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Yung-Da Sun
Department of Marine Environment and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan, R.O.C., mrbig.g9114072005@gmail.com

Shiahn-Wern Shyue
Department of Marine Environment and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan, R.O.C.

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A HYBRID SEABED CLASSIFICATION METHOD USING AIRBORNE LASER BATHYMETRIC DATA

Yung-Da Sun and Shiahn-Wern Shyue

Key words: Hybrid method, bathymetric LiDAR data, K-means and Support Vector Machine (KSVM), gray co-occurrence matrices (GLCM).

ABSTRACT

In recent years, Airborne Bathymetric Light Detection and Ranging (LiDAR) has been applied intensively to map coastal depth as well as for seabed classification. In this study, we proposed a hybrid K-means and Support Vector Machine (KSVM) algorithm based on depth-derived gray-level co-occurrence matrices (GLCM) from bathymetric LiDAR. First, the calculated GLCM data set was used to sort K-means into various clusters. Second, training samples were selected on merged clusters before applying SVM classification. Finally, we evaluated the proposed hybrid algorithm in overall accuracy and the Kappa index. Compared to pure SVM, the proposed hybrid KSVM improved the overall accuracy by 24%, and the Kappa index by 0.31. The results showed that the proposed KSVM method provided promising results, in terms of accuracy and visual inspection. The benefits of the proposed classification method applied unsupervised classification of K-means as prior information for unseen seabed sediment types. This method was useful, particularly when only depth-derived information was available, or where the intensity/waveform had poor discrimination properties.

I. INTRODUCTION

There is increasing interest in seabed classification for various applications, such as coastal planning, geological studies, and marine habitat monitoring. Traditionally, the collection of seafloor sediment samples has involved a time-consuming and low-coverage method for seabed characterization, but it continues to be the basis for verification of the automatic seabed machine learning classification method. Comparing the small sample volume of grabs and cores, relative to the extensive seabed area that could be sampled acoustically, indicates that ground-truth techniques are time-consuming, poorly replicated, and expensive (Brown et al., 2004; McGonigle et al., 2009).

The shipboard acoustic remote sensing technique, known as the single-beam or multi-beam echo-sounder (MBES) system, is useful for characterizing seafloor sediment (Haris et al., 2012). The MBES system provides complete coverage of high-resolution bathymetry and backscatter information of seabed topography with limited cost (Simons et al., 2009), which can accurately define detailed topography and potential seabed habitats (Wilson et al., 2007, Zavalas et al., 2014). However, due to the potentially high risk in the near-shore region, caused by heavy wave interaction or dangerous bottom topography (e.g., reefs), the MBES system has several limitations when applied to coastal or inshore boat-based surveys (Ryan et al., 2007).

Airborne bathymetric Light Detection and Ranging (LiDAR) is a recent development in remote sensing, with great potential for providing high resolution and accurate Digital Surface Models (DSMs) in shallow water (Irish et al., 1999). It is a practical, efficient, and low-cost approach that overcomes deficiencies of the MBES system in shallow water surveys (Costa et al., 2009).

Recently, seabed type and habitat classification, using videography, MBES, and airborne bathymetric LiDAR data, have attracted a considerable amount of attention. MBES backscatter or LiDAR intensity has been modeled to be compared to experimental data. Alternatively, secondary features were extracted from MBES backscatter and LiDAR intensity using statistical or texture analyses. Until now, however, bathymetric LiDAR data have only been processed to generate sea depth information and seabed topography. However, we are still interested in processing data from this system that allows information extraction with actual seabed properties. Some studies have compared bathymetry and backscatter data training samples, in terms of density distribution and transect profiles over various bottom features (Costa et al., 2009; Zavalas et al., 2014). These studies motivated us to use depth-derived features as input for the classification method.

Seabed or habitat classification is a complex, multi-source problem. Machine learning methods (e.g., Support Vector Machine [SVM], K-means algorithm, neuro-fuzzy classifiers) have been applied to the extracted features by performing seafloor or habitat classification, and provide significantly improved classification accuracy (Hasan et al., 2012; Tyner et al., 2014). The methods noted above might be useful when data types differ in

Paper submitted 09/08/16; revised 11/18/16; accepted 12/30/16. Author for correspondence: Yung-Da Sun (e-mail: mrbig.g9114072005@gmail.com).
Department of Marine Environment and Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan, R.O.C.

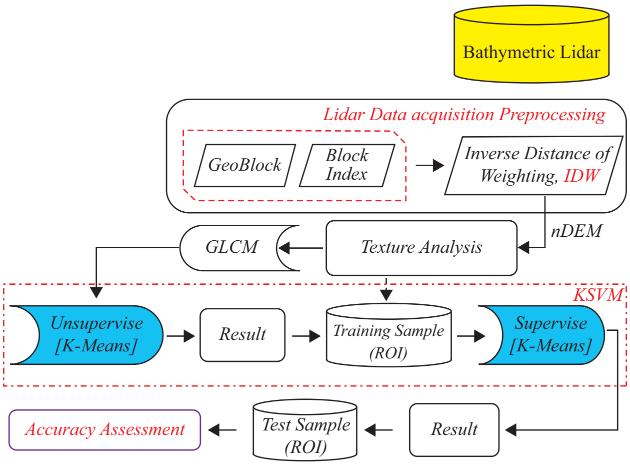
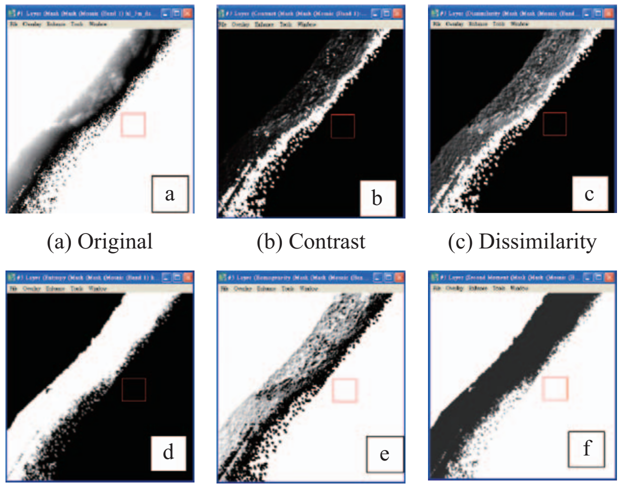


Fig. 1. Flowchart of proposed hybrid seabed classification method.



(a) Original (b) Contrast (c) Dissimilarity
(d) Entropy (e) Homogeneity (f) Second Moment

Fig. 2. Lidar bathymetry for texture feature analysis derivatives

their statistical distribution in one stacked dataset. Among them, the SVM method, a non-parametric classifier based on statistical learning theory, is suitable for classifying remote sensing, high dimensional, small sample size data (Lodha et al., 2006; Waske and Benediktsson, 2007).

In previous studies, De Almeida et al., (2000) proposed an algorithm to speed up SVM learning with a priori cluster selection using the K-means method with simulation data. Another study proposed a hybrid K-means and SVM method to extract features from cardiotocography records to perform fetal state classification (Chamidah and Wasito, 2015). As with the present study, the objective of the classification algorithm in these two studies was to enhance the performance of the SVM classification. In this study, we proposed a hybrid algorithm comprising a two-step classification method utilizing K-means and SVM (KSVM) for seabed sediment classification that applies to depth-derived features from bathymetric LiDAR topography data. First, we applied unsupervised K-means classification to the gray-level co-occurrence matrix (GLCM) features calculated from bathymetric LiDAR topography data. Then, we selected training data samples based on the K-mean results to avoid ambiguity. Finally, we performed SVM classification to the GLCM features, and evaluated the feasibility of the proposed hybrid algorithm in overall accuracy and Kappa index. The details pertaining to the methodology will be introduced in the following section. The experimental results are presented and compared to the MLC and SVM approaches in Section IV.

II. METHODS

Most previous classifiers were based on single classification methods, even when handling different types of data. Although these classifiers could address the limitations of traditional parametric algorithms, resulting in greater accuracy, these techniques have drawbacks, including high computational cost and time consumption, to obtain optimal classification parameters. Many previous studies have indicated that, if we could remove or separate ambiguous data from input sources for a classifier, it would be much easier to solve the difficulties in classification applications.

Fig. 1 shows the workflow of the proposed method, comprising a hybrid algorithm for two-step seabed classification. Initially, the bathymetric LiDAR data were interpolated to generate the topography DEM. Then, we used the DEM image to perform texture analysis to calculate the GLCM. We selected six types of gray reflectance co-occurrence matrix texture statistics for testing, including statistical values of homogeneity, contrast, dissimilarity, entropy and second moment, and correlation. We used a hybrid classification method, including unsupervised K-means and supervised SVM algorithms. Finally, the classification output was stored in ENVI native image format, and the classification accuracy was assessed in the overall accuracy and the Kappa index.

A major advantage of the proposed hybrid classification method is its simplicity. This method could be used with common commercial remote-sensing software tools, such as ERDAS Image, Exelis ENVI, or PCI Geomatics, without programming (Pathak and Dikshit, 2010).

1. Feature Extraction

Initially, we took the bathymetric LiDAR data, with a geographic management function, to process a large depth dataset. Then we applied the Inverse Distance of Weighting (IDW) method to generate the digital elevation model (DEM). We used grayscale DEM images, which were composed of depth data, to do texture analysis. In this step, all of the texture analysis techniques were based on GLCM as proposed in Soh et al. (1999). A matrix represents the number of occurrences of the relationship between pixel values and neighboring processing windows, within a specified distance and direction (Collin et al., 2011). We selected six textural features in this study, including statistical values of homogeneity, contrast, dissimilarity, entropy and angular second moment, and correlation. Observing the image recognition results could provide rich classified information as a reference. Fig. 2 presents the results from texture analysis. The following equations define these features. Let $p(i, j)$ be the (i, j)th entry in a normalized GLCM. The textural features can be calculated from the following equations (Haralick and Shanmugam, 1973):

(1) Homogeneity

$$f_1 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i, j) \tag{1}$$

(2) Contrast

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i, j) \| i-j | = n \right\} \tag{2}$$

(3) Dissimilarity

$$f_3 = \sum_i \sum_j |i-j| \cdot p(i, j) \tag{3}$$

(4) Entropy

$$f_4 = \sum_i \sum_j p(i, j) \log\left(p(i, j)\right) \tag{4}$$

(5) Angular second moment

$$f_5 = \sum_i \sum_j \left\{p(i, j)\right\}^2 \tag{5}$$

(6) Correlation

$$f_6 = \frac{\sum_i \sum_j (i, j) p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{6}$$

where μ_x and μ_y, and σ_x, and σ_y are the means and standard deviations, respectively, of p_x and p_y. $p(i, j)$: (i, j)th entry in a normalized gray-tone spatial dependence matrix, $= P(i, j)/R$.

2. KSVM hybrid Classification Method

In remote sensing classification applications, the rules are usually based on the training datasets, which are acquired based on visual inspection from remote sensing imagery. After classification, separate validation datasets are used to evaluate classification accuracy. However, it is very straightforward to select training and test data from remote sensing imagery. In the seafloor classification application, the only training and test datasets are ground truth. Because sampling the seafloor ground truth is time-consuming and costly, the numbers of feasible training and test datasets are limited.

To overcome this limitation, we often select training and test datasets using region of interest (ROI) on the stacked depth-derived raster features to increase the number of training and test pixels. However, selecting and identifying accurate seabed sediment types to compile training and testing datasets for classification is not as straightforward as using remote sensing imagery for land-cover applications. In addition, the position accuracy for ground-truth sampling is sometimes limited by the equipment used or influenced by the sea status. Furthermore, most seafloor sediment is complex and might vary over time, which is influenced by wave or ocean current transportation effects in the near-shore region.

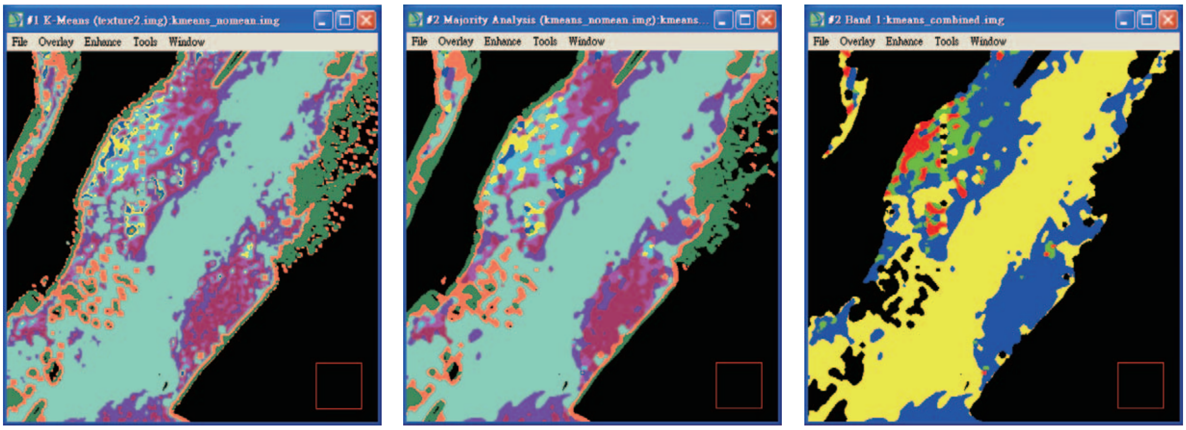
To overcome the above-mentioned limitations, we applied the K-means unsupervised classification in advance. The K-means algorithm was particularly suitable for clustering large amounts of data. K-means clustering is a rapid and simple method to partition feature space. It can be used to divide the individual measurements of bathymetric depth data into several mutually exclusive clusters. The K-means cluster analysis involves an iterative alternating fitting process, and the optimal split-level is determined by the number of classes resulting from the ground truth.

Because the K-means algorithm is an unsupervised classification method, it is necessary to determine if the K-means derived clusters exist for more than one label in a small region. If this is the case, further treatment is necessary to eliminate small patches. In this study, we classified 11 categories of seabed sediment types with 10 iterations, as shown in Fig. 3(a). Then, we applied the majority filter to merge the smaller classification results into larger patches, as shown in Fig. 3(b). Finally, we manually combined similar categories into four major categories based on field sediment samples. Fig. 3(c) shows the resulting output, which was used as the background imagery to select the ROI polygon as training samples using remote sensing software. While acquiring training samples, we should keep the size of the ROI polygon as small as possible. This could avoid the selection of ROI polygons that might include a variety of sediment characteristics, as shown in Fig. 4.

Although we used the training sample based on K-means classification results, ambiguity between types still existed. They could not be resolved by traditional parametric classification methods, such as Maximum Likelihood Classification (MLC).

To address this problem, we proposed SVM as the second classifier of KSVM. The SVM is a powerful multivariate machine learning algorithm based on statistical learning theory (Vapnik et al., 1995). It is basically a binary classifier that maximizes the margin between the training patterns and the decision boundary. The main task of the SVM training is to find an *Optimal Hyperplane Algorithm* that can separate the two class labels, represented as (-1) and (+1), and if they exist, the vector w and scalar b were shown in Eq. (7):

$$\begin{aligned} w \cdot x_i + b \geq 1 \quad \text{if } y_i = 1 \\ w \cdot x_i + b \leq -1 \quad \text{if } y_i = -1 \end{aligned} \tag{7}\#$$



(a) (b) (c)

Fig. 3. (a) Results from the K-means classification. (b) Results from applying the majority filter to the results from the K-means classification. (c) Combined results from the K-means classification.

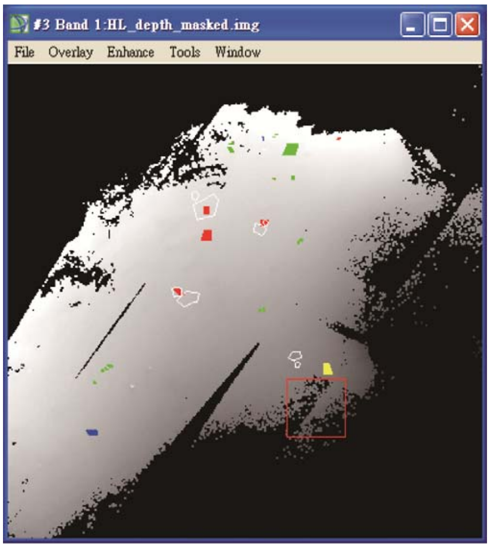


Fig. 4. The selected ROI.

Given a training set of instance-label pairs (x_i, y_i), $i = 1, \ldots, l$ where $x_i \in R^n$ and $y_i \in \{1, -1\}^l$, the SVM requires the formulation of the following optimization problem.

$$\min \frac{1}{2} w^T w + C\sum_{i=1}^{l} \zeta_i$$
$$S.t \begin{cases} y_i \left[w^T \varnothing(x_i) + b \right] \geq 1 - \zeta_i \\ \zeta_i \geq 0, i = 1, 2, \ldots, l \end{cases} \tag{8}$$

where w is an n-dimensional vector perpendicular to the hyperplane, and C is the penalty parameter that controls the edge balance of the error ζ. Using the technique of Lagrange multipliers, the optimization problem becomes:

$$\min \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j x_i y_j K\left(x_i, y_j\right) - \sum_{i=1}^{l} \alpha_i$$
$$S.t \begin{cases} \sum_{i=1}^{l} y_i \alpha_j = 0 \\ 0 \leq \alpha_i \leq C, i = 1, 2, \ldots, l \end{cases} \tag{9}$$

where $K(x_i, y_j) = \varphi(x_i), \varphi(y_j)$ is a kernel function used to project the data from input space into feature space.

Our study classifying in the test area implemented an algorithm using SVM after K-means classification to separate four types of seabed material and obtain a classification for the seabed.

III. DATA

1. Study Area and Datasets

The study site, Hualien Harbor, is an international harbor located in the eastern coast of Taiwan (Fig. 5). It is a narrow and long artificial harbor leaning towards the Taiwan Central Mountains to the west. The dominant seafloor sediment types in the Hualien Harbor coastal area are mostly sand and gravel, due to streams importing offshore turbid water. Near shore regions have several reefs and rock sediment types.

LiDAR data were acquired in 2008, using the Optech bathymetric LiDAR, Scanning Hydrographic Operational Airborne LiDAR Survey (SHOALS) 1000T system. This system utilized remotely collected topographic and bathymetric measurements, using infrared (1064 nm) and blue-green (532 nm) scanning laser pulses with a vertical accuracy of ±20 cm and a horizontal accuracy of ±1.5 m.

The flight height of this experiment was 300 m to 400 m, using the fixed-wing aircraft BN-2B with 22 routes for the region near the Hualian Harbor. The maximum depth of this area was about 28 m. Two sets of scan parameters were used in this

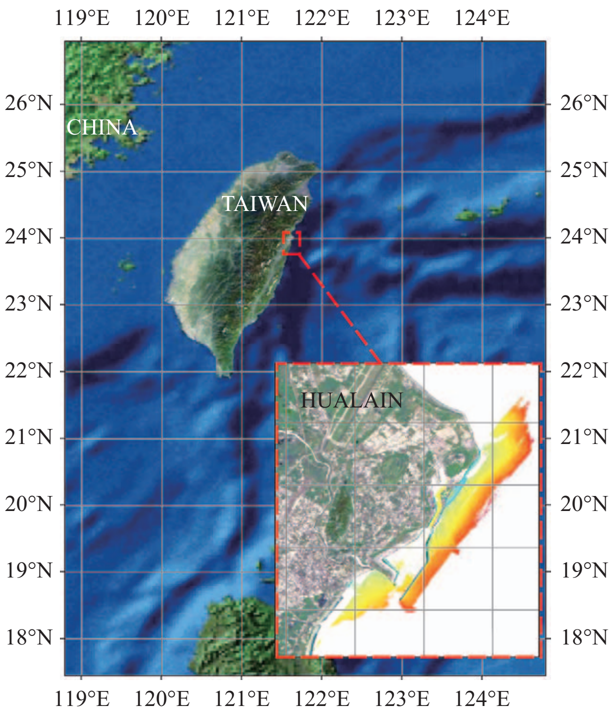


Fig. 5. Study area.

survey area. One set was 300 m flying height and a point cloud density of 3 × 3 m, and another was 400 m flying height with 5 × 5 m point cloud density. The total amount of bathymetric LiDAR data from the Hualien Harbor was 1,262,383 data points, with a grid density of 500 m × 500 m. In the past, multi-beam echo sounders and side scan sonar were based on the intensity of the sonar transmitter to trace the reflectance for extracting sediment characteristic information. Hewitt et al. (2010) used multi-beam echo sounders investigation which was based on the backscatter to characterize seafloor features. Hamilton et al. (2011) also research acoustic seabed segmentation from direct statistical clustering of entire multi-beam sonar backscatter curves. We have cited them in this section.

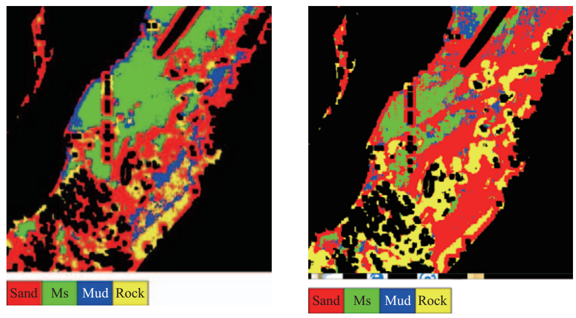
2. Ground-Truth Data

Researchers discovered an estuary of the Hua-lien, Gei-An, and Mei-Lun Rivers Large streams (e.g., Hualien River) would discharge mud and suspended sediment to the sea. Most coastal sediments were composed of mixed silt. In the past, most soft-sediment ground truth relied on the use of traditional sediment-sampling gear, such as grabs and corers. During 2003 and 2004, we collected sediment samples with grabs during a single beam hydrographic survey.

The seabed sediment consisted of different sizes, shapes, and specific gravities. To assign ground-truth classes to seabed classified data, the hybrid method was applied by searching for the nearest majority class within the feature of the relative location. The spatial position of the different categories was chosen by different depths and along survey lines. About 70% of all available reference data were randomly sampled for model development, and 30% for final verification and accuracy assessment. In our experiments, total training samples from four seabed categories (sand, mud, mud-sand, and rock) were selected from the bathymetric LiDAR depth data (952 pixels), and 267 pixels for test samples (Table 1).

Table 1. The training data and tests used for study area.

Categories	Training Samples	Test Samples
Sand	229	71
Mud	234	82
Mud-Sand	239	54
Rock	250	60



(a) Maximum likelihood classifier (b) Support vector machine

Fig. 6. Seabed classification comparison map.

IV. RESULTS AND DISCUSSION

1. Hybrid Classification Experiments

Traditional statistical MLC and SVM classifications were performed as two standard cases for comparison to investigate the accuracy of our proposed hybrid seabed classification method. The feature vectors used for this experiment were LiDAR depth-derived GLCM features, including homogeneity, contrast, dissimilarity, entropy and angular second moment, and correlation. Because the SVM non-parametric classifiers required numerous parameters, the SVM classifier with the set of parameters resulting in the highest accuracy is reported here. To effectively identify parameters for SVM, we adopted libSVM and image SVM (Vierling et al., 2008; Chih-Chung Chang et al., 2011) tools to obtain optimal penalty parameters and the gamma value of the radial basis kernel function. Next, the hybrid classification, based on unsupervised K-means and SVM (case KSVM), was used to compare the performance and accuracy of seabed classification.

Table 2 lists accuracy assessment results for the three experiments. The test area was classified correctly, assuming that classification derived from the ground truth by hydrographic grab was accurate, and estimated from the confusion matrix. Overall accuracies of the standard MLC and SVM experiments were 57.39% and 61.42%, respectively. Figs. 6(a) and (b) present the results from MLC and SVM, respectively, which illu-

Table 2. Comparative results using MLC, SVM, and hybrid (KSVM) algorithms.

Experiment	OA (%)	KI	Producer Accuracy (%)				User Accuracy (%)			
			S	MS	Mud	R	S	MS	Mud	R
MLC	57.39	0.4243	32.39	59.26	76.83	60.87	62.16	47.76	80.77	29.17
SVM	61.42	0.49	98.59	44.44	21.95	86.67	62.50	38.71	94.74	70.27
KSVM	85.39	0.8037	87.32	62.96	89.02	98.33	79.49	80.95	100	79.73

Notes: *KSVM* means, *K-mean,s* and *SVM.*

OA: Overall accuracy (%)
KI: Kappa index
S: Sand
MS: Mud-Sand
M: Mud
R: Rock

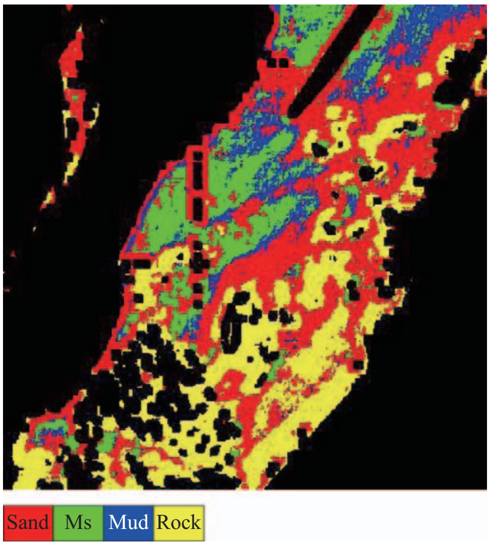


Fig. 7. Classification results from the hybrid method.

strate the classification results for standard cases, using the pure MLC and SVM methods.

From Table 2, we can see that the Kappa statistic value obtained in the analysis for MLC was 0.4243, which was lower than the overall accuracy (0.5739). Differences between these two values were to be expected, as each incorporated information from the confusion matrix. Overall accuracy only included data along the major diagonals and excluded the errors of omission and commission, whereas the K-statistic incorporated the non-diagonal elements of the confusion matrix. The same situation could be observed in the SVM case.

The overall accuracy of the standard KSVM experiment was 85.39%, and the Kappa index for the KSVM experiment was 0.8037. Fig. 7 shows the classification results from the hybrid method, which indicate that the proposed hybrid classification method KSVM is superior to pure MLC and SVM.

The producer and user accuracy were calculated to investigate the individual class accuracy. According to Table 2, although the producer accuracy of the SVM (98.59%) was better than the KSVM (87.32%), in general, the KSVM experiment was superior. User accuracy indicates the probability that the actual map pixel represents the category on the seabed, while producer accuracy is the probability of a reference pixel being correctly classified (Jensen, 2005).

2. Discussion

Our test area was about 10 km^2, which was selected to represent the complexity in bathymetry data over the Hualien Port. The hybrid method was used to classify the depth variables derived from bathymetric LiDAR data to distinguish seabed habitats. Generally, numerous classifiers are capable of using LiDAR backscatter intensity or waveform data to classify different habitats. Some classifiers provide higher accuracy. The application of automated classifiers using backscatter data has become more common, but has seldom involved bathymetry data, due to the relatively small amount of information that could be extracted.

For a classification method based on texture analysis features, it was important to confirm that the size of ROI of training pixels was large enough with respect to the texture variation, to ensure that the training samples were invariant within feature types. In contrast, to construct a classifier, it was expected to be small enough to ensure that each training ROI did not contain more than one feature type. Therefore, it was very difficult to select an optimal ROI size, with respect to various GLCM processing window sizes, for a classification system based on GLCM features. Therefore, the SVMs machine, based on a priori cluster selection derived from the K-means unsupervised method, could provide a feasible method to select proper ROI size over various GLCM window sizes. Accuracy increased with increasing GLCM processing window size, which could be observed from the overall accuracy and Kappa coefficient (Table 3).

We calculated the GLCM features for the KSVM experiment with 7×7, 9×9, and 11×11 processing windows. Comparing the accuracy of these datasets, we assessed the confusion matrix. The results of the comparison showed that the 11×11 window was the optimum processing window, as defined in Eqs. (1) through (6). The overall accuracy and Kappa coefficient both indicated that the classification result was proportional to the processing window.

Table 3. Comparison of accuracy of different windows with hybrid classification.

Windows	Seabed	
	Overall Accuracy (%)	Kappa Coefficient
7×7	73.52	0.6474
9×9	77.90	0.7028
11×11	85.39	0.8037

V. CONCLUSIONS

In this study, we proposed a new approach to suitable seabed classification, based on the bathymetric LiDAR depth-derived features as input for classification. It was useful, particularly when only depth-derived information was available or where intensity/waveform might have poor discrimination properties. This study showed that the seabed classification based on LiDAR depth-derived features provided promising results, in terms of accuracy and visual inspection. The proposed classification method applies K-means unsupervised classification as a prior knowledge for unseen seabed sediment types. It provides a feasible way to select proper ROI over various GLCM windows sizes, for a classification system based on GLCM features. The proposed hybrid classification method shows how unsupervised K-means classification resolves the difficulty, while applying pure SVM to GLCM-based feature classification applications (this can be seen by comparing Figs. 6 and 7). In this study, we proposed a hybrid method to classify seabed sediment types for substratum maps, in particular those lacking adequate ground truthing. The method used the fact that K-means can be used to estimate the number of cluster centers related to different unknown seabed types and subsequently sampled at several obvious sites to verify their physical characteristics.

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