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SUPPORT VECTOR MACHINE FOR SEAGRASS AND BENTHIC BOTTOM TYPES CLASSIFICATION USING HIGH RESOLUTION COASTAL DIGITAL AERIAL IMAGES

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Abstract

The need for mapping Submerged Aquatic Vegetation (SAV) is essential because the benthic habitats are important component of the Philippine marine ecosystem and food chain. A classification system was evaluated for mapping and monitoring benthic habitats and bottom types in shallow tropical marine waters using digital aerial images. The study shows that the use of a consumer-based digital camera mounted on an unmanned aerial vehicle can generate an orthophoto for remote sensing application. The subsequent use of support vector machine is a good classification tool which provided a test result of 85% accuracy for seagrass, and an overall accuracy of above 80% for SAV and bottom type mapping. This accuracy sufficiently provides basis for the local government units in administering rules and regulations in preserving and managing their coastlines.

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I. Introduction

Classification algorithms from trees to neural networks provide many possible choices as to what classifier to use. However, Support Vector Machines (SVM) is used due to its high generalization performance without the need to add a priori knowledge, even when the dimension of the input space is very high. SVM was used by [1] in comparing Worldview-2 and aerial photographs to classify species with the overall Kappa statistics providing a strong correlation between the classification and validation data. SVMs have frequently been found to give higher classification accuracies than other generally utilized pattern recognition procedures.

Image processing of colored aerial image photograph has been proven successful within marine Phanerogram seagrass beds with the use of various satellite data [2]. Mapping the distribution extent of benthic life forms is critical step in shallow-subside estuarine habitat management and projection, and also as a baseline information for government units, agencies, and the scientific communities.

Seagrass is known to play a critical role in protecting coastlines from damaging waves, and helps to sustain abundant sea life and protects shorelines around the world from coastal erosion. This study presents a tool for evaluating the magnitude of human prone disturbances to the shallow coastal habitat of the aquatic plant. This technology would aid local government in managing their coastlines and putting in place proper regulation to preserve them.

Quantitative measurements from satellite remote sensing through analysis are hardly done in this area of study due to the expensive nature. Most satellite images are acquired once or twice yearly based on the rotational capturing of images. Airborne digital camera imaging was selected in this study because of several reasons. Firstly, the airborne digital images provide higher spatial resolution for mapping and monitoring a small study area. Secondly, the airborne digital data acquisition can be carried out according to planned survey.

This study aims to evaluate optical remote sensing techniques for mapping seagrass habitats in a shallow coastal area of Lian, Batangas using the digital camera as a sensor for obtaining image input; to evaluate SVM Classifier for discriminating seagrass and bottom types in an aerial orthophoto; and to evaluate preprocessing algorithms for digital aerial image enhancement.

II. Review of Related Literature

(a) Coastal monitoring with digital aerial photography

The major source of optical remote sensing data for most resource management agencies remains to be aerial photography [3]. However, much of the aerial photography used for seabed mapping has been captured for assessing terrestrial landscapes. Optimum conditions for shallow-water mapping as well as atmospheric and water column conditions, on the other hand, were not considered. That is why they were of poor quality. Most photogrammetric literature focused on broad scale mapping programs of the coastline and/or near shore bathymetry [4]. Recently, comprehensive manuals detailing methodologies for mapping seagrass habitats were produced by large agencies such as NOAA Coastal Services Center, UNESCO, and the Joint Nature Conservation Committee (JNCC) [5]. At the same time small format aerial photography (SFAP) has seen renewed interest and technique development in the process of acquiring photographs [6] as it was well suited to low cost, specialized remote sensing for resource management purposes that target limited areas, with a particular focus on temporal monitoring.

The key developments that took place in aerial photography for habitat mapping in shallow coastal waters include: (a) sensor advances and improved availability of small format digital cameras; (b) development of image capture methods, including a reduced need for ground control; (c) improving image interpretation and analysis, such as object oriented classifications; and (d) an increasing range of applications such as, fine-scale spatial metric studies.

(b) Support vector machine

Among the machine learning algorithms, SVM has recently received a lot of attention and the number of works utilizing this technique has increased exponentially. The most important characteristic is SVM's ability to generalize well from a limited amount and/or quality of training data. Compared to other methods like artificial neural networks, SVMs yield comparable accuracy using a much smaller training sample size, due to the "support vector" concept that relies only on a few data points to define the hyperplane that best separates the classes [7]. The method is presented with a set of labelled data instances (the sample objects) and the SVM training algorithm finds a hyperplane that separates the dataset into a discrete predefined number of classes that are consistent with the training samples [9]. The "hyperplane" is used to refer to the decision boundary that minimizes misclassifications, obtained in the training step. SVM approach is viewed as a good candidate because of its high generalization performance without the need to include from the earlier learning, even when the dimension of the input space is very high compared to other classifiers. A two-class classification problem can be stated in the following manner: N training samples are available and can be represented by the set pairs $\{(y_i, x_i), i = 1, 2, 3, ..., N\}$ with y_i a class label of value ± 1 and $x_i \in n$ feature vector with n components. The classifier is represented by the $f(x; \alpha) \to y$ with α as the parameter of the classifier. The SVM method consists of finding the optimum separating hyperplane so that: (1) samples with labels $y = \pm 1$ located on each side of the hyperplane; and, (2) the distance of the closest vectors to the hyperplane in each side of maximum. These are called support vectors and the distance is the optimal margin.

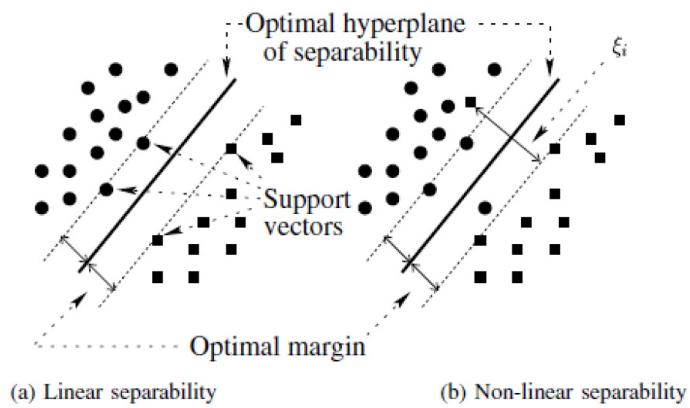

Figure 1. Linear separable classes; right: nonlinear separable classes. Measures the error of the fitting hyperplane [11].

The hyperplane is defined by $w \cdot x + b = 0$, where (w, ξ) that are not on this hyperplane lead to: $w \cdot x + b \gtrless 0$, and allow the classifier to be defined as: $(x; \alpha) = sign(w \cdot x + b)$. The support vectors lie on two hyperplanes, which are parallel to the optimal hyperplane, of equation: $w \cdot x + b = \pm 1$. The maximization of the margin with the equations of the two support vector hyperplanes leads to the following constrained optimization programs:

$$\min\left\{\frac{1}{2}\| w \|^2\right\} \quad \text{with } y_i(w \cdot x) + b \geq 1, \quad i = 1, ..., N.$$

Using the technique of Lagrange Multipliers, this optimization problem can be formulated into the following quadratic programming problem:

$$\underset{\lambda_i, \ldots, \lambda_1}{\text{Maximize}} \sum_{i=1}^{I} \lambda_i - \frac{1}{2} \sum_{i=1}^{I} \sum_{i=1}^{I} \lambda_i \lambda_j y_i y_j x_i \cdot x_j \tag{1}$$

$$\text{subject to} \sum_{i=1}^{I} \lambda_i y_i = 0, \lambda_i \geq 0, \quad i = 1, \ldots, I. \tag{2}$$

The solution of the SVM is given by:

$$w = \sum_{i=1}^{I} \lambda_i y_i x_i, \quad b = y_i - w \cdot x_j. \tag{3}$$

The decision function for the classification is given by:

$$f(x) = sign(w \cdot x + b) = sign\left(\sum_{i=1}^{I} y_i \lambda_i (x \cdot x_i) + b \right). \tag{4}$$

In the solution for this problem, those vectors for which $\lambda_i > 0$ are called support vectors, and all other training vectors have $\lambda_i > 0$. It is often found that the number of support vectors is dependent on the intrinsic dimensionality for classification in the training points, not on the dimensionality of the feature vectors; therefore, one does not need to worry about the cause of dimensionality in the support vector machine method [10].

III. Methodology

(a) Study area

The main study area is in the Talim Bay, on the coastal area of Sito Kayreyna, Barangay Lumaniang, Lian, Bantangas (13°59’35’’, 120°37’43’’E) with 29.22 hectares of seagrass [11]. The seagrass beds are extensive along the shorelines with some areas of mixed bottom types.

(b) Document image acquisition

A remote control (RC) plane UAV was used to gather all of the imagery used in this study. Aerial images were collected with the downward pointing consumer-based digital (Canon SX220) camera. The UAV was flown over sites of interest at various altitudes between 150 m and 200 m and captured an image with 1 second interval between images.

The trajectory of the UAV was in a parallel line known as lawn mower, with large overlapping imaging. The UAV flight paths were designed to ensure a sufficient amount of both forward and lateral photographic overlap, which would better allow the post processing software to identify common points between each image. In [12], suggested overlaps of 80% (forward) and 70% (lateral/side), produced enough overlapping photographs that worked with the post-processing software. Aerial images were mosaicked to form a coherent picture of the survey site.

IV. Results and Discussion

The UAV was flown at a height of 150 m and 104 aerial images were acquired; only 94 images, however, were used for the generation of the orthophoto. The unused images were those collected at turning ends of the line of flight, which were outside of the area of concern.

(a) Coastal aerial image

Orthophotograph data are combination of the visual attribute of an aerial photograph with the special accuracy and reliability of a planimetric map to from high-resolution aerial images. For this study, the aerial orthophoto used was generated with agisoft photoscan from a series of stitched digital areal images acquired on May 10, 2015, from an altitude of 150 m.

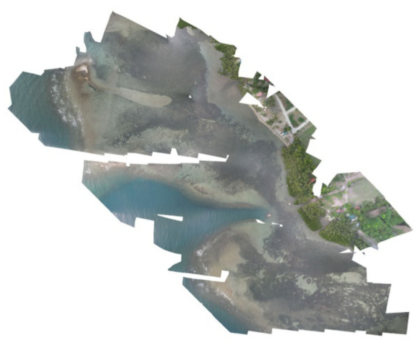

Figure 2. Orthophoto.

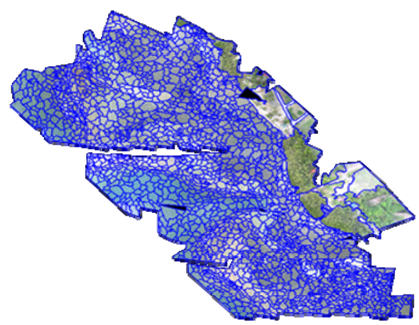

Figure 3. Sample end-result of segmentation.

(b) Image processing

The image was geo-referenced using ground points collected with Garmin handheld GPS of error margin 2m. Segmentation was done to capture the target subclasses and to select subclass samples from each of the super-classes. Samples were collected for building an optimized support vector machine. The current super-classes are the following; seagrass, algae, sand, rock, coral and deep water. The benthic feature class objects were resegmented using the multi-resolution segmentation algorithm in eCognition with a scale parameter of 20, shape of 0.3, and compactness of 0.7.

Using the equations of the hyperplanes that separated the different classes in the six-dimension feature space, a rule-set was then built in eCognition. It should be noted that the equation of each hyperplane is of the form $K(x_i, x_j) = \exp(-\| x - x_i \|^2)$, where K is the normal vector to the hyperplane and x is the feature vector. The results of the classification are shown below.

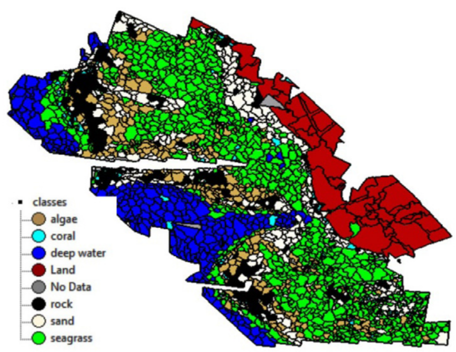

Figure 4. Result of classification.

V. Summary and Conclusion

This study presents a baseline method for benthic habitat mapping. A series of images acquired from a small digital camera was used to generate a high-resolution orthophoto with ground sampling distance of less than 1 m, using trail software from Agisoft. This showed high level of success even with no ground control point and non-geotagged camera. The result of the study showed that UAV can be used from small scale coastal monitoring. Applying SVM algorithm on the original orthophoto performed well and gave an 87% overall accuracy. Specific derivation from the RGB images for benthic habitats features like RGB Intensity, and One Dimensional Scalar Constancy was proven to be reliable features in discriminating other benthic habitat classes.

VI. Recommendation

This study looks at the benefits and possible utility of low cost UAV and consumer-based digital camera for coastal habitat mapping. Future studies that address orthophoto enhancement issues vis-a-vis optimal quality would be necessary, while the benefits of other classifiers such as the KNN and Artificial Neural Network approaches must be explored.

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