A graph-cut-based method for spatio-temporal segmentation of fire from satellite observations

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Outline

Introduction

2 Proposed spatio-temporal segmentation method

Conclusions and perspectives

Automated mapping of burned areas

 Biomass burning has a significant impact on a climate system



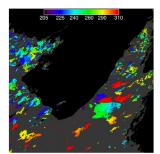
- \downarrow
- Automated mapping of burned areas to:
 - help heal the scars
 - prevent future fires

Objective:

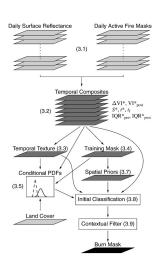
- Segment growing burned areas in time series of images
- By analyzing Terra Moderate Resolution Imaging Spectroradiometer (MODIS) measurements

State of the art

- MODIS Collection 5.1 Direct Broadcast Monthly Burned Area Product (MCD64A1)
 - change detection approach [Giglio 2009]
 - uses MODIS Level 2G (bands 1, 5, 7) and Level 3 daily active fire products
 - spatial filtering within the closest fixed neighborhoods

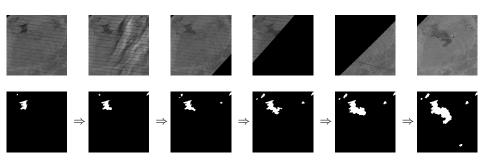


Estimated days of burn, MODIS tile h31v10



Our objective

- Compute globally-optimal spatio-temporal segmentation of growing burned areas
- From a time series of very noisy data
 - Cloud contamination, missing data
- In a low computational time



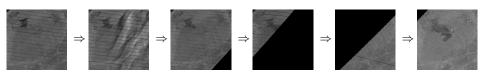
Our objective

- Compute globally-optimal spatio-temporal segmentation of growing burned areas
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- We propose a new graph-cut-based method
 - For simultaneous segmentation of an image sequence
 - With the constraint of shape growth

Data set



- Forty days of Terra MODIS Level 2G measurements (MOD09GA)
 - Over tropical savannas in the Northern Australia (tile h31v10)
 - Acquired in September October 2011 (days 244-283)
 - Band 5 (1.24 μm) 500-m land surface reflectance data
 - \bullet T=40 images with spatial dimensions of 400 imes 400 pixels
- MCD64A1 burned area product
 - Training: computing an initial histogram of burned areas
 - Validation



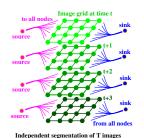
Training mask (days 213-243)

Graph cut for image segmentation

• **Goal:** Compute $T(t \in [1, T])$ segmentation maps $L^{t} = \{L_{(x,y)}^{t} \in [0,1], x = [1..H], y = [1..W]\},\$

$$L_{(x,y)}^t = \begin{cases} 1, & \text{if } (x,y) \in \text{burned area at time t;} \\ 0, & \text{otherwise.} \end{cases}$$





*[Boykov&Kolmogorov 2004]

- Graph-cut globally-optimal segmentation*:
 - \bullet map each image I(t) onto a graph
 - minimize a submodular energy of the form:

$$E^{t}(L) = \sum_{\text{pixels } i} V_{i}^{t}(L_{i}^{t}) + \sum_{i \sim j} W_{i,j}^{t}(L_{i}^{t}, L_{j}^{t})$$

- L_i^t = label of pixel i at time t
- individual potential $V_i^t(L_i^t)$ = penalty for a pixel i to have a label L_i^t
- $W_{i,i}^t(L_i^t, L_i^t) = \text{interaction term between neighboring pixels } i \text{ and } j$

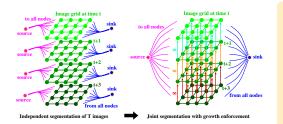
Joint segmentation with fire growth enforcement



Enforcing fire growth:

$$= \text{ if } L_i^{t_1} = 1 \rightarrow L_i^{t > t_1} = 1$$

- = pair of pixels ((x, y, t), (x, y, t + 1)) cannot have pair of labels (1,0)
- = we set a directed infinite link from each pixel to its predecessor in time



Criterion to be minimized:

$$E = \sum_{t} E^{t}$$

under the constraint of shape growth

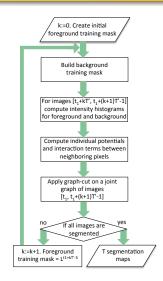
 Apply graph cut to find globally-optimal solution

Proposed spatio-temporal segmentation method

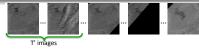
Initialization:

- k := 0
- MCD64A1[$t_1 D, t_1 1$] \rightarrow initial **burned** training mask R_k^B
- **Unburned** training mask $R_k^U = \text{complementary (dilation } (R_k^B))$





Proposed spatio-temporal segmentation method



For images
$$t = [t_1 + kT', t_1 + (k+1)T' - 1]$$
:

- Compute intensity histograms of MODIS band 5 for burned $p^t(I|B)$ and unburned $p^t(I|U)$ areas
 - using masks R_{ν}^{B} and R_{ν}^{U}
- Compute individual potentials and interaction **terms**, assuming $p^t(B) = p^t(U) = 1/2$:

Compute individual potentials and interaction terms between neighboring pixels $V_i^t(1) = -In[p^t(B|I_i^t)] = -In\left[\frac{p^t(I_i^t|B)}{p^t(I_i^t|B) + p^t(I_i^t|U)}\right].$ Apply graph-cut on a joint graph of images [t1. t1+(k+1)T'-1] $V_i^t(0) = -In[p^t(U|I_i^t)] = -In \left[\frac{p^t(I_i^t|U)}{p^t(I_i^t|B) + p^t(I_i^t|U)} \right],$ If all images are $W_{i,j}^t = \delta_{L_i \neq L_j} \beta \exp \left[-\frac{(I_i^t - I_j^t)^2}{2\sigma^2} \right],$ segmented k:=k+1. Foreground T segmentation training mask = Lt1+kT'-3 maps

 $\sigma =$ standard deviation of I^t .

 β controls the importance of spatial interaction.

If I_i^t is missing, $V_i^t(1) = V_i^t(0) = 0$

k:=0. Create initial foreground training mask

> Build background training mask

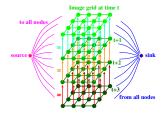
For images [t₁+kT', t₁+(k+1)T'-1] compute intensity histograms

for foreground and background

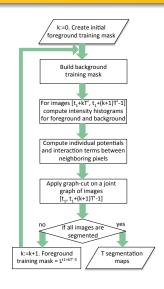
Proposed spatio-temporal segmentation method

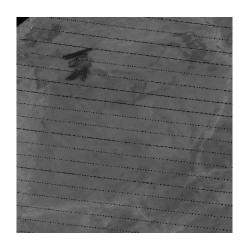


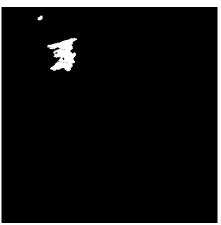
• Apply graph-cut on a joint graph of images $[t_1, t_1 + (k+1)T' - 1]$

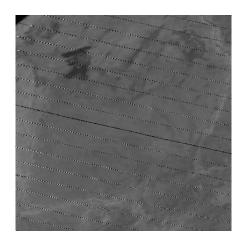


- If all images are segmented, exit. Otherwise:
 - k := k + 1
 - Burned training mask $R_k^B = L^{t_1+kT'-3}$
 - ullet Go to step 1 (Consider the next T' images)

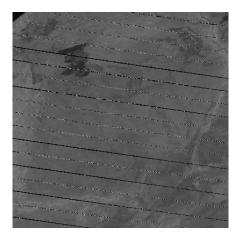




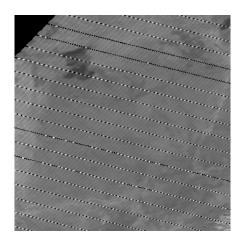




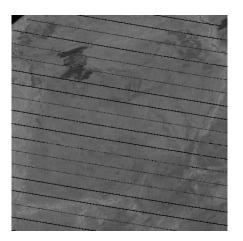








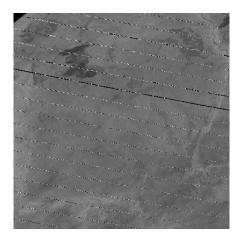


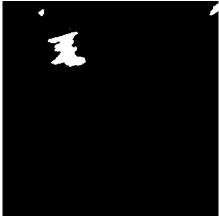


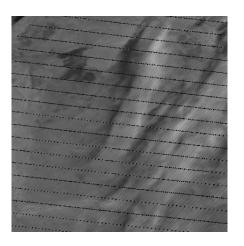




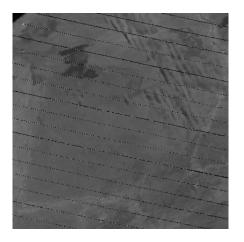




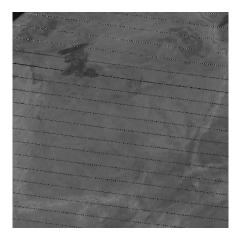




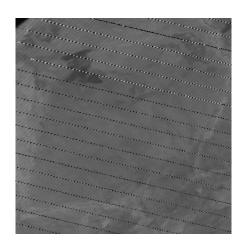




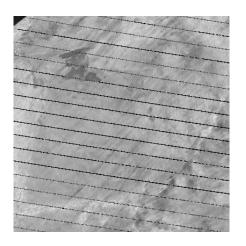




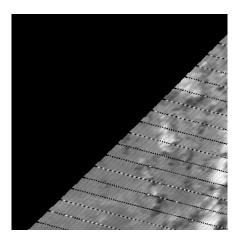




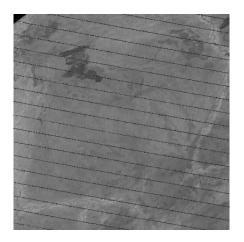


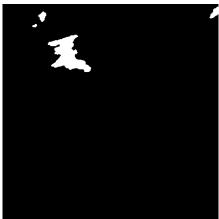


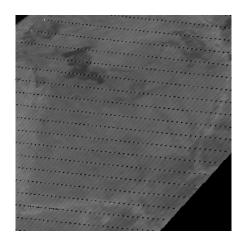




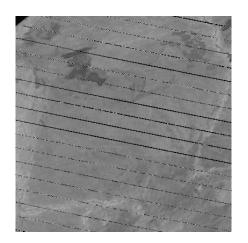




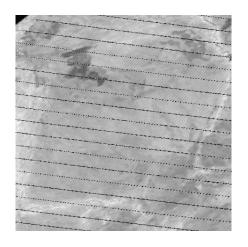


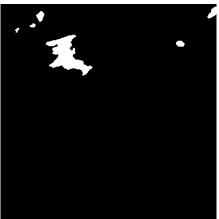


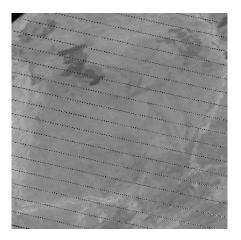




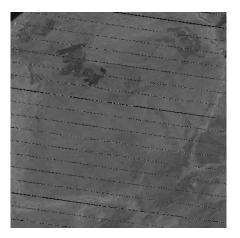




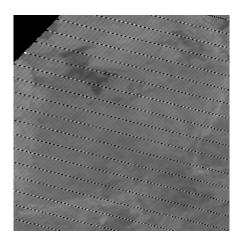




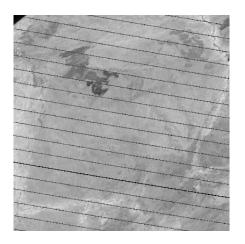




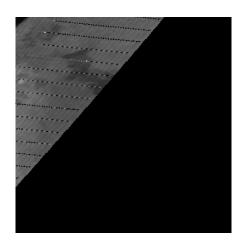




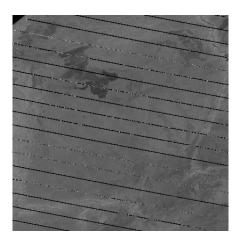




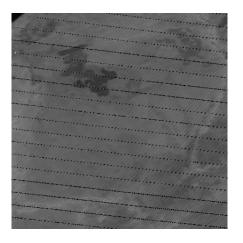




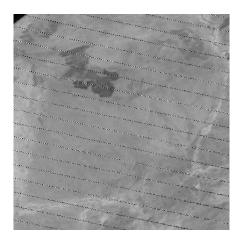




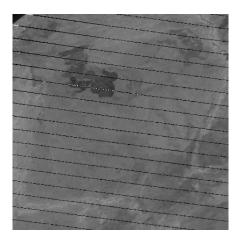




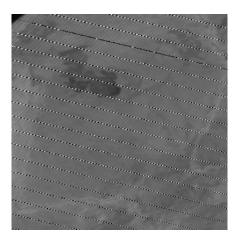


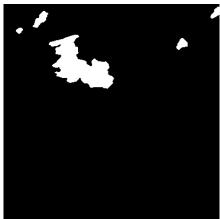


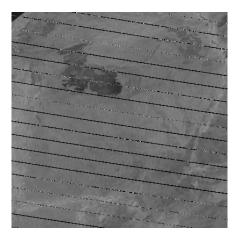




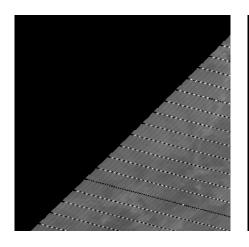




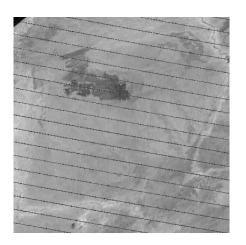




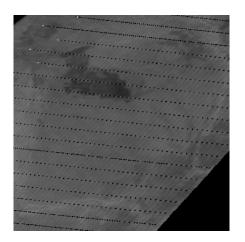




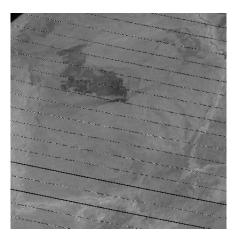




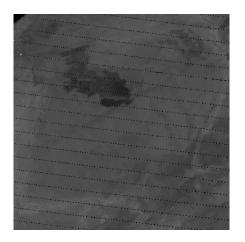




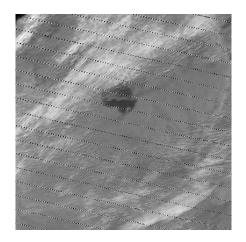




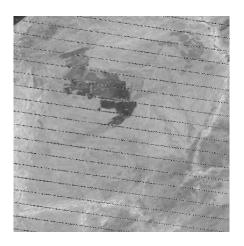




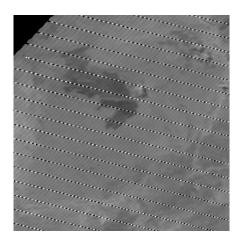




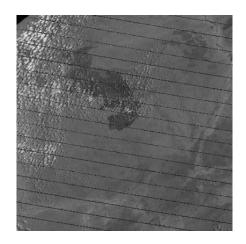








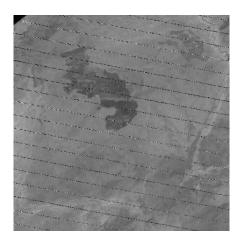




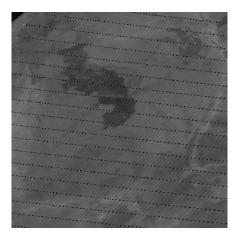






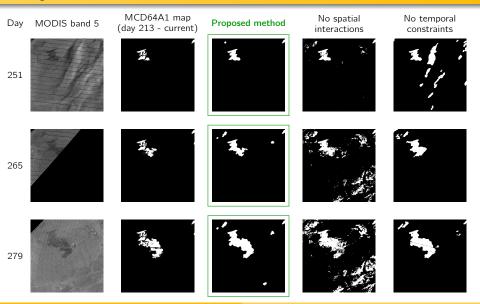




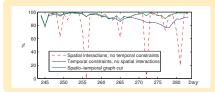




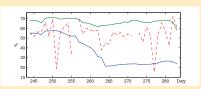
Segmentation results



Segmentation results

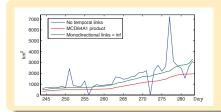


Percentage of pixels identified as burned by the **proposed method** method *AMONG* the pixels identified as burned during [day 244 - current] by MCD64A1

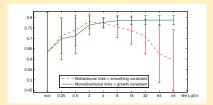


Percentage of pixels identified as burned during [day 213 - current] by MCD64A1 *AMONG* the pixels identified as burned by the **proposed method**

Segmentation results



Burned area as a function of time, when using no temporal links, monodirectional infinite links and MCD64A1 product



Mean and standard deviation for the dice score (proposed *versus* MCD64A1) as a function of the temporal link's weight, when using mono- and bidirectional temporal links

Conclusions and perspectives

Conclusions

- We proposed a new graph-cut-based method
 - for segmentation of burned areas from time series of satellite observations
- We introduced directed infinite links in spatio-temporal graph to enforce fire growth
- The new method:
 - proved to be robust to low-contrast images and missing data
 - showed linear complexity

Perspectives

• Extend the method for segmenting long time series of satellite data

Introduction
Proposed spatio-temporal segmentation method
Conclusions and perspectives

Thank you for your attention!

A graph-cut-based method for spatio-temporal segmentation of fire from satellite observations

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