TOWARD A GLOBAL TUAMOTU ARCHIPELAGO COCONUT TREES SENSING USING HIGH RESOLUTION OPTICAL DATA

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ABSTRACT

This study is part of a regeneration program of the coconut grove of French Polynesia where most coconut palm trees of the Tuamotu archipelago were planted in the 1980's following the various hurricanes that had struck islands. The French Polynesia government acquired one-meter pansharpened RGB Ikonos images over the Tuamotu archipelago. To exploit these data, a pilot study is conducted on the island of Tikehau, well-known from the specialists and easily accessible from Tahiti. A Maximum Likelihood (ML) classification is performed to segment the high vegetation in images. Thus, a Support Vector Machines (SVM) classification allows the high vegetation to be classified in different patterns. And finally, a robust segmentation process based on markers controlled watershed segmentation is proposed to extract tree crows. Through the ground mission, the trees detection accuracy is estimated which is then used to compute the number of trees the closest to the reality by applying a weighted factor to the number of trees located in each class.

Index Terms— SVM, Maximum Likelihood, classification, segmentation, watershed, texture.

1. INTRODUCTION

French Polynesia government wants to improve the coconut tree field exploitation in order to develop the extraction of the Coprah oil as an alternative fuel and also the use of senile trees wood. The Coprah oil exploitation already constitutes one of the principal financial resources of the inhabited atolls. Remote sensing technics minimize the cost of these studies by automating this task and avoiding ground missions.

The aim of this work is to characterize the coconut field type typology, *i.e.* the spatial distribution of coconuts. This goal is reached by first segmenting the coconut trees and then by classifying them according to their spatial distribution. Several steps are required to perform the automatic enumeration of coconut trees: a coconut field segmentation keeping the area of interest, a coconut field classification among a set of classes describing the different type of coconut fields encountered in Tuamotu using texture features and the SVM classifier, and finally, a robust segmentation process of coconut trees crown. An enumeration is now possible and an identification / segmentation of these trees according to some objective criteria such as the size of canopy, the average color, local density of the coconut trees field. A ground truth validation is performed in order to estimate the detection rate and error in each coconut trees class type leading to a precise extrapolation of the global number of trees. The convergence between results obtained with the proposed method and ground truth missions highlights the robustness of the method and authorizes a large-scale production on all islands.

2. DATA AND SITE STUDY

IKONOS optical data is widely available through the whole Tuamotu archipelago and its high spatial resolution (about one-meter resolution at ground level) is sufficient to carry out our objective. The study focuses on the atoll of Tikehau that is well-known from the specialists and easily accessible from Tahiti as a validation study area before extending the method to the rest of Tuamotu's atolls. Tikehau data set was acquired by IKONOS2 on July and August 2003 and is already orthorectified and registered in the WGS84 projection. The atoll of Tikehau is constituted of several islands called *motu*. As the full mosaic of the atoll of Tikehau has a resolution of 28517 by 28617 pixels, the original image is cut out into sub-images, each one locating a *motu*.

3. TREE FIELDS CLASSIFICATION METHODOLOGY

The coconut trees crown segmentation process must be applied in coconut fields areas to avoid false alarms and reduce the number of pixels to classify. In images, several structures are distinguished such as the sea, the sand, the coral and

some dwellings as well as the vegetation (coconut trees and other atoll vegetation types). In a first step, it is necessary to generate high vegetation masks before applying the segmentation process. Due to the lack of the near infra-red (NIR) band (not available in our database), it is not possible to compute the well known normalized difference vegetation index (NDVI) which is relevant for characterize the vegetation. An alternative solution has been tested and chosen: a Bayesian classification using a ML algorithm. However, this implies a manual selection of the training sets for each different available structures in the image. Then, a texture analysis [1, 2] is performed on the vegetation class to separate the high vegetation (which has been proved to be exclusively coconuts in Tuamotu) from the low vegetation. Once the segmentation is completed, areas are classified in three types of planting: natural (non spatial organization), artificial (trees are positioned on a grid spaced by 8 meters) and mixed fields (artificial fields where activities were dropped). The tree crown segmentation process depends on a pixel's neighborhood to compute the minimal network of the darkest pixels. The planting type classification is needed to adjust the size of the research window. For this case, a supervised SVM classification is used to segment these fields based on some training sets representing each kind of these fields that were selected in order to extract features like texture information [2, 3, 4, 5].

3.1. SVM Principle

The SVM classifier was introduced in 1995 by [6]. This Subsection briefly describes this classifier, details can be found in [7]. The Figure 1 illustrates the principle of the optimal hyperplan and the optimal margin used in the SVM classifier.

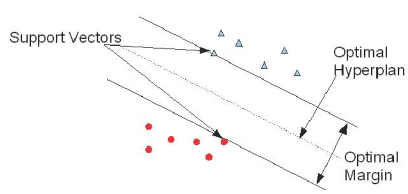


Fig. 1. SVM Classifier principle

Let's consider the case of a two-classe classification problem. A training set data is constituted of N samples described by data X_i and the labels Y_i take -1 or $+1$ as values. For the linear separability data, the SVM classifier is defined as the function

$$f_i(x) = sign(\langle \omega, X_i \rangle + b) \quad (1)$$

which maximizes the margin between the optimal hyperplan and the support vectors. The problem can be solved by using the Lagrange multipliers

$$f(x) = sign\left(\sum_{i=1}^{N} y_i.\alpha_i \langle x, x_i \rangle + b\right) \quad (2)$$

where α_i are Lagrange multipliers.

In the case of nonlinear separable data, one possible method to solve the problem is to use a kernel. This kernel is a function which project the initial data into a higher dimension space feature, $\Phi : {}^n \rightarrow$, in a such way that data are now considered as linearly separable. In equation (2), the dot product $\langle x, x_i \rangle$ is replaced by the dot product associated to the space feature defined as:

$$K(x, x_i) = \langle \Phi(x), \Phi(x_i) \rangle \quad (3)$$

and then the function to classify data becomes

$$f(x) = sign\left(\sum_{i=1}^{N} y_i.\alpha_i.K(x, x_i) + b\right) \quad (4)$$

In this study we use the Radial Basis Kernel (RBF) defined with $K(x, x_i) = e^{-\frac{|x-x_i|^2}{2\sigma^2}}$. This kernel gives the best results in our case compared to other kernels we have tested.

3.2. Application to Ikonos images

We use a modified ground truth made by Jacq [8] on the main *Motu* to describe our classes. For each class, an equalized random samples of 1100 pixels is taken for the training set as described in [9]. The definition of training set classes is listed in Figure 2. The SVM classification was performed using [10, 11] available in ENVI Software on a stack composed by the RGB components and the normalized Haralick's texture descriptors (with a total of 11 bands). The classification result has been improved using a majority analysis with a 45×45 window size. The Figure 2 shows the final fields type classification on the main *motu* of Tikehau.

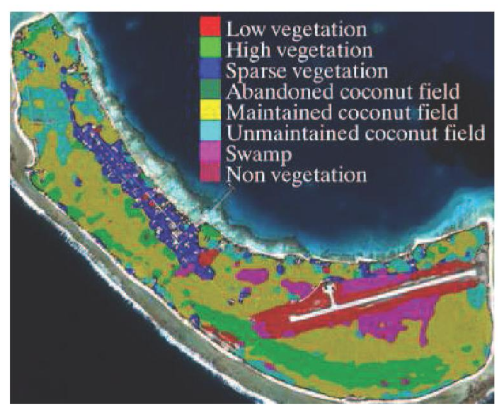


Fig. 2. SVM classification result on the main *motu* and classes color.

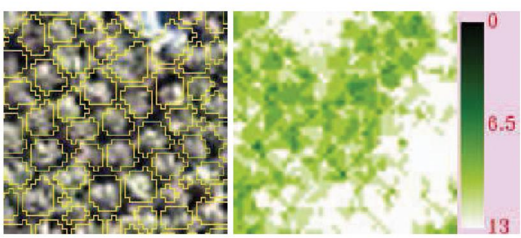
4. TREE CROWN DELINEATION METHODOLOGY

The crown delineation method is based on [12] which uses a watershed segmentation to extract tree crowns. However, several modifications has been bring to take into account specificity of image and trees: after an anisotropic filtering [13]

of high vegetation areas on the first PCA component [14] of the RGB image, local maximums are detected and used as markers for the watershed; these maximums are located closed to the crowns center [15]. The assumption that there are the darkest pixels between each crown is used to compute a boundary crown network [16, 17]. This minimal network of dark pixels is computed as the local minima of a searching window which the size depends on the planting type. The minimal network of dark pixels and markers are used as new minimum for the watershed segmentation process and to compute a topographic surface using the L_2 distance map. To avoid too small regions, we discriminate them according to their area using a coconut tree crown approximation by a circle within a radius R. Once the crowns delineation is made, the center of mass, weighted by the values of the pixels in each RGB channel, is computed to estimate the center of canopies. For details, the reader is referred to [18].

5. RESULTS, VALIDATION AND EXTRAPOLATION

In order to validate the whole method, some sample areas characterizing various fields type are chosen. For each of these sample areas, the segmentation process is executed and all tree crowns are extracted. The validation is made using a photo ground truth and a ground mission. The Figure 5 shows a result of the crown segmentation on a small region and the corresponding local density map.



(a) Tree crown delineation (b) Density Map

5.1. Validation

A first validation is performed on images (acquired in 2003) by human interpretation (manual localization of the coconut trees canopy) in order to estimate the detection error for each kind of fields type. This validation provides a mean detection error of less than 10% (see table 1) which proves that our method locates a majority of the coconut trees visible in images.

A ground mission was planed in 2006 by Jacq [8] which has counted coconut trees within 12m radius circular plots, each plot being located by its GPS coordinates. Moreover, the tree height had been recorded. This mission had covered the entire atoll of Tikehau. To compare our results with the ground mission results, the tree delineation process is used to compute a local density map with the same radius circle

Table 1. Method accuracy using a photo interpretation ground truth

Id Area	# Method	Photo	accuracy
1	908	818	9,91%
2	986	912	7,51%
3	495	450	9,09%
4	346	356	-2,89%
5	436	399	8,49%
6	1269	1198	5,59%
Total	4440	4133	6.81%

whose centers are given by GPS coordinates. Two similar local density maps are build from the ground mission data considering trees having more than 4-meter height and trees having more than 5-meter height, these heights representing trees likely visible on the remote sensed images. The Table 2 shows that our method detects between 66% to 89% (for H > 5m) of the visible trees according in which class the trees are. In maintained fields, where trees density is the highest (distance between each tree is about 8m), the accuracy is closed to 83%. The zeros values for classes 3 and 8 indicate that no measurements have been made in this regions during the different ground missions.

Differences between validations come from the fact that the photo interpretation is done on the image taken in 2003. The ground truth missions was planed in 2006, 3 years later. During this period of 3 years, some trees not visible on the image may have arrived to the top of the canopy, also other trees may have been able to grow (especially in unmaintained fields) and some may have died.

5.2. Trees Extrapolation

Once the method's accuracy is estimated for each class, we can estimate a number of coconut trees in each class and on all over the atoll of Tikehau. We believe it is wise to take as precision for each class an average accuracy from all trees, those over 4-meter height and those over 5-meter height (see the last column in Table 2). Excepted for classes 3 and 8 whose the accuracy can not be measured, we only keep the same number of detected trees for those classes. The estimated number is computed by applying a weighting factor to the number of trees located in each class and summing them to obtain a global estimation.

6. CONCLUSION

Despite of the lack of the NIR band, combining the use of ML and SVM classification on Haralick's texture descriptors provides a good classification of various coconut field types. The segmentation process based on a markers controlled watershed algorithm gives good results since that the photo interpretation shows less than 10% of false detections. Our tree crown segmentation method is robust and allows a production on all atolls. The ground truth surveys in each class provides an accuracy of good detection for each type of planting. Ap-

Table 2. Ground truth accuracy on the entire atoll

Class Id	number of trees				Accuracy			
	all	H > 4m	H > 5m	Method	% Diff 4m	% Diff 5m	% Diff All	% Mean
1	73	50	48	51	102,00%	106,25%	69,86%	92,70%
2	228	206	185	132	64,08%	71,35%	57,89%	64,44%
3	0	0	0	0	0,00%	0,00%	0,00%	0,00%
4	687	584	540	399	68,32%	73,89%	58,08%	66,76%
5	174	133	123	102	76,69%	82,93%	58,62%	72,75%
6	8	6	6	4	66,67%	66,67%	50,00%	61,11%
7	22	21	16	11	52,38%	68,75%	50,00%	57,04%
8	0	f0	0	0	0,00%	0,00%	0,00%	0,00%

Table 3. Final coconut trees estimation all over the island of Tikehau

	Class Id								
	1	2	3	4	5	6	7	8	
Mean accuracy	92,70%	64,44%	0,00%	66,76%	72,75%	61,11%	57,04%	0,00%	Total
Detected	13771	21735	650	87824	23439	1334	973	904	150630
Extrapolated	14855	33728	650	131546	32220	2183	1706	904	217792

plying different weighting factor according to a class, we obtain an estimated number of coconut trees the closest to the reality. A drawback of the classification method is its high computational cost as the classification is directly performed on pixel values leading to a big configuration space. To fix this problem, we propose to perform the classification of coconut plantation type directly on the crown center coordinate which is a small configuration space. A relevant representation of these coordinates using wavelet or Poisson process is probably required to obtain good classification results.

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