [day 244 - current day] by the MCD64A1 product (average = $95\%$). Most of newly burned pixels are well detected by the proposed approach, and accuracies are significantly better when compared to graph-cut-based results with no spatial interactions (average = $91\%$) or no temporal constraints (average = $85\%$). Fig. 3(b) shows a graph of the percentage of pixels estimated as burned during the days [213 - current day] by the MCD64A1 product, among the pixels identified as burned by the proposed method (average = 67%). This graph confirms the importance of using both spatial energy term and temporal constraints. As explained above, it is expectable to have more burned pixels in the obtained segmentation maps when compared to the considered MCD64A1 maps.

The computational time for the proposed graph-cut-based segmentation of the considered 40-image data set is 9 s on a 2.7 GHz Intel Core i7 processor with 16 Go 1600 MHz DDR3, and it grows linearly with the number of images.

We can conclude that the proposed approach achieves comparable results with the method [3] by using only one Terra MODIS band and no post-processing, while [3] used data from Terra and Aqua products, three bands (1, 5 and 7) and post-processing. Furthermore, the new method copes better with the missing or noisy data thanks to the introduced spatio-temporal graph.




(a)




(b)

**Fig. 3**. (a) Percentage of pixels identified as burned by the proposed method among the pixels identified as burned in the period [day 244 - current day] by the MCD64A1 product. (b) Percentage of pixels identified as burned in the period [day 213 - current day] by the MCD64A1 product among the pixels identified as burned by the proposed method. Comparison with results of graph cut with no temporal constraints or no spatial interactions.

## 5. CONCLUSIONS

While satellite remote sensing provides a critical means for monitoring biomass burning over large areas, there is a need to develop effective and automated techniques for fire mapping. We have proposed a new graph-cut-based method for the segmentation of burned areas from time series of satellite observations. We introduced directed infinite links in the spatio-temporal graph of an image sequence in order to enforce fire growth. Experimental results on MODIS images did show the effectiveness of the proposed approach. The new method proved to be robust to low-contrast images and missing or noisy data, and showed linear complexity.

As both spatial and temporal resolutions of modern satellite sensors increase, this raises the importance of applying spatio-temporal methods for analyzing data acquired by new sensors. In the future, we are interested in extending the proposed method for the segmentation of long time series of satellite data. By replacing directed infinite links by directed finite links in the graph, we can encourage (but not impose) fire growth in the dry (high fire) season, and encourage biomass recovery in the wet season.

## 6. ACKNOWLEDGEMENTS

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