MANGROVE DETECTION FROM HIGH RESOLUTION OPTICAL DATA

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1. INTRODUCTION

Mangroves are a specific type of forest present in tropical regions. They develop in the intertidal region along coastal areas and are present extensively in Southeast Asia. Besides the unique and interesting biodiversity of these forests, mangroves provide valuable environmental services such as coastal protection [1]. In addition, mangroves are also forests with high levels of productivity and have been exploited extensively by man for its numerous natural products. Due to increasing losses of mangroves from exploitation, it is necessary to monitor the status of mangroves regularly to determine the sustainability of exploitation, as well as the preservation of existing mangroves.

Due to the extensive coastline present in Southeast Asia (Fig. 1), the work required to map and monitor mangroves for the whole region is very tedious. Moreover, most mangroves are located in developing countries, where changes to the land cover can be quite rapid. Therefore easing the task of mapping would speed up the production of data over a huge region such as Southeast Asia.

(a) (b)

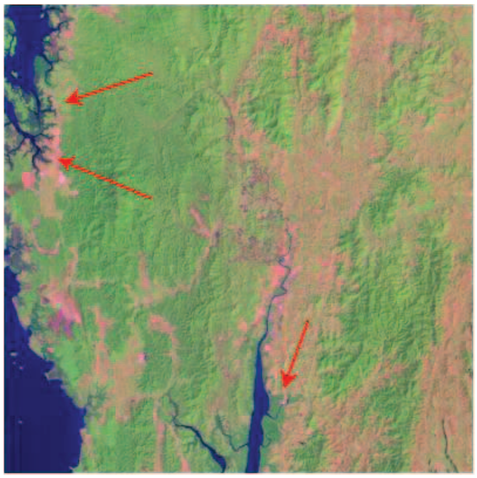
Fig. 1. Area of interest: mangroves location in Southeast Asia (a) and one example of the desired output over a small example area on the west coast of Malaysia (b) (result of manual extraction from low resolution images)

2. OBJECTIVES OF THE ALGORITHM

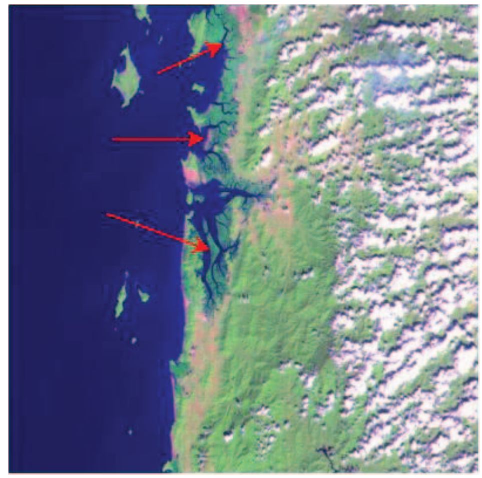
Currently, in a yet to publish study, most of the extraction is done manually as no satisfactory algorithm are available. As the region of interest is huge, it is not possible to process the whole region at the highest resolutions available. A reasonable compromise between resolution, accuracy and the speed of manual map production, for the whole region of Southeast Asia, is to use a resolution of 80 to 100 meter per pixel. This relatively low resolution has an impact on the detection of mangroves on satellite imagery. To provide accurate results, as well as locality information, it is important to produce higher resolution maps (e.g. 20 meters).

Due to the complexity of the task (see images on Fig. 2) and the amount of expertise required, the goal is not to obtain a final detection for the mangrove using a fully automatic algorithm but rather to assist the human expert in producing the maps faster.

The data used are multi-spectral data from the SPOT 4 and SPOT 5 sensors which are at a resolution of 20 m and 10 m respectively. Both sensors comprises four spectral bands: green, red, near infrared (NIR) and short wavelength infrared (SWIR).



(a)



(b)

Fig. 2. Example of mangrove location

3. PRINCIPLES

The algorithm is based on a Support Vector Machine classification based on a set of features extracted from the satellite images.

3.1. SVM

Support Vector Machine (SVM) classifier [2, 3] have proven to be suitable for remote sensing image classification. They are quite robust provided the feature provided are diverse enough.

The main factor here is to choose the class used for the learning step. SVM perform well if the classes are not a mix of too diverse content (to be able to find the plan separator) even if some of the features are redundant. Here five simple classes are used: mangroves, water, clouds, vegetation which is not mangrove and the rest.

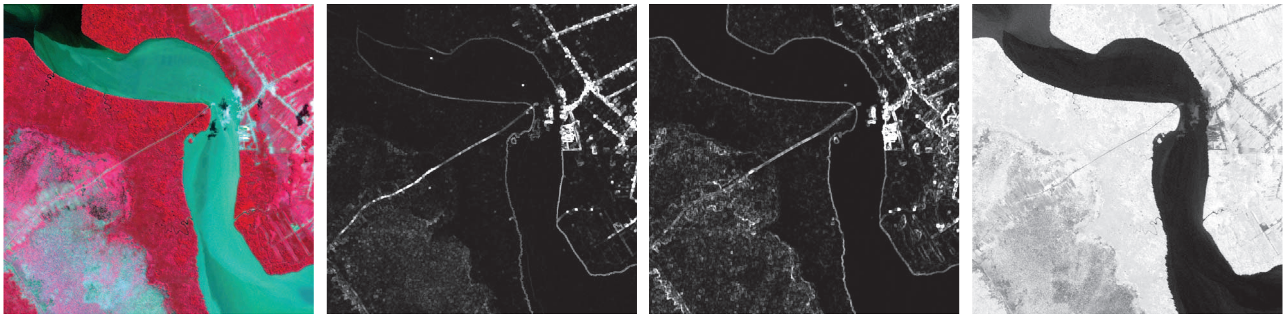
3.2. Features

Several features are extracted from the image and from other available data. These features try to draw on the expert knowledge. First, it is relatively easy to detect the water bodies from SPOT images and we know that mangroves grow at a proximity of water.

The first feature will be the distance to water bodies using a simple water detection algorithm (water index with thresholding) and the Danielsson distance map computation[4]. We also know that mangroves lie in low altitude area. This is particularly important to distinguish them from secondary forest which can look similar from the satellite. The elevation map, derived from SRTM is also provided as a feature. Finally, features from the image itself are also extracted. The most obvious features are coming from the pixel themselves and allow to compute vegetation index such as NDVI or moisture index. Additionally, mangroves are also characterized by a very smooth appearance. This is introduced in the feature set by computing Haralick texture indexes[5]. Fig. 3 presents some of the features used here.

3.3. Preprocessing

As we do not want to reproduce the learning phase for each image, the images have to be radiometrically corrected. A simple conversion to top of atmosphere (TOA) reflectance is applied. Images are also orthorectified.



(a) (b) (c) (d)

Fig. 3. Example of feature computed from the original image (a): with the contrast on the red channel (b), the Haralick sum variance on the SWIR channel (c) and the NDVI index (d)

4. RESULTS

The results are compared with a manual extraction. On a second step, it is planned to do the comparison with ground truth.

The detection result is evaluated using the normalized confusion matrix. Several measures are computed: the standard true positive (TP), true negative (TN), false detection (FD), no detection (ND) and kappa coefficient, and also accuracy, specificity and precision.

The first results show a correct detection of more than 90% of the mangrove (TP) with a very good reliability on the discarded area at more than 97% (TN). This enable the expert to focus only on the most difficult areas and save a significant amount of time.

All processing is done using the open source library Orfeo Toolbox (OTB) [6] enabling the possibility for the reader to easily reproduce the result presented here.

For the final version of the paper, a extensive study is planned to compare the contribution of different features to the final results. More than 30 features (texture features and radiometric features) are expected to be compared and raise the final performance. The method will also be compared with a more physical method closer to the expert intuition: hierarchical classification.

5. REFERENCES

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