FEATURE SELECTION IN LIDAR HEIGHT METRICS USING DECISION TREE FOR SVM CLASSIFICATION: APPLICATION IN AGRICULTURAL RESOURCES MAPPING

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ABSTRACT: The fusion and combined use of LiDAR and other remotely sensed data have been widely explored in land cover and land use mapping. With the scarcity of available imagery data, this study focuses on classifying agricultural resources from LiDAR data only. Specifically, using object-based image analysis on non-ground objects, classes with CHM > 0.5m were extracted. It has been found that even without spectral data, LiDAR data alone can be used to map agricultural resources. Initially, confusion among classes was observed in doing Support Vector Machine (SVM) classification because of the presence of too many inputs, e.g. popular forestry metrics and other height information from LiDAR data, which contain irrelevant and redundant data. In addition, processing takes longer time because SVM needs to solve a quadratic programming problem on all the input variables. Thus, feature selection on the input layers and the variables derived from them is essential. In this study, a Decision Tree (DT) was constructed to determine the importance of 56 variables derived from 14 LiDAR height metrics. The input layers were filtered for SVM classification based on the results of the DT. The effectiveness of the method was assessed in three different locations. Through this method, the relevant features derived from the LiDAR height metrics were accurately identified. At least 71% reduction in the number of variables was achieved, as well as 56% reduction in SVM's training and classification time. With the DT-based feature selection, the overall accuracy and kappa index of agreement were effectively increased, saving time and minimizing inputs for SVM.

1. INTRODUCTION

Extraction of natural resources in the Philippines, such as agricultural, coastal, hydrological, forestry and renewable energy resources, are currently performed by the three-year program of the Department of Science and Technology (DOST) known as Phil-LiDAR 2 (Blanco, Tamondong, Perez, Ang, & Paringit, 2015). The program, which started in 2014, aims to use LiDAR datasets to extract natural resources and present them in form of maps.

Most of the output maps of the Phil-LiDAR 2 program more or less contain land use and land cover information. For study areas that contain large agricultural lands, the participation of various height metrics become crucial in the application of SVM classification when considering not only the accuracies of the maps but also the efficiency of the map production. Hence, this study focuses on the feature selection in LiDAR height metrics. Specifically, this research covers agricultural resources mapping that uses the Decision Tree (DT) algorithm for SVM classificaiton

1.1 Works on Land Cover Mapping

Land cover maps support a broad range of applications, such as in "forestry, natural hazards, urban climatology and agriculture" (Stefanski, Mack, & Waske, 2013). Human surveys became impractical as the need to create land cover maps with larger geographical areas increased. Therefore, land cover mapping that uses aerial and satellite images has greatly reduced the amount of resources expended in the generation of such maps (Aonpong, Kasetkasem, Rakwatin, Kumazawa, & Chanwimaluang, 2016).

In essence, a land cover map shows "the observed biophysical cover on the Earth's surface" as per FAO definition of land cover. The level of detail of the biophysical covers present in a particular study area depends on the input images used. As far back as 2009, it was found that RADARSAT-2 data can be used to distinguish rice fields between other low vegetation classes. (Hoang, Bernier, Duchesne, & Tran, 2011) By 2011, classification accuracies of more than 90% were already achieved for main forest classes in a study conducted by Hoan et al. in mapping a tropical forest using optical and microwave data of ALOS.

A number of satellite images have become available to the public in the previous years that aided the production of land cover maps. In December, 2008, even the Landsat data became available to the public at no charge. Because of the availability of such data, image processing algorithms were applied to the available aerial and satellite data in performing classification of land cover features, such as water, forest and grassland.

Earlier remotely-sensed data had relatively low resolution, which introduced several problems in classifying land cover classes. A multi-layer approach has been proposed by Sophie et al. to address the "critical requirements of stability." Another problem with the then available remotely-sensed data was the shadow, which has been addressed in the research conducted by Kasetkasem and Varshney in 2011.

In 2011, Zhai et al. were able to map a 68,401-square-kilometer island using Landsat data with an accuracy of 79.80%. In the same year, an accuracy of 83.93% was achieved by Liao on a national-scale land cover map. Though it seemed that the input image limits the quality of the classification of the land cover classes, accuracy of the generated land cover maps according to Aonpong, et al. is largely dependent on the algorithm used.

Image processing techniques that have been applied to remote-sensing images shifted from the conventional pixel-based approach to the object-based image analysis (OBIA). In OBIA, the adequacy of the classification methods is greatly dependent on the accuracy of the segmentation used (Stefanski, Mack, & Waske, 2013). While OBIA is the key factor in the accuracy of the land cover map created then, the adequate classification result relied on the quality of the segmentation.

As data with higher resolutions, such as LiDAR, become available, improvements were introduced. Automations in the land cover classification were made using Landsat TM/ETM+ images (Licciardi, Pratola, & Frate, 2009). Data fusion, such as in the study conducted by Barbanson et al., applied fusion to LIDAR and RADAR data at the feature level.

Hyperspectral images aided in the advanced classification of land cover. Integration of LiDAR and hyperspectral images improved classification accuracy. However, García-Sopoet al. in 2015 found that in order to be successful in integrating data when performing classification, it is highly needed that some aspects be addressed such as those that are "related with radiometric and geometric distortions." While data fusion generally applies to image layers, other information can be attributed to the image layers to improve the classification. Other details, such as crop rotation information can be fused with multi-temporal high-resolution optical images to improve the results of the classification (Osman, Inglada, Dejoux, Hagolle, & Dedieu, 2012). A very high resolution IKONOS-2 was used by Gil and Abadi in 2015 and it was found that this image has been accurately classified especially by using k-Nearest Neighbor and Maximum Likelihood Classifications.

In 2013, a robust methodology was made that can even attain accuracies of more than 90% (Berger, Voltersen, Hese, Walde, & Schmullius, 2013) by fusing LiDAR and HSR multi-spectral data, hence, a detailed urban land cover map has already been achieved in that year. By using LiDAR data alone and working on height and intensity data, user and producer accuracies that range from 86.8% to 93.6% have already been achievable in 2013 (Zhou, 2013).

A new land cover mapping technique was introduced by combining the strengths of the Random Forest Algorithm and the Level Set Method (Aonpong, Kasetkasem, Rakwatin, Kumazawa, & Chanwimaluang, 2016). Superresolution mapping is currently being applied on land cover mapping that is able to produce fine spatial resolution out of a coarse-spatial-resolution image (Ling, Foody, Ge, Li, & Du, 2016).Recent improvements in land cover mapping are focused on developing algorithms and on increasing the resolution of the land cover map, along with the accuracy.

1.2 Agricultural Production in Batangas

According to Philippine Statistics Authority, there are 287.7 thousand farms for agricultural use in 2002, covering 588.5 thousand hectares has been registered in Region IV-A (Philippine Statistics Authority, 2004). The total agricultural land area of the region consist of 36.3% of the total land area. The number of farms decreased by 11.6% and agricultural land area by 16.3% over the 1991 estimation. Statistics show a decrease from 2.20 hectares per farm in 1991 to 2.08 hectares per farm in 2002 based on the average farm size. Generally, the conversion of these lands to residential or commercial lands can be attributed to the region's annual growth rate of 4.1%.

Agriculture is the main economic activity in Batangas. Its major crops are rice, sugarcane, coconut, mango, banana and coffee (Department of Agriculture-Region IV-A, n.d.).

Coconut is considered the principal permanent crop in the region in terms of the number of trees/vines/hills. This crop accounted for 43.5 million trees in 167.4 thousand farms (Philippine Statistics Authority, 2004). Between 1998 and 2008, the coconut hectarage in Region IV-A and V increased by 105,000 hectares (Philippine Coconut Authority).

In 2010, the province of Batangas ranked 6th among the top mango producing provinces in the country, sharing 3.65% of the total production. It was the major producer of the commodity in the region accounting for 74.11% of the total production in 2011. It has also the largest area harvested of the crop contributing 80.40% of the total area harvested in the region in 2011 (Department of Agriculture-Region IV-A, 2011).

Batangas was the highest banana production in the area followed by Quezon. The two provinces contributed 58.35% of the total banana production in the region. Area harvested of the crop increased by 1,128.50 MT from an output of 28,577 ha in 2007 to 29,705.50 ha in 2011. (Department of Agriculture-Region IV-A, 2011)

Sugar is a major industry in the province. Sugarcane fields are abundant in all towns of Batangas, and this could be the reason why the province is home to a wide variety of sweets. Batangas is home to Central Azucarera Don Pedro, one of the biggest cane and sugar refining establishments in the Philippines located in Nasugbu town (Batangas-Philippines.com, 2012). Batangas also ranked third in 1991 for the highest sugarcane producing in the region with 30.1 thousand farms reporting, covering 25 thousand hectares where corn ranked second. (Philippine Statistics Authority, 2004) Sugar block farming have also adopted in some areas in Batangas like Tuy, Lian and Nasugbu. This block farming increased productivity of 60 tons to 75 tons of sugarcane per hectare (Department of Agrarian Reform, 2013).

2. METHODOLOGY

2.1 Study Area and Materials

The study area covers three municipalities in Batangas, Philippines: Alitagtag, Balayan and Calatagan (Fig. 1). Alitagtag is a 4th class municipality with a land area of approximately 27.03 km^2 and a LiDAR coverage of 64%. Balayan is a 1st class municipality with a land area of approximately 94.45 km^2 and LiDAR coverage of 76%. Calatagan, fully covered with LiDAR data, is a 2nd class municipality with a land area of approximately 106.33 km^2. The income classification is based on Department of Finance’s order effective 29 July 2008. All the LiDAR data were acquired in 2014 by the Disaster Risk and Exposure Assessment for Mitigation.

(a) Alitagtag, Batangas (b) Balayan, Batangas (c) Calatagan, Batangas

Figure 1. Google Earth image showing the study sites (municipal boundaries from National Statistics Office).

Table 1. LiDAR height metrics rasterized using LAStools.

Acronym	Meaning
CHM	Canopy Height Model derived using the algorithm of Khosravipour, et al. (2013)
CHM MAX	Focal statistics showing maximum value of the CHM raster computed with a rectangular 3x3 neighborhood
CHM STD	Focal statistics showing standard deviation of the CHM raster computed with a rectangular 3x3 neighborhood
DSM	Digital Surface Model
nDSM	Normalized Digital Surface Model
SLOPE	Computed gradient of the DSM raster
HT KUR	Kurtosis of height based on LiDAR points
HT MAX	Maximum value of height based on LiDAR points
HT MIN	Minimum value of height based on LiDAR points
HT P01	1st Percentile of height based on LiDAR points
HT P99	99th Percentile of height based on LiDAR points
HT QAV	Quadratic average of height based on LiDAR points
HT SKE	Skewness of height based on LiDAR points
HT STD	Standard deviation of height based on LiDAR points

LAStools was used to process the raw LiDAR point clouds, enabling the derivation of raster layers needed for the object-based classification. Listed on Table 1 are the height information and popular forestry metrics used in this study. The object-based image analysis was carried out using eCognition, while ArcMap was used for GIS-related processes. From the 14 LiDAR-derived height metrics, statistical variables were calculated including mean, standard deviation, 50th quantile and mode, amounting to 56 input variables. Note that each statistic is computed per segmented object.

2.3 Feature Selection

Even with the use of LiDAR derivatives and orthophoto for SVM classification, confusion among classes were reported by Phil-LiDAR 2 partner institutions, testing various classifiers in different locations (David & Ballado, 2015a; Jalbuena, et al., 2015; Pada, et al., 2015) With the unavailability of orthophoto for many LiDAR flight missions, classification can be even more challenging, resulting to slight decrease in accuracy (David & Ballado, 2015b). Classifiers can perform poorly because of the presence of redundant and irrelevant data.

Relying solely on LiDAR derivatives for LULC mapping, many variables (e.g. 56 for this case) can serve as input for SVM training; in which unknowns are the redundant and irrelevant variables. Hence, a feature selection technique is necessary for this problem. Generally, there are three goals for implementing a feature selection technique: (1) to improve prediction performance of the predictor; (2) to provide faster and more cost-effective predictors; and (3) to provide better understanding of underlying process that generated the data (Guyon & Elisseeff, 2003).

Although SVM performs well, a major drawback is its computational cost, particularly occurring on the training phase (Cristianini & Shawe-Taylor, 2000; Chang, et al., 2010). This happens because training the classifier requires solving a quadratic programming problem (QPP), which is a computationally expensive task (Cervantes, Farid García Lamonta, Mazahua, & Ruíz, 2015). Cervantes et al. (2015) further noted that solving the QPP becomes impractical when the data sets are huge because the amount of time and memory invested is between $O(n^2)$ and $O(n^3)$.

Recently, studies are focusing on various data reduction techniques for SVM classification. Reduction techniques prior to SVM classification have been tested by Georgescu, et al. (2010), including Principal Component Analysis, Partial Least Squares, Structurally Random Matrices and Orthogonal Matching Pursuit.

Decision Tree, a machine learning algorithm widely used in data mining, has been a tool for data reduction. DT is a binary tree wherein a series of decisions are made to segment the data into homogeneous subgroups (eCognition, 2014). The decision tree is built by undergoing a recursive process; sorting data from a node, where a test is made based on an attribute, branching to another node, where another test is made, until it reaches a final classification at the leaf node (Mitchell, 1997).

A novel algorithm was developed by López-Chau, et al. (2012) to select the most important sample from training data by guiding the sample selection giving more chance to be selected to those examples that are on the boundaries of clusters discovered by a decision tree. Although the size of training data was reduced, there was a slight decrease in the accuracy of the classifier; but they claimed that it works well for large datasets.

More recently, Cervantes, et al. (2015) improved their previous work by applying a data filter based on a decision tree that scans the entire data and obtains a small subset of data points. They also noted that the proposed algorithm works very fast even with large data sets and that it outperforms the current state of the art SVM implementations without substantial reduction of accuracy.

The built decision tree is not only used for prediction, but also for further data analyses. An important property of the constructed decision tree is its ability to compute the importance value (relative decisive power or information gain) for each feature (Mitchell, 1997; OpenCV). This can be performed in eCognition by querying the attributes of the trained DT using Query operation.

Aside from its applications in remote sensing, DT has been a popular choice as a pre-processing step for SVM classification, as discussed above. For this study, five minimum number samples per node was arbitrarily chosen for all the decision trees. Furthermore, we applied a five-fold cross validation in order to address the issue of having either too few splits (poor predictive accuracy) or too many splits (complex tree).

In a cross-validation procedure, the DT is computed from the learning samples and its predictive accuracy is tested by test samples. A poor cross-validation results when the costs for the test sample exceed the costs for the learning sample; thus, a different sized tree might cross-validate better (eCognition, 2014).

3. RESULTS AND DISCUSSION

Figure 2 shows the decision tree generated for the LiDAR datasets in Balayan, Batangas. SVM classification was initially applied to the LiDAR-derived height metrics with a total of 56 features. Execution of the SVM classifier took 1690 seconds, achieving an accuracy of 90.6%. Using this decision tree, 16 important features were identified and used in the SVM classification instead of the original 56 features. Execution time only took 742 seconds, while the accuracy obtained was 92.7%. These account for a 56% reduction of execution time and 71% reduction in features.

Figure 2 Decision tree generated for Balayan, Batangas LiDAR datasets

Tables 2 summarizes the results of the trial performed on Balayan, Batangas LiDAR datasets. Similarly, Table 3 provides the summary of another trial performed on the datasets for Alitagtag Batangas.

Table 2. Summary of results for Trial 1

TRIAL 1 (Balayan)	SVM Training & Classification Time (Seconds)	Number of Features Used in Training	Overall Accuracy	Kappa Index of Agreement	Reduction of Time	Reduction of Features
SVMALL	1690.162	56	0.9061748	0.7632732	0.00%	0.00%
SVMDT1	742.377	16	0.9276146	0.8142084	56.08%	71.43%

Table 3. Summary of results for Trial 2

TRIAL 2 (Alitagtag)	SVM Training & Classification Time (seconds)	Number of Features used in Training	Overall Accuracy	Kappa Index Agreement	Reduction Time	Reduction of Features
SVMALL	436.569	56	0.9006121	0.8765474	0.00%	0.00%
SVMDT1	134.098	13	0.9475013	0.9347012	69.28%	76.79%

Using all the LiDAR-derived height metrics obtained for Alitagtag, Batangas datasets, 56 input features were used in the SVM classification with an estimated execution time of 436.6 seconds. However, the decision tree dictated that there were only 13 features necessary to perform the classification. Another SVM classification trial was performed but instead of using 56 features, only the DT-determined 13 features were used as inputs. The result of the DT-based SVM classification had a 69% reduction in time, while increasing the overall accuracy by at least 4.7%.

For Calatagan, Batangas datasets, the generated decision tree is shown in figure 3. Table 4 shows the important features determined using the DT algorithm. As with the other trials, the number of features have been reduced greatly. Apparently, the three decision trees put varying importance considerations to input features.

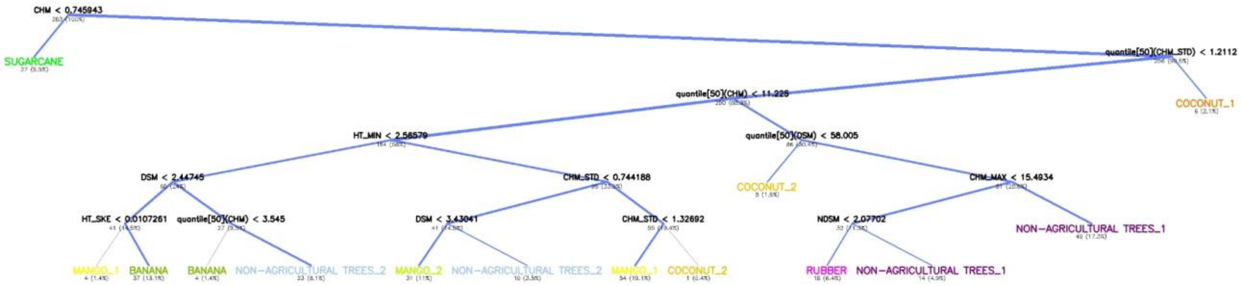

Figure 3. Decision tree generated for Calatagan, Batangas LiDAR datasets

Table 4. Important LiDAR-derived height metrics for Calatagan, Batangas datasets

FEATURE	IMPORTANCE
Standard deviation DSM	0.110697081
Standard deviation CHM	0.105259921
Mean HT_MAX	0.093572728
Mean SLOPE	0.088415847
quantile[50](DSM)	0.087006619
Mean HT_MIN	0.08229746
mode[Minimum](CHM_MAX)	0.079741594
Mean CHM_STD	0.068658086
Standard deviation NDSM	0.053137279
quantile[50](CHM_STD)	0.052629961
mode[Minimum](HT_P01)	0.051996817
Mean HT_SKE	0.043959886
quantile[50](CHM)	0.041871844
quantile[50](SLOPE)	0.040754876

Figure 3 provides the comparison for the three classified images generated using SVM, DT, and the DT-based SVM. Visually, DT-based SVM output provides a cleaner classification output than the result of the SVM classifier that uses all the LiDAR-derived height metrics as inputs.

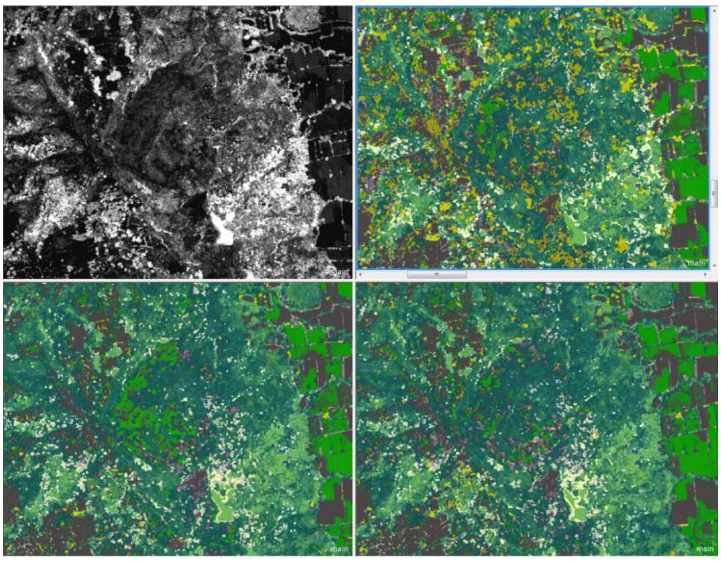

Figure 4. Comparison of CHM layer (upper left), SVM output using all 56 height metrics (upper right), DT-classified (lower left), and DT-based SVM with reduced input features (lower right), for Balayan, Batangas datasets.

4. CONCLUSION

The use of decision tree as a feature selection tool enables the assessment of each layers and its derived variables. Based on the table of importance, we can evaluate the features that we think are relevant for SVM classification.

The methodology introduces an effective and efficient feature selection technique prior to SVM classification. It exhibits effectiveness in the sense that the classifier produced better generalization as it avoided over-fitting indicated by the increase in overall accuracy and kappa coefficient. Also, DT-based SVM is more efficient as it reduces the number of input for training and classification at an average of 71% reduction; and, it makes the processing time shorter, resulting to a reduction of at least 56%. For the study area with slightly lower OA and KIA, adding more training samples can lead to better results.

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