INTEGRATION OF TEMPLATE MATCHING AND SVM TECHNIQUE FOR COCONUT TREE DETECTION

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ABSTRACT: The research on feature extraction of typical objects like trees and buildings has intensified. Previous studies have demonstrated that the use of LiDAR data is very effective, especially for detailed land cover mapping. In this study, LiDAR derivatives such as Canopy Height Model (CHM), Digital Surface Model (DSM), Digital Terrain Model (DTM), LiDAR Intensity, number of returns and DSM ruggedness measure are used in image analysis in order to extract meaningful features. Detection algorithm integrating template matching and support vector machines (SVM) are then applied to extract coconut trees in the selected study area. Comparative experimental results show that this algorithm is able to detect coconut trees more effectively. The methodology of this study is very useful for the rapid assessment, monitoring and sustainability of coconut trees in the Philippines, which is the second biggest producer of coconut; but at the same time, the third most exposed countries to natural disasters.

1. INTRODUCTION

According to the latest data of Food and Agriculture Organization of the United Nations Statistics Division, the Philippines is the second biggest producer of coconut. Since Philippines is also one of the most exposed country to natural disasters, technology for rapid assessment and monitoring of coconut trees plays a vital role in sustaining the coconut industry of the country. Moreover, precise crop mapping is vitally important in coconut industry such as crop damage estimation, crop acreage and yield estimation.

Light detection and ranging (LiDAR) technology can obtain high resolution topographic data and penetrate vegetation, measuring features subdued by the rugged and vegetated terrain. It has proven to be a powerful and promising tool to detect crops and map features. A range of LiDAR derivatives, including Digital Terrain Model (DTM), Canopy Height Model(CHM), LiDAR Intensity, number of returns, surface ruggedness and slope have been widely used for qualitative visual interpretation and image analysis (Liu et. al. 2015; McCoy et. al. 2011; Antonarakis et. al. 2008; Koch et. al. 2006).

Pixel-based and object-based methods are the two general image analysis approaches for image classification. Recent studies have found that object-based methods are more effective than pixel-based approach (Duro et. al. 2012; Hussain et. al. 2013; Yan et. al. 2006; Yu et. al. 2006). Thus, most of the image classification applications have focused more on object-based image analysis using LiDAR derivatives and other high resolution multispectral images. The object-based method produced thematic maps with more meaningful objects, but it also suffered from absorption of small rare classes into larger objects and the incapability of spatial parameters (e.g. object shape) to contribute to class discrimination (Dingle Robertson et. al. 2011).

Support vector machine (SVM) is a machine learning algorithm that is mostly used in object-based image classification because of its capability to generalize well on difficult image classification problems (Zhu et. al. 2002). On the other hand, template matching is a high-level pixel-based method that allows to identify the parts of an image (or multiple images) that match the given image pattern (Perveen et. al. 2013).

Mambusao, Capiz is a town in the Western Visayas region of the Philippines, with abundant coconut. However, due to the recent typhoons that devastated the town, which includes super typhoon Haiyan, coconut plantations were greatly affected. Developing a method in detecting coconut trees would significantly help in monitoring, rapid assessment and vulnerability assessment of coconut plantations.

In this study, an integrated object-based and pixel-based coconut tree detection method, which uses LiDAR data, feature selection method and machine learning algorithms (SVM and template matching technique), was developed and implemented in Mambusao, Capiz.

2. METHODOLOGY

2.1 Study Area and Data

Mambusao is a third class municipality in the province of Capiz, Philippines with an area of 136.9 km^2. Its economy is based on agriculture with rice and coconut as the primary products and crops. Due to its strategic location, it is also identified as district agro-industrial center by the National Economic and Development Authority in Western Visayas region. Figure 1 shows the municipal boundary of Mambusao.

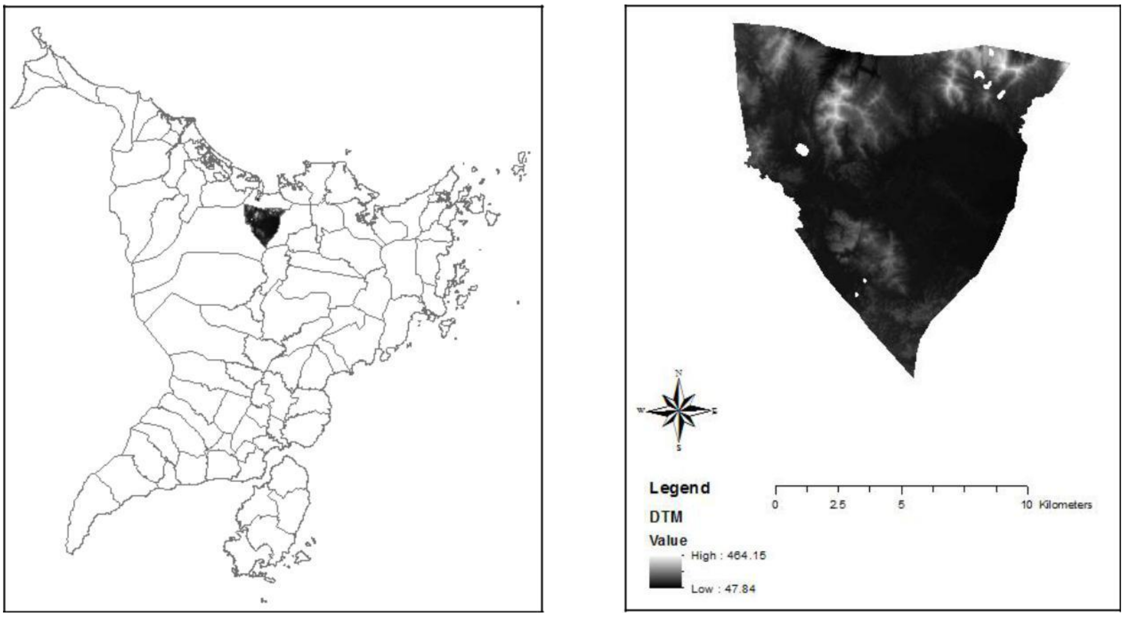


Figure 1. Location Map of Mambusao, Capiz.

The following table shows the data used in this study and their corresponding acquisition date.

Table 1. Data sources and their corresponding acquisition dates.

Data	Source	Acquisition Date
LiDAR data	UP Diliman Disaster Risk Exposure and Assessment for Mitigation (DREAM) Program Data Acquisition Component	August, 2013
Mambusao Municipal boundary	Global Administrative Areas database	November, 2015
Training and Validation Points	Ground truth validation, Secondary Data with visual interpretation	July, 2016

The following LiDAR derivatives were used in this study:

a. Canopy Height Model (CHM)
b. Digital Surface Model (DSM)
c. Digital Terrain Model (DTM)
d. LiDAR Intensity
e. number of returns
f. DSM ruggedness measure

2.2 Sampling Method and Statistical Analysis

Field visit and appropriate ground control points were collected for visual, training and validation area selection (Ghorbani et. al. 2013). Since this study is focused on coconut tree detection, coconut and non-coconut classes are the only classes in training and validation samples. Simple random sampling was used in data collection (Congalton 1988).

Table 2 shows the quantitative distribution of training and validation samples of both classes. Figure 2 shows the spatial distribution of training and validation points.

Table 2. Quantitative Distribution of Points

Class	**Training Samples**	**Validation Samples**
Coconut	63	32
Non-coconut	66	33

Figure 2. Spatial Distribution of Points.

Accuracy assessment or KAPPA analysis was implemented to measure the agreement of results in image classification for each experiment (Cohen 1960). The result of performing KAPPA analysis is a KHAT statistic (an estimate of KAPPA). The KHAT statistic is calculated as:

$$\hat{k} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{i+})}{N^2 - \sum_{1=1}^{r} (x_{i+} * x_{+i})} \qquad (1)$$

where:

r = the number of rows in the error matrix
x_{ii} = the number of observations in row I and column
i x_{i+} = the marginal totals of row i
x_{+I} = the marginal totals of column i
N = the total number of observations.

Kappa analysis was used to compare the image classification methods being experimented in this study. It has the ability to determine if the accuracy level between the two classifications is significantly different. The estimated variance of Kappa can be calculated as:

$$\hat{V} = \frac{1}{N(1-p_c)^4} \left\{ \sum_{i=1}^{m} p_{ii} [(1-p_c)(p_{i+} + p_{+i})(1-p_o)]^2 1 + (1-p_o)^2 \sum_{i=1}^{m} \sum_{j=1}^{m} p_{ij} (p_{i+} + p_{+j})^2 - (p_o p_c - 2p_c + p_o)^2 \right\} \qquad (2)$$

where:

$\hat{V}$ = the estimated variance of Kappa
N = the total number of observations
m = the number of categories
p_c = the proportion of observations that agree by chance
p_0 = the proportion of observations correctly classified.

Using the result of KHAT statistic, $\hat{k}$, and its estimated variance of Kappa, $\hat{V}$ for each classification method, the normal deviate, Z, can be calculated as (Congalton et. Al. 1983):

$$Z = \frac{(\hat{k}_1 - \hat{k}_2)}{[V(\hat{k}_1) + V(\hat{k}_2)]_{½}} \quad (3)$$

where:

Z = the standard normal deviate
$\hat{k}_1$ = the Kappa Coefficient of Agreement (KHAT statistic) for the first classification method
$\hat{k}_2$ = the Kappa Coefficient of Agreement (KHAT statistic) for the second classification method
$V(\hat{k}_1)$ = the estimated variance of $\hat{k}_1$
$V(\hat{k}_2)$ = the variance of $\hat{k}_2$.

If Z exceeds 1.96, then the difference is significant at the 95 percent confidence level (Rosenfield et. al. 1986). If it is found that no significant difference exists, either classification can be used since they are essentially the same in terms of accuracy.

2.3 Experimental Methods

In this section, experimental methods performed in this study are discussed. Image segmentation and classification were done in eCognition program for all the experimental methods. In addition to, the same image segmentation method and samples were used for all the methods in order to prevent bias in comparing the results of image classification.

2.3.1 Coconut Tree Detection Using SVM Algorithm

In this experiment, common object-based classification workflow was implemented. Figure 3 shows the process workflow of object-based image classification used in this experiment. Multi-threshold segmentation and multiresolution segmentation algorithm were performed to create meaningful objects from the LiDAR derivatives. Using field points collected during the ground truth data collection, training samples were randomly selected. SVM attribute evaluation feature selection method was also applied using the features of training samples to filter out redundant features. SVM attribute evaluation assesses the worth of an attribute by using an SVM classifier. Attributes are ranked by the square of the weight assigned by the SVM (Guyon et. al. 2002). Then, support vector machines algorithm was used in image classification. Accuracy assessment was used to evaluate the result of classification.

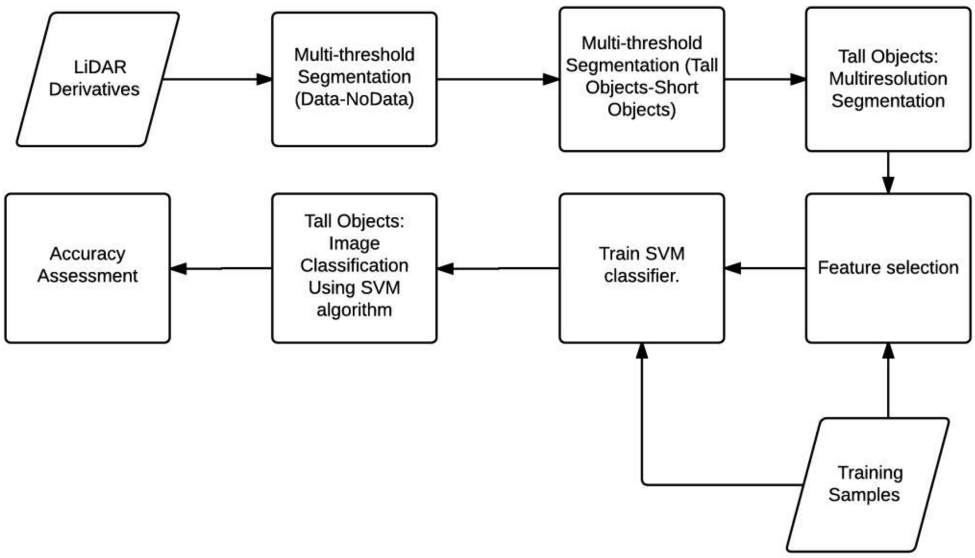


Figure 3. Process Workflow of Object-based Image Classification Using SVM

2.3.2 Coconut tree detection using Template Matching Technique

In this experiment, common object-based classification workflow combined with pixel-based method was implemented. Figure 4 illustrates the process of image classification using template matching technique. The template matching capabilities inside the Trimble eCognition software suite were taken. Random samples of coconut in the CHM image layer were selected and a library of coconut tree templates was generated. After template generation, template matching algorithm in eCognition was performed. Coconut objects were classified using the points generated by template matching algorithm. Finally, the classification result was evaluated through accuracy assessment.

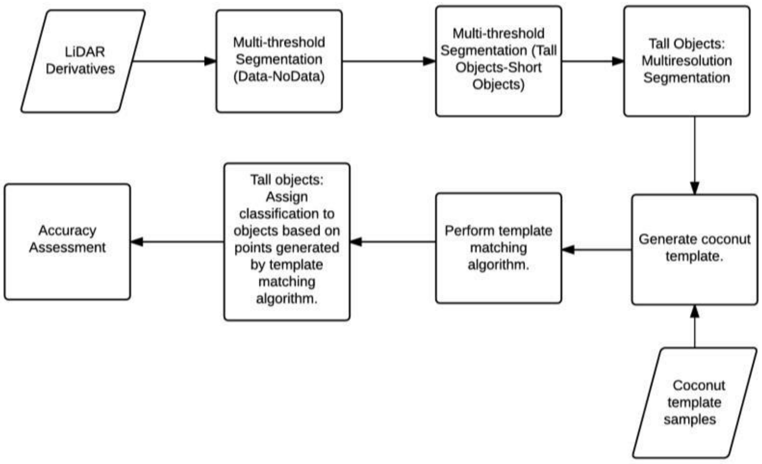


Figure 4. Process Workflow of Image classification
Using Template Matching

2.3.3 Coconut Tree Detection Using Integrated SVM and Template Matching Method

For this experiment, the result of template matching algorithm was used to identify areas with coconut trees. In that case, SVM algorithm was used to classify the areas identified by the template matching algorithm. Figure 5 above shows illustrates the flow of the proposed template matching and SVM technique in detecting coconut trees.

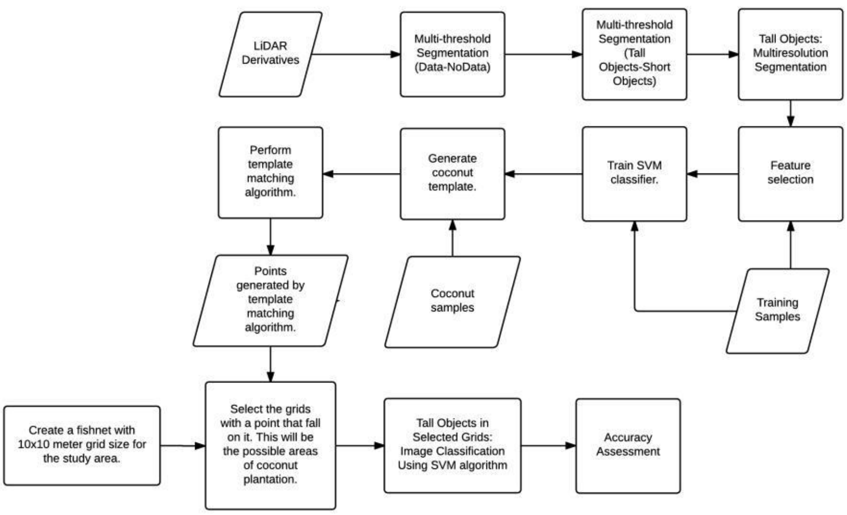


Figure 5. Process Workflow of Image Classification
Using Template Matching and SVM Algorithm

3. RESULTS AND DISCUSSION

3.1 Accuracy Assessment

Table 3 shows the performance of the different coconut tree detection methods being experimented. Results show that the integrate SVM and template matching method has the highest overall accuracy (96.9%) and KIA (86.8%). It is followed by a template matching method with 96.7% overall accuracy and 87.4% KIA. SVM method has the lowest overall accuracy and KIA with 94.2% and 80% respectively. It can also be noted from the accuracy assessment that coconut class in SVM method suffers from over-classification with KIA per class of coconut class below 80%. On the other hand, coconut class in template matching method suffers from under-classification with the Kia per class of coconut class below 80%.

Table 3. Accuracy Assessment of Different Coconut Tree Detection Methods.

Accuracy Reference	SVM only	Template Matching only	SVM and Template Matching
Coconut - Kia Per Class	0.9614786	0.7764168	0.8598875
NonCoconut - Kia Per Class	0.68535053	1	0.8965791
Overall Accuracy	0.9416269	0.9674254	0.969
KIA(KHAT statistic)	0.8002342	0.8741381	0.8778501

Figure 6a below shows a case of over-classification of coconut class in SVM image classification method. Figure 6b illustrates a case of under-classification of coconut class in template matching image classification method. Figure 7 shows a case wherein integrated SVM and template matching method reconciled the problems of under-classification and over-classification.

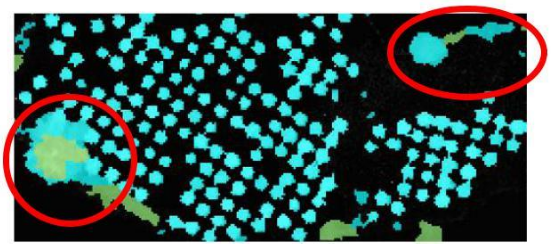


Figure 6a. Zoomed-in result SVM method.

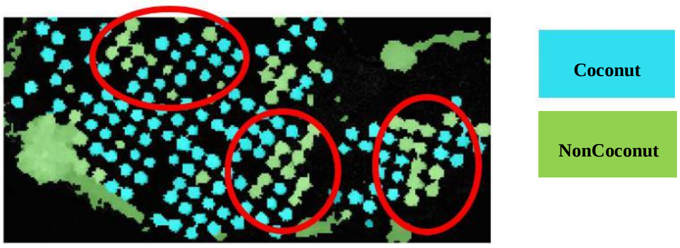


Figure 6b. Zoomed-in result template matching method.

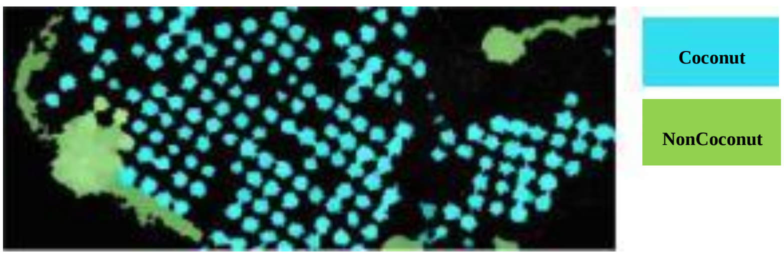


Figure 7. Zoomed-in result of integrated SVM and template matching method.

3.2 Statistical Analysis of Accuracy Assessment

Using the statistical analysis explained in the methodology, the existence of significant difference between the accuracy of the three experimented methods was tested. Table 4 depicts the results of KAPPA analysis test of significance each classification algorithm vs. random classification algorithm. Based from the result of KAPPA analysis, all classification algorithms being experimented in this study are significantly different compared to random algorithms. It implies that the accuracies of all experimented coconut detection algorithms are significantly different from other random algorithms.

Table 4. Results KAPPA Analysis Test of Significance of each Coconut Detection Algorithm vs. Random Algorithm.

Coconut Detection Algorithms	KHAT Statistic	Z Statistic	Result*
SVM method	0.80	106.50	S**
Template matching method	0.87	127.59	S
Integrated SVM and template matching method	0.88	136.14	S

***** At the 95% confidence level.
** S = significant.

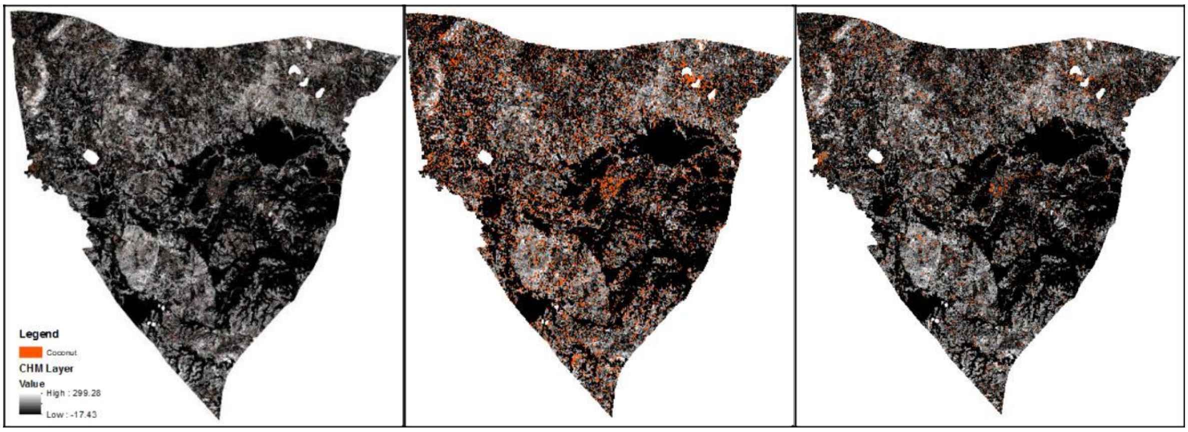
Moreover, table 5 shows the results of the KAPPA analysis test of significance of each coconut detection algorithm. Results demonstrated that the accuracy of template matching coconut detection method vs. the proposed integrated SVM and template matching algorithm does not have significant difference. This implies that there is no credible evidence that the proposed coconut tree detection algorithm is better than template matching algorithm in terms of accuracy. On the other hand, KAPPA analysis results proved that either a template matching method or integrated SVM and template matching method are better algorithms for coconut tree detection compared to the SVM method.

Table 5. Results KAPPA Analysis Test of Significance of Proposed Algorithm vs. Other Experimented Algorithms.

Comparison	Z Statistic	Result*
Template matching vs. Integrated SVM and template matching	0.53	NS**
Template matching vs. SVM	7.24	S
SVM vs. Integrated SVM and template matching	7.6	S

***** At the 95% confidence level.
** S = significant, NS = not significant.

3.3 Visual Comparison of Image Classification



8a. Template matching 8b. SVM 8c. Integrated

Figure 8. Detected Coconut Trees.

Figure 8 illustrates the result of each coconut detection algorithm being experimented. Result of template matching algorithm method shows no noticeable coconut plantations being detected. On the other hand, the SVM algorithm result shows that almost all areas in the municipality have coconut. Finally, the image classification result of the proposed integrated SVM and template matching algorithm shows noticeable coconut plantation in the study area.

4. CONCLUSION AND FUTURE WORK

An integrated SVM and template matching approach for coconut tree detection was proposed. The results of the experiment show that the proposed algorithm has the best overall accuracy and KIA. In addition to, it was found out that the template matching approach and the proposed coconut detection algorithm are significantly different compared to the SVM approach. Moreover, the results of the experiment showed that the SVM approach of coconut tree detection suffers from over-classification while the template matching approach suffers from under-classification.

Although statistical analysis showed no credible evidence that the proposed algorithm is significantly different to template matching algorithm in terms of accuracy, it should be noted that the integrated SVM and template matching approach produced more visually appealing image classification. Consequently, we recommend testing the algorithm to other large area coconut to test the consistency of its accuracy.

Furthermore, this study focuses only on detecting sparse coconut trees since there are only few dense coconut plantations in the study area and this would limit the sample size of each class. Thus, it is suggested to test the proposed algorithm in areas with dense coconut plantations.

In the future, we will try to use the proposed algorithm in change detection of coconut plantations before and after the super typhoon Yolanda devastated the study area.

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