An automatic water body area monitoring algorithm for satellite images based on Markov Random Fields

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1. Abstract

In this study, we present an automatic algorithm for water body area monitoring based on maximum a posteriori (MAP) estimation of Markov Random Fields (MRF). We solve the optimization problem using graph cuts technique. A graph with two terminals is constructed, after which the most probable realization of the field is defined by finding the max-flow (min-cut) solution. Then to measure the uncertainty for the solution, max-marginal probability for each pixel of water mask is measured in the residual graph. The outputs of our algorithm are time series of water area, water body shapefiles, probabilistic maps of water body and uncertainty of water body area estimation.

2. Motivation

An appropriate classification technique to separate water and land is the backbone of each automatic water body monitoring algorithm. Most of the pixel-based classification techniques fail to determine accurate water masks because of various source of error. Apart from pixel intensity, water bodies have strong spatial and temporal correlation which is another source of information should be considered to make a better decision about the label of pixels. Therefore taking advantages of all source of information in images to derive the water masks improves their accuracy significantly.

Markov random fields (MRF) provide a convenient prior for modeling spatial (or temporal) interactions between pixels. In remote sensing MRF is quite popular because of its ability to integrate information related to pixel intensity and spatial and temporal correlation. In these methods, to extract the object from the background, the maximum a posteriori (MAP) estimation on the MRF must be found.

3. Overview of the method

The problem of finding the MAP estimation is usually solved by describing an energy function specified toward the problem. Then, looking for a realization of the fields minimize the energy function. This equation is the general energy function in the energy based optimization method in image processing

$$E_{\text{total}}(f) = (1-\lambda)E_{\text{data}}(f) + \lambda E_{\text{smooth}}(f)$$

In this equation:

$$E_{\text{data}}(f) = \sum_{p\in\mathcal{P}} D_p(f_p)$$

is a function measures the agreement between the pixel intensity I_p and the label f . Here we define this function as followed:

$$D_p(f_p) = \begin{cases} D_p(\mathrm{l}) & = \mathrm{P}\left(\mathrm{l}\middle|I_p\right) \\ D_p(\mathrm{w}) & = \mathrm{P}\left(\mathrm{w}\middle|I_p\right) \end{cases}$$

where

$$\mathrm{P}\left(\mathrm{l}\middle|I_p\right) = \frac{\mathrm{P}(\mathrm{l})\,\mathrm{P}\left(I_p\middle|\mathrm{l}\right)}{\mathrm{P}(\mathrm{w})\,\mathrm{P}\left(I_p\middle|\mathrm{w}\right) + \mathrm{P}(\mathrm{l})\,\mathrm{P}\left(I_p\middle|\mathrm{l}\right)}$$

$$\mathrm{P}\left(\mathrm{w}\middle|I_p\right) = \frac{\mathrm{P}(\mathrm{w})\,\mathrm{P}\left(I_p\middle|\mathrm{w}\right)}{\mathrm{P}(\mathrm{w})\,\mathrm{P}\left(I_p\middle|\mathrm{w}\right) + \mathrm{P}(\mathrm{l})\,\mathrm{P}\left(I_p\middle|\mathrm{l}\right)}$$

The conditional probabilities ($\mathrm{P}\left(I_p|\mathrm{l}\right)$,$\mathrm{P}\left(I_p|\mathrm{w}\right)$) reveal a high possibility if the pixel label is appropriate for the pixel value based on the initial solution. The unconditional probabilities ($\mathrm{P}(\mathrm{l})$, $\mathrm{P}(\mathrm{w})$) present the possibility of occurring the label based on the long term behavior of the pixel. The second term is

$$E_{\text{smooth}}(f) = \sum_{\{p,q\}\in\mathcal{N}} V_{\{p,q\}}(f_p, f_q)$$

$V_{\{p,q\}}(f_p, f_q)$ is a function measures the agreement between two adjacent pixels in terms of their values and labels. Our problem is categorized as piecewise smooth prior information. So we have

$$w_{pq} = \frac{(I_p - I_q)^2}{\sigma^2},$$

in which I_p and I_q are the pixel values and σ^2 is the variance of pixel values over the whole image. Now we introduce two events and define them based on the temporal behavior of the water body:

- A: two pixels have the same label
- A': two pixels have different labels

now we measure the probability of assigning the same label for two adjacent pixels regarding their pixel values and temporal behavior

$$V_{\{p,q\}}(f_p, f_q) = \mathrm{P}\left(\mathrm{A}|w_{pq}\right) = \frac{\mathrm{P}\left(w_{pq}|\mathrm{A}\right)\mathrm{P}(\mathrm{A})}{\mathrm{P}\left(w_{pq}|\mathrm{A}\right)\mathrm{P}(\mathrm{A}) + \mathrm{P}\left(w_{pq}|\mathrm{A}'\right)\mathrm{P}(\mathrm{A}')},$$

we construct a graph based on the image and by using the graph cuts technique, the MAP solution for the MRF is found.

4. Graph cuts technique

$\mathcal{G} = \langle\mathcal{V},\mathcal{E}\rangle$ is a directed weighted graph where vertices, $\mathcal{V}$, is the set of all pixels of an image together with two additional ones called terminals (*source* and *sink*) and edges, $\mathcal{E}$, is the set of lines that connect neighboring vertices. The edges connect vertices to the terminals are called terminal links (t-links) and the function $D(.)$ defines their weights. Also, the edge connects two neighbor vertices is named neighbor link (n-link) and their weight is defined using function $V(.)$

A cut like C is a set of edges in the graph, which separates graph into two discrete graphs in a way that every vertices should connect to just one terminal via a t-link in the new configuration of the graph. The goal is to find the cut with the smallest cost (Figure 1). To solve this problem we take advantages of this primary fact in combinational optimization that the minimum cut problem can be solved by finding a maximum flow from source to sink.

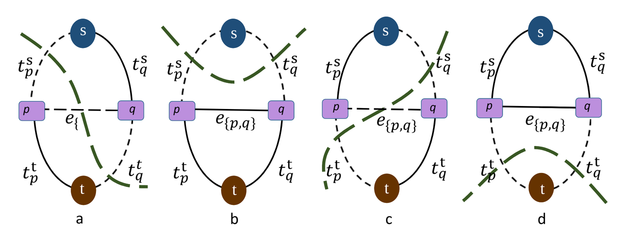

Figure 1: *For a graph with two pixels, four different cut can be considered. The cost of each cut is equal to the sum of the weight of the dashed lines. The scenario with the smallest weight will be selected and regarding remain edges in the graph, new labels for the pixels will be assigned*

Here to find the max-flow solution, we update the residual graph by augmenting the shortest st-paths until all the ways between terminals are saturated. The procedure of generating water masks is presented in the following Figure.

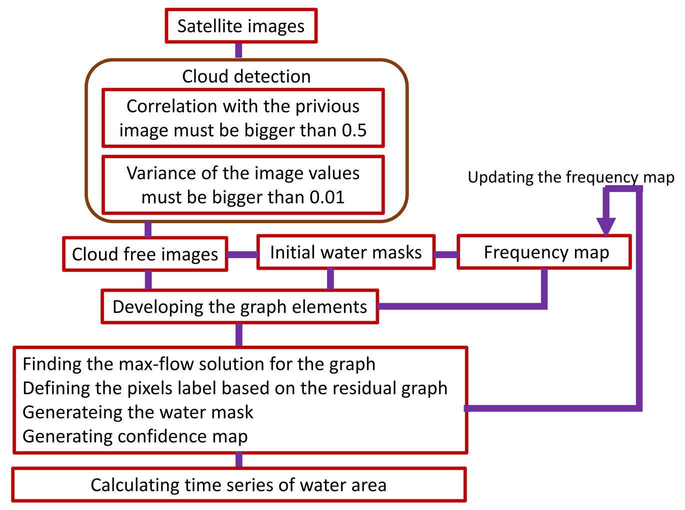

Figure 2: *Flowchart for the proposed method*

5. Case study and data

Our case study is part of the Niger River. This area is one of the most fragile ecosystems of Sub Saharan Africa. The amount of precipitation in the basin in the dry and wet season are significantly variable. We use MODIS Surface-Reflectance MOD09Q1 which is available in red and near near infrared bands with 250 m spatial resolution and 8 days revisit time.

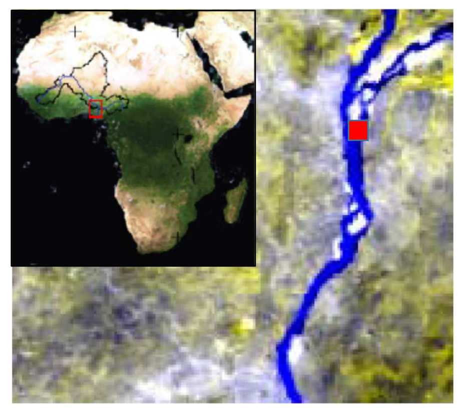

Figure 3: *Part of Niger river selected as case study. The location of in situ gauge is also defined(red). For this station daily in situ measurements are used from 2000–2006 from GRDC*

6. Result

We start this section with presenting four different situations of the River to assess the performance of the proposed method.

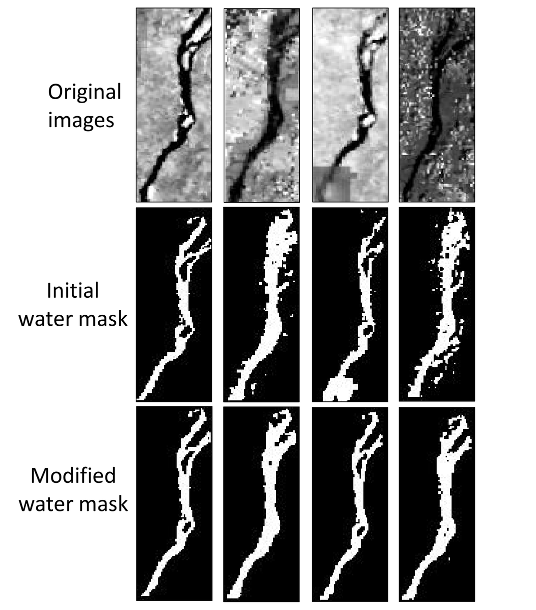

Figure 4: *Some examples of generated water masks in different situations.*

More than binary water mask, the method is able to measure the marginal probability for every pixel of water mask and also the background based on the final residual graph. Measuring the marginal probability for the pixels provides the opportunity to evaluate the quality of labeling for each image.

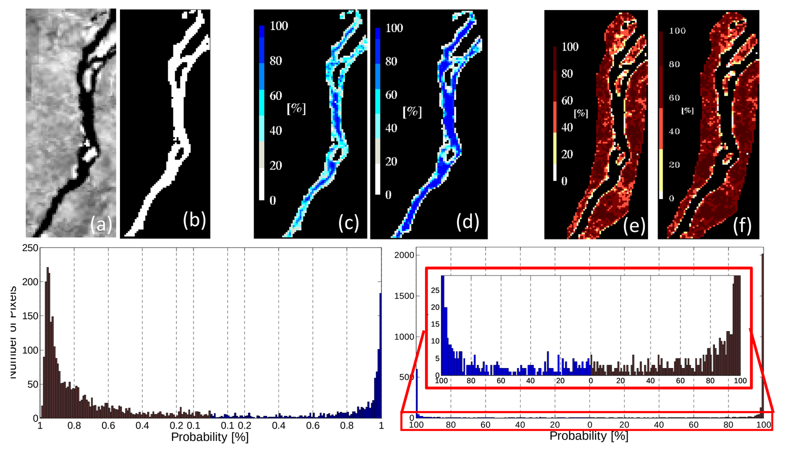

Figure 5: *An example of probabilistic water mask. (a) is the original image, (b) is the derived water mask. (c) and (d) are the probabilistic map of the water mask and the background. The percentage shows the level of confidence to the label*

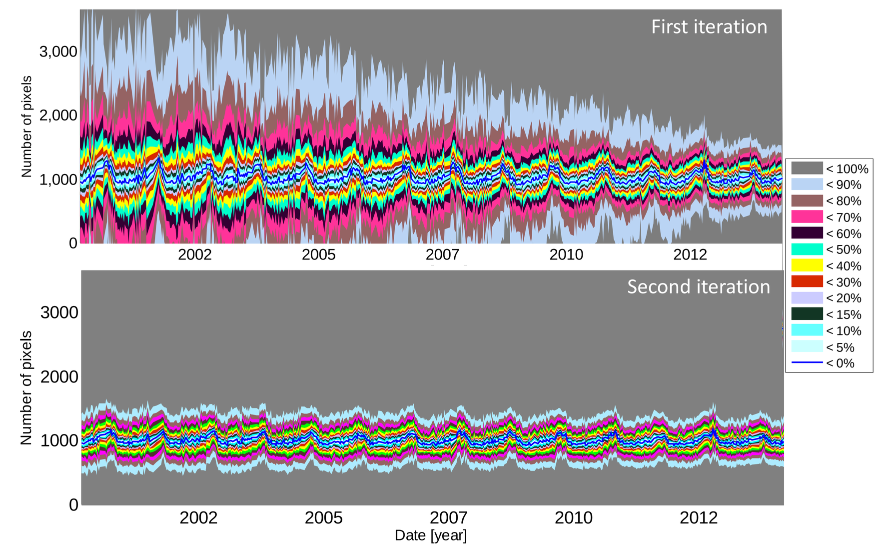

Figure 6: *Time series of marginal probabilities for all images in the first and second iterations*

After the first iteration the average of marginal probabilities for the water mask is around 50%. But after the second iteration, this number is increased to about 70%. The reason of this improvement is updating the initial water masks and the frequency map in the second iteration.

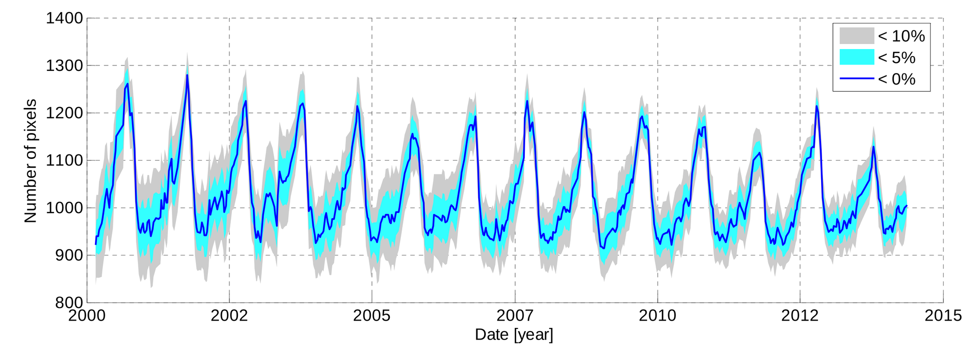

Figure 7: *Time series of water area with two uncertainty levels*

At the end to evaluate the correctness of the results, we validate water area time series against the River discharge measured at the station.

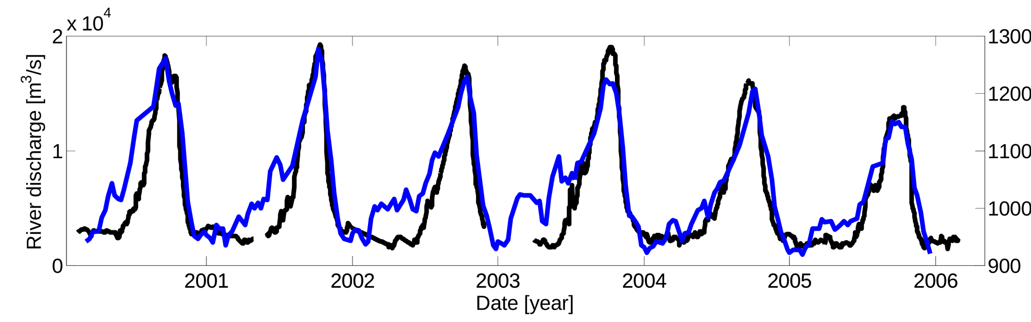

Figure 8: *Comparison between water area time series and in situ river discharge*

The agreement between the behavior of water area and river discharge reveals that the algorithm is able to extract the water body correctly. By looking at Figure 7 and Figure 8, it is obvious that the water area is estimated in wet seasons more correctly and accurately. The main reason of this weakness is the relatively poor spatial resolution of the MODIS images (250m). By using the images with better pixel size we could expect better estimation even in dry season.

7. Conclusion and outlook

We introduce an automatic algorithm to extract the water bodies from satellite images. Apart from water area time series, the method provides a number of valuable products like water body shapefiles, probabilistic water mask, and uncertainty of the labeling and water area. Considering additional source of data like in situ observations and terrain elevation models could be a potential improvement for the method. Also for reducing the computational afford, applying more advanced techniques for the max-flow problem may be the next step of this study.

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