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Detection and characterization of an archaeological wreck site in Sunda Strait, Indonesia

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Abstract

A number of shipwreck archaeological sites worldwide have underlined the importance of shipwreck localization and detection. Accidents that led to sinking are one of the possible causes of those shipwrecks. The shipwreck of MV Bahuga Jaya, which is located in the Sunda Strait, Indonesia could be such an example. A multibeam swath survey is a suitable technique to map the wreck location since it can produce high-resolution Digital Elevation Model (DEM) and backscatter imagery. Both the analysis of the bathymetry DEM and backscatter use visual examination. However, morphometric analysis of the DEM and texture analysis of the backscatter, subsequently combined with the machine learning classification, could give a preferable result in shipwreck detection and monitoring. In this paper, slope analysis of DEM bathymetry and texture analysis of multibeam backscatter imagery are presented. Those first-order textural features are used to carry out a Support Vector Machine (SVM) classification to separate between the wreck and non-wreck objects. A combination of SVM classification and slope analysis is investigated to detect the wreck location. Following that, K-means clustering is also performed to obtain the seabed characterization. Results indicate that the combination of machine learning and morphometric analysis can give a promising outcome in shipwreck detection. In addition, the result of K-means clustering reveals that soft seabed is more dominant than the hard seabed in the study area with 56.4% and 43.6% respectively. This study could play a role as a complementary tool to monitor and manage the shipwreck archaeological site location.

Keywords: *archaeological site, wreck, multibeam backscatter, slope and texture analysis, SVM classification, K-means clustering, Indonesia*

Rezumat. Detectarea și caracterizarea unui sit arheologic cu epave în Strâmtoarea Sonde, Indonezia

O serie de situri arheologice subacvatice din întreaga lume au evidențiat importanța localizării și detectării epavelor. Accidentele sunt o posibilă cauză a scufundării acestor nave. Naufragiul vasului MV Bahuga Jaya, situat în Strâmtoarea Sonde, Indonezia, ar putea fi un astfel de exemplu. Sondajul multi-fascicular reprezintă o tehnică adecvată pentru cartografierea locației epavei, deoarece poate produce un model digital (DEM) de înaltă rezoluție, cât și imagistică de radioreflectie. Pentru ambele se utilizează examinarea vizuală. Cu toate acestea, analiza morfometrică a DEM și analiza texturii obținute prin retrodifuzie, combinate ulterior cu clasificarea automată, ar putea oferi un rezultat mai bun în detectarea și monitorizarea epavelor. Lucrarea de față prezintă analiza pantelor pe baza batimetriei DEM și analizei texturii pe baza imaginilor de radioreflectie. Aceste caracteristici texturale de prim ordin sunt folosite pentru a efectua o clasificare SVM (Support Vector Machine), cu scopul de a distinge între epavă și elementele ce nu aparțin acesteia. Pentru a detecta locației epavei, se folosește o combinație între clasificarea SVM și analiza pantelor. Ulterior, un algoritm de grupare (K-means clustering) este utilizat pentru a caracteriza fundul mării. Rezultatele indică faptul că o combinație între învățarea automată și analiza morfometrică poate oferi rezultate promițătoare în detectarea epavelor. În plus, rezultatul aplicării algoritmului de grupare menționat relevă faptul că în arealul în studiu domină fundul marin cu duritate scăzută, care deține 56,4%, față de 43,6%, cât revine celui dur. Acest studiu ar putea juca rol de instrument complementar în monitorizarea și gestionarea locației sitului arheologic subacvatic.

Cuvinte-cheie: *sit arheologic, epavă, analiza pantelor și a texturii, clasificare SVM, Indonezia*

Introduction

On the early morning of the 26th of September 2012, there was a marine accident, following the collision of two vessels in Sunda Strait, Indonesia along the traffic route, involving Indonesian Ro-ro Passenger Ferry MV Bahuga Jaya and Singapore tanker MT Norgas Cathinka. MV Bahuga Jaya was 92.30 m long and 16.20 m wide, with a draft of 5.23 m (National Transportation Safety Committee (KNKT), 2013). Paroka et al. (2014) explained that the accident, resulting in more than 7 casualties and 10 serious injuries of passengers, was caused by poor maneuvering of both vessels due to the wind and wave condition. The MV Bahuga Jaya finally sank 40 minutes after the collision. The body of this vessel remains in the location and becomes a shipwreck archaeological site in Sunda Strait.

According to UNESCO, there are over three million wrecks as archaeological heritage on the seafloors around the world. However, those shipwreck sites are vulnerable by the threat of damage due to human activities such as mobile fishing, trawling, and dredging and the quantifying of this damage has not been finished recently (Brennan et al., 2012). Additionally, Masetti & Calder (2012) also asserted that shipwrecks could contribute to marine pollution by releasing toxic materials from their corrosive body and could harm the environment. As a result, several projects have been carried out to map and diagnose the underwater archaeological site (Reggiannini & Salvetti, 2016). Thus, Bahuga Jaya wreck as one of that archaeological wreck sites also needs to be mapped and investigated.

Marine surveying and mapping of the wreck site aim to examine the texture and stratigraphy of the wreck location and the seafloor surroundings. The distinction between areas of wreck archaeological interest and its surroundings can be useful for determining archaeological prospection (Thabeng et al., 2019). Moreover, the result then could be used to monitor and to manage the site, particularly related to morphological alteration and anthropological impacts (Geraga et al., 2017). Depicting and analyzing the environmental condition of a wreck-site is an essential action in examining the quality of remaining wreck debris.

To date, underwater acoustic and imaging technologies have been used widely in underwater sea wreck studies. The multibeam echosounder and side-scan sonar become two major technologies to investigate the wreck sites for decades and can be found in several studies (Brennan et al., 2012; Roberts et al., 2017; Delgado et al., 2018; Ødegård et al., 2018). A shallow seismic survey such as sub-bottom profiling also could perform the estimation of the thickness of the seafloor sediment layers in the wreck location (Geraga et al., 2017). In addition, photographic and video imaging also have been predominant techniques either for direct investigation or as complementary ground truth data for the multibeam and side-scan sonar system. Due to its popularity, the multibeam swath system was chosen for landscape mapping in a wreck site investigation in this study. It is due to its capabilities to not only produce a dense and high-resolution bathymetric digital terrain model (DTM), but also the intensity of returned pulse (backscatter) that can be used for wreck investigation.

The bathymetric digital terrain model (DTM) analysis is well-known as "geomorphometry" or "morphometric analysis" (Brown et al., 2011). This model as a representation of the seabed topography could be derived to several terrain attributes (e.g. slope, aspect, curvature) and could contribute for several purposes such as seafloor classification and object detection (Lecours et al., 2016). Several comprehensive literatures regarding marine geomorphometry can be found in Lecours et al. (2016) and Lucieer et al. (2018). Micle et al. (2010) argued that marine geomorphometry becomes a promising technique to analyse the shipwreck archaeological sites.

On the other hand, the backscatter intensity usually builds up an acoustic grayscale image of the seafloor. Parnum & Gavrilov (2011) asserted that the backscatter data could represent the composition and morphological characteristics of the seabed. In general, the low backscatter values in the image represent soft and smooth surfaces, whereas high backscatter values depict hard and/or rough objects (Febriawan et al., 2019). Brown et al. (2011) explain that the backscatter imagery resulted from multibeam system has generally a lower quality to the side-scan backscatter imagery. However, the analysis of both backscatter imageries is relatively the same. Image-based segmentation is the most popular method for multibeam backscatter image analysis. They also stated that several backscatter characteristics such as textural features and surface features (shape) could be used in image segmentation. The textural features are then used as parameter inputs for classification and detection.

The growth of machine learning techniques has led to various research of its technology in seabed classification and object detection. Support Vector Machine (SVM) is one of the supervised machine learning methods in classification and object detection of multibeam and side-scan sonar. Febriawan et al. (2019) have demonstrated that this method has predominance in the classification of side-scan sonar mosaics using small numbers of training samples. Application of SVM classification in archaeological fields can be found in Gu et al. (2018) and Thabeng et al. (2019). In addition, unsupervised classification such as cluster analysis also could be an additional supporting tool in helping to characterize the general morphology of the wreck site. Parnum & Gavrilov (2011) explained that cluster analysis of similar regions of backscatter data could reveal its relationship to seabed morphology (phenomenological approach). In studies without adequate ground-truth sample data, cluster analysis can be a beneficial method for understanding the environmental surroundings of the wreck location especially for site securing prediction.

However, there are few studies of morphometric and textural features analysis and SVM application for underwater archaeological wreck site investigation. K-means clustering method in predicting site morphology also could be an interesting approach to characterize the seabed with an absence of field samples. Thus, this study attempts to undertake several morphometry parameters of the DTM and textural analysis of the backscatter to locate the Bahuga Jaya wreck location and to depict the peripheral seabed covers. While the Support Vector Machine classification was used to detect wreck archaeological debris, the K-means clustering technique was examined to characterize the seabed morphology. The combination of wreck localization and seafloor morphology could be an alternative solution for monitoring wreck location and managing the archaeological site location.

Methodology

Study area and data acquisition

The multibeam swath survey was carried out by the Technology Center for Marine Survey, Agency for the Assessment and Application of Technology (BPPT), Indonesia on 28th of November 2017, using

RV. Baruna Jaya I in the location of Bahuga Jaya wreck site (Figure 1).

The study area covers approximately 696,766.93 m^2, the depth varying between 59 and 110 m.

Fig. 1: Study location

A Teledyne HydroSweep DS full-depth multibeam system, which was mounted in RV Baruna Jaya I, was used for data acquisition. This multibeam system was operated in the frequency of 14 kHz and has a beam resolution of 2° x 2°.

In addition, this system also has 140° swath coverage and 320 beams in both sides (port and starboard). The multibeam system was equipped with a Hemisphere R330 DGPS system (± 20 cm of horizontal accuracy) (Jensen et al., 2017) and a TSS Saturn 10 Fiber Optic Gyrocompass (heading accuracy: 0.1°, pitch/roll accuracy: 0.01°, and heave accuracy: 5 cm) (TeledyneMarine, 2020b) for positioning and inertial motion system. A surface Sound Velocity Keel Sensor AML Micro and a Sound Velocity Profile AML Minos X (accuracy: ± 0.025 m/s, precision: ± 0.006 m/s) (AML Oceanographic, 2020) were also used to perform sound velocity correction both in the water surface and through the water column.

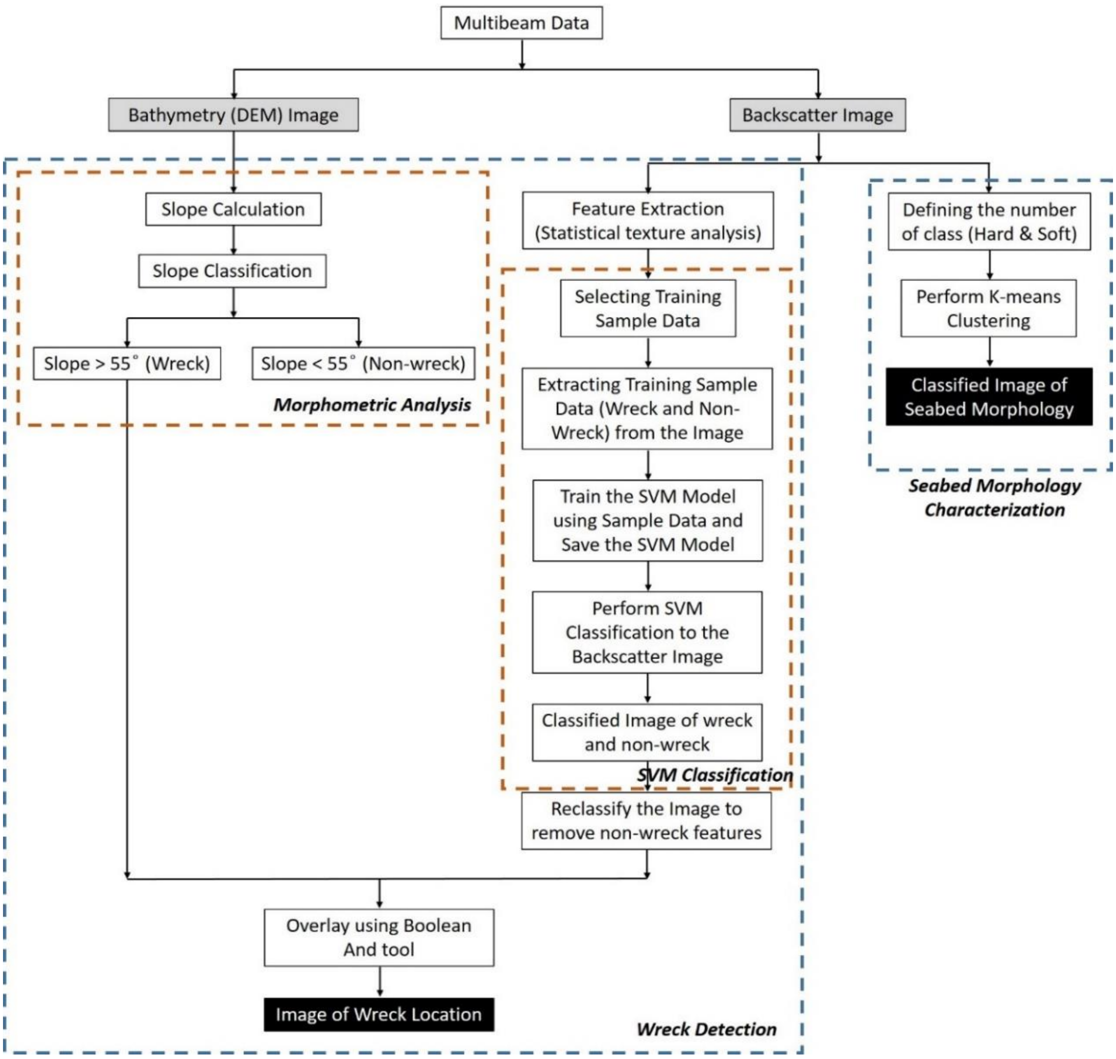

Fig. 2: Flowchart of the study

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Both bathymetric raw data and backscatter data were recorded during the acquisition using a PDS 2000 software (TeledyneMarine, 2020a). By default, this software records the raw data in *.pds format but has options to record in other formats (e.g. *.s7k, *.all, etc.), too. Overall, the flowchart of the study can be seen in Figure 2.

Data processing

The raw MBES data was processed using PDS 2000 software with a standard processing workflow as conducted by Junior & Jeck (2009). A sound velocity profile acquired with AML Minos was used in the data processing. The manual editing technique by the human operator was performed to remove data outliers that can lead to inaccurate digital elevation model (DEM). After that, a DEM with a grid cell size of 1 m was produced from the bathymetry data.

The backscatter data—resulted from relationship calculation of backscatter intensity value and angular response—was also processed using PDS 2000 software. The processing of backscatter data yielded the amplitude value of each point in the survey area. This method is called *mosaicking of backscatter data* and could give information of sediment characteristics of the seabed. Thus, as the focus of this study, the backscatter mosaic of Bahuga Jaya wreck provided some distinct amplitude values to distinguish from its surroundings.

The processing of backscatter data was carried out by integrating beam swath coverage and backscatter swath volume. Subsequently, magnitude calibration was performed using coverage of beam survey area, backscatter swath volume, and calculation of absorption coefficient. Finally, the mosaicking process was carried out to create a backscatter base-surface, which then can be exported in XYZ format or geoTIFF imagery in 1 m of cell size.

Wreck detection

Feature extraction

Feature extraction is aimed to determine the properties of the image that represents the objects and can be used as parameters for classification (Solomon & Breckon, 2011). The two common features used in underwater mapping and classification are Terrain Features and Texture Features. While Terrain Features are based on a number of terrain parameters which is derived from a digital terrain model (DTM) and including in morphometric domain (Di Stefano & Mayer, 2018), textural features (patterns segmentation) are based on the group pixels of the image and then be derived to several textural features (images) which could reveal seafloor characteristics (Reggiannini & Salvetti, 2016).

In archaeological studies, slope analysis could be an effective instrument for archaeologists to detect the wreck location and analyze its location with the surroundings (Micle et al., 2010). Thus, this study tried to examine the slope as a feature derived from the DTM using the Benthic Terrain Modeller (BTM). BTM is an add-on plug-in in ArcGIS well-recognized for geomorphometry features extraction. Then, the slope was reclassified in ArcGIS into two different classes: wreck (slope > 55°) and non-wreck (slope < 55°). Based on the interpretation of the Slope image, the wreck location produced a high sloping feature of its surroundings. Subsequently, the wreck of slope > 55° was used for the final detection of wreck location.

In regards to the backscatter imagery, several first-order textures (Variance, Skewness, Kurtosis, Standard Deviation) have been tested to segment and detect the wreck location. Febriawan et al. (2019) stated that the first-order textures are based on a statistical calculation of the pixel's grey values. Those features calculations are based on the following formulas:

$$Skewness = \frac{|\sum(BV_{ij}-\mu)|^3}{(n-1)(V)^{3/2}} \quad (1)$$

$$Kurtosis = \frac{\sum(BV_{ij}-\mu)^4}{(n-1)(V)^2} \quad (2)$$

$$Variance\ (V) = \frac{\sum(BV_{ij}-\mu)^2}{(n-1)} \quad (3)$$

$$\mu = \frac{(\sum BVij)}{n} \quad (4)$$

where:
n = number of pixels in the window
$BVij$ = brightness value of pixel *(i,j)*
μ = mean grey values in the moving window

Implemented in Matlab, a moving window method, which usually has an odd number of window size, was used to produce the textural images mentioned above. A 19 x 19 pixels of the moving window dimension was chosen to derive the textural images as it was suggested by Hamilton (2017).

The new pixel value of the textural images was calculated from the central pixel of the window. After that, visual interpretation was carried out to examine the most suitable textural features in wreck detection. Brown et al. (2011) also asserted that an expert (visual) interpretation is commonly used. This method is involving "expert's eye" and "expert's knowledge" to delineate the imagery based on similar texture and usually be used as training samples in case the ground-truth data is not possible as was conducted in this study.

Support Vector Machine for textural classification

Support Vector Machine (SVM) represents one of the machine learning techniques in supervised classification. It works by fitting an optimal hyperplane in the feature space to split the data into different classes (Liu et al., 2015). Foody & Mathur (2006) explained that the hyperplane is determined by using data points (support vectors) that are located close to the hyperplane. The optimal hyperplane with the maximum margin would be selected if there were several numbers of hyperplanes exist. Although there are some options in tuning the parameters (e.g. using non-linear kernels), this study used a linear kernel in defining the hyperplane.

Febriawan et al. (2019) have demonstrated that the linear kernel is more suitable for side-scan sonar classification using texture features than the Gaussian kernel. The SVM model is created to store the information of hyperplane after the hyperplane has been determined by training the sample data.

Initially, the training data set of a number of images that represent each class (wreck and non-wreck) were obtained by clipping the backscatter image based on each class. After that, those images were set up in order and labelled accordingly. Then, the data set was trained to fit the multiclass model for SVM (*fitcecoc).* Only then does the classification of an image recall the model to check on which class of the data (pixel) is located.

In the present study, two different classes (wreck and non-wreck) were established in the classification based on sample data that trained previously. This method then resulted in a textural SVM classified image of the wreck and non-wreck. In order to get the result of a binary image of the wreck and non-wreck objects, the result of SVM classification then was combined with the slope analysis result using Boolean logic "And" operator in ArcGIS. This operator has proven to be an effective tool in raster operation to overlay spatial layers and removing all unnecessary objects in the image (Cheng & Thompson, 2016). The final result was the map of the wreck location.

Seabed morphology characterization

K-means unsupervised classification

K-means unsupervised classification is a clustering method that divides the data into clusters (classes) and produces an index of the cluster that has been assigned to each data (Matlab, 2019). In multibeam backscatter data analysis, k-means clustering has demonstrated its capability for seabed classification particularly with the lack of ground-truth data.

Some research in using k-means clustering for seabed classification can be found in Fonseca & Calder (2007), Fakiris et al. (2012), and Samsudin & Hasan (2013). Initially after the number of classes has been defined, the centroid of each cluster will be created randomly.

After that, the distance of each data (point) to each centroid is calculated. By default, K-means uses Euclidean distance to calculate the distance of each point. The distance calculation could be based on either the closest distance of each point to the closest centroid or assign points to a different centroid individually.

Then, the centroid locations are up-dated based on the average of the data to each cluster. The iteration is repeated until all of the centroids are stable and converge (below the user's tolerance) or it reaches the maximum number of iterations.

As a result, points in a cluster will be as close to each other as possible and will be far from points in other clusters. In the application of K-means for image clustering, the algorithm of K-means requires converting the image into a vector before assigning this vector along with the number of clusters into the algorithm. After the class index of each point has been created, it needs to reshape back into an image to get the classified image.

Results

Bathymetry and backscatter image

Bathymetry processing resulted in a Digital Elevation Model (DEM) of the seabed in an 8-bit georeferenced image (*.tif) as shown in Figure 3(a).

It can be seen that the depth of the study area varies between 59.14 meters and 110.41 meters. Visually, the wreck location can be detected from the colour contrast that represents the depth of 59 meters to 70 meters.

There is an underwater seabed channel at 350 meters, northwest of the wreck location. This channel is approximately 240 meters wide, the depth ranging from 90 meters to 110.41 meters. It can be noticed that the north-west side of the study area shows a shallower depth and goes deeper through the southeast of the area.

Figure 3(b) depicts the backscatter image of the study area that has backscatter values ranging from -18.94 dB to -37.62 dB. The wreck itself has backscatter values between an approximately -35 dB and -37.62 dB. One interesting thing that can be noticed is that although both DEM bathymetry and backscatter images cover the same area, it shows a different pattern of features.

While in bathymetry DEM, the seabed topography relief can be easily distinguished (e.g. shallow area, channel, or wreck), the backscatter image only depicts clear features of the wreck and the southeast side of the channel. The wreck, as it is a man-made structure, reflects different backscatter signals than the surroundings and resulting noticeable backscatter values.

However, the notably backscatter values at the southeast side of the channel do not represent the

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morphology type and are probably due to the incidence angle of the location during the acquisition since the vessel sailed in the northwest–southeast direction. This resulted in the southeast side of the channel reflected the backscatter signal stronger than the opposite side and created different backscatter values.

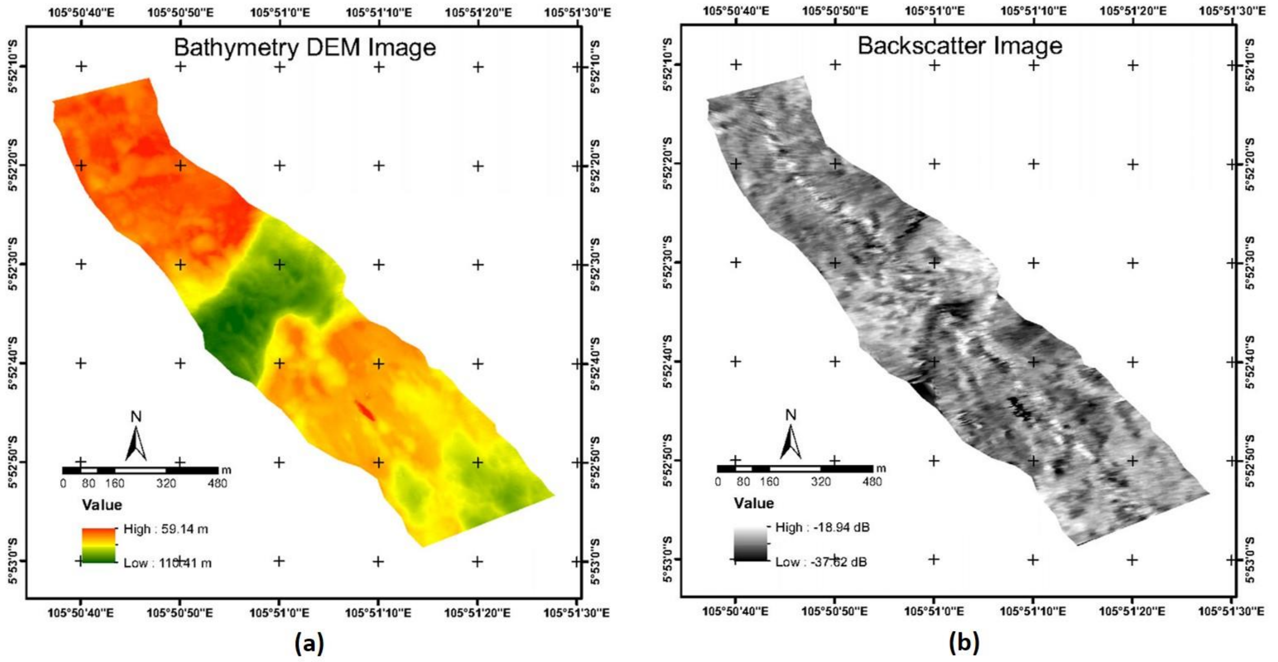

Fig. 3: Results of: Digital Elevation Model (DEM) bathymetry (a), Backscatter imagery (b)

Feature extraction

Initially, the slope feature was created as a terrain derivation feature and the result can be seen in Figure 4(a). The result shows clearly that only wreck feature and the edge of the channel that has a high degree of slope since the elevation difference is high than its surroundings.

However, for the wreck detection purpose, slope > 55° was classified to remove the flat terrain (Figure 4(b)). The result of classification indicates that there are some terrains at the edge of the channel that has slope over than 55°.

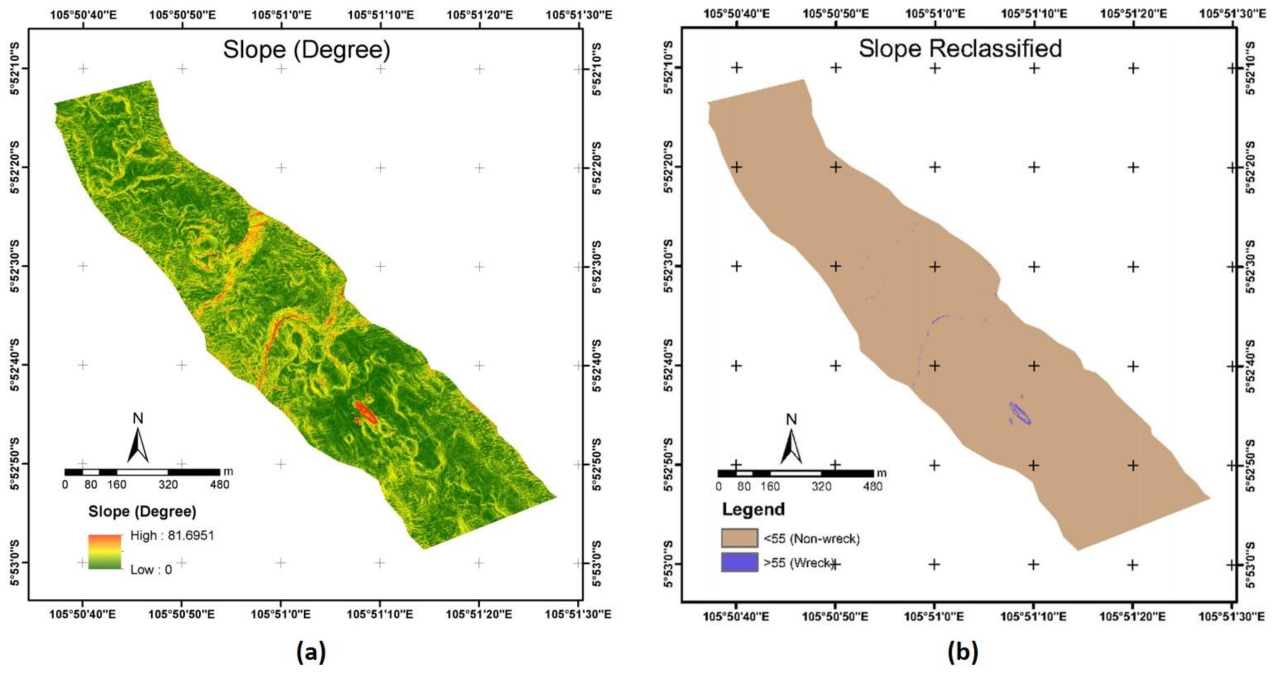

Fig. 4: Slope in degree (a), slope reclassified into wreck and non-wreck classes (b)

In addition to the slope feature, the textural feature extraction also shows a good result. Of the four first-order textures tested, variance and skewness seemed to be the most suitable features for the classification (Figure 5). In visual, the wreck location can be well noticed in both textures and differentiate with the surroundings.

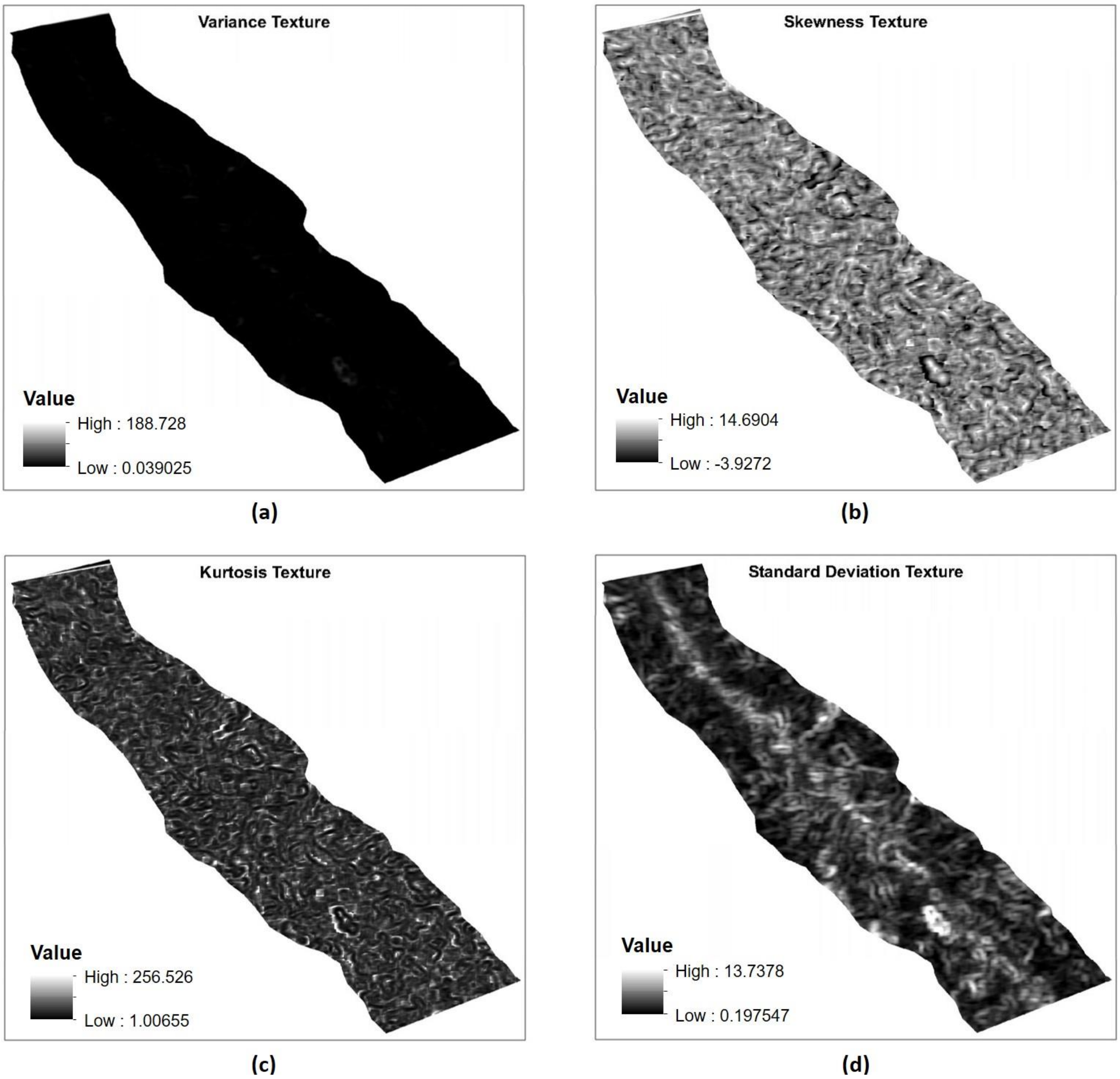

Fig. 5: Results of textural features: Variance (a), Skewness (b), Kurtosis (c), Standard Deviation (d)

Classification and wreck detection

There were six training samples of wreck location and 12 training samples of the non-wreck locations taken from the backscatter image and covered the entire image. Those samples were then trained in SVM to get the model that will be used for the classification. Afterward, the SVM model was used in the classification of a backscatter image. The result of the classification can be seen in Figure 6.

It can be inferred that the result of classification still contains several non-wreck features (terrain) that were classified as a wreck. It is assumed that the texture features used in the classification did not work quite well to detect the wreck. Thus, it needs another feature for the final detection. For that reason, the slope feature became a suitable combination feature for wreck detection. The classified image and slope feature were then overlapped using *"Boolean And"* tool in ArcGIS (result in Figure 7).

The result of wreck detection indicates that the wreck position can be accurately recognized. Although there are still a few issues of miss-detection of channel edge, however, the number was significantly reduced compared to the previous input features (slope, as well as Support Vector Machine/SVM results).

The result of segmentation (Figure 8(b) revealed that the soft seabed is more dominant than the hard seabed (56.4% and 43.6% respectively).

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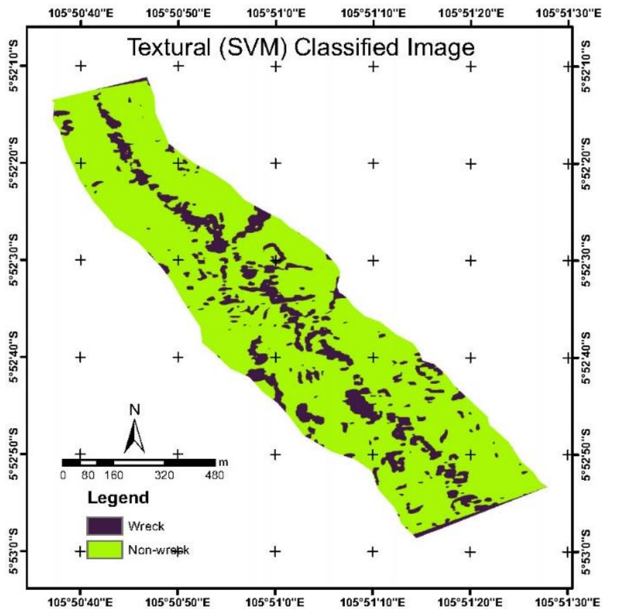

Fig. 6: Result of SVM classification

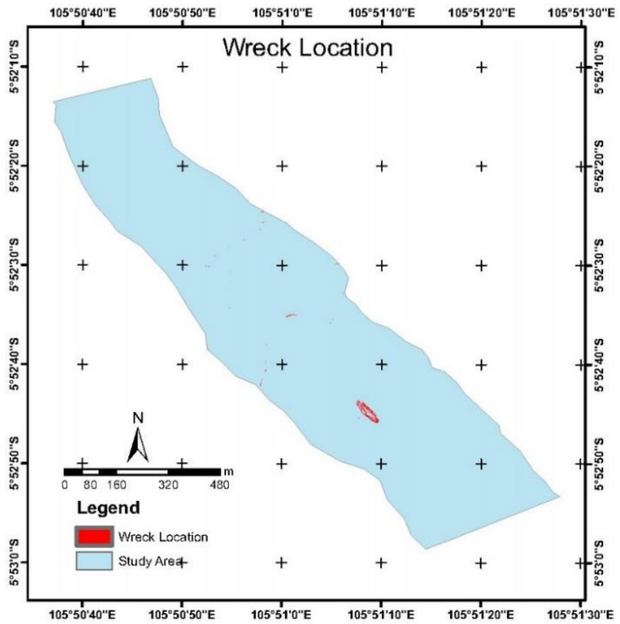

Fig.7: Result of wreck location detection

The study area is the northern slope of the Sunda Strait channel and lies closer to Sumatra Island. Astawa & Wayan (2014) reported that this seabed area covered by igneous rock (interpreted as andesite and diorite), volcanic rock, and sedimentary rock. In addition, Novico et al. (2015) conducted numerical modelling of the current condition at Sunda Strait and was found that the current velocity was up to 4.6 m/s, which possibly could cause sub-aerial erosion.

These conditions are also represented by seabed morphology in this research. Based on the segmentation result, the distribution of seabed geomorphology could be classified as igneous rock and volcanic rock for hard seabed and sedimentary

Morphology characterization

In order to get a general overview of the seabed morphology of the study area, the backscatter image was segmented using K-means clustering into two classes (hard and soft seabed). The result can be seen in Figure 8(a).

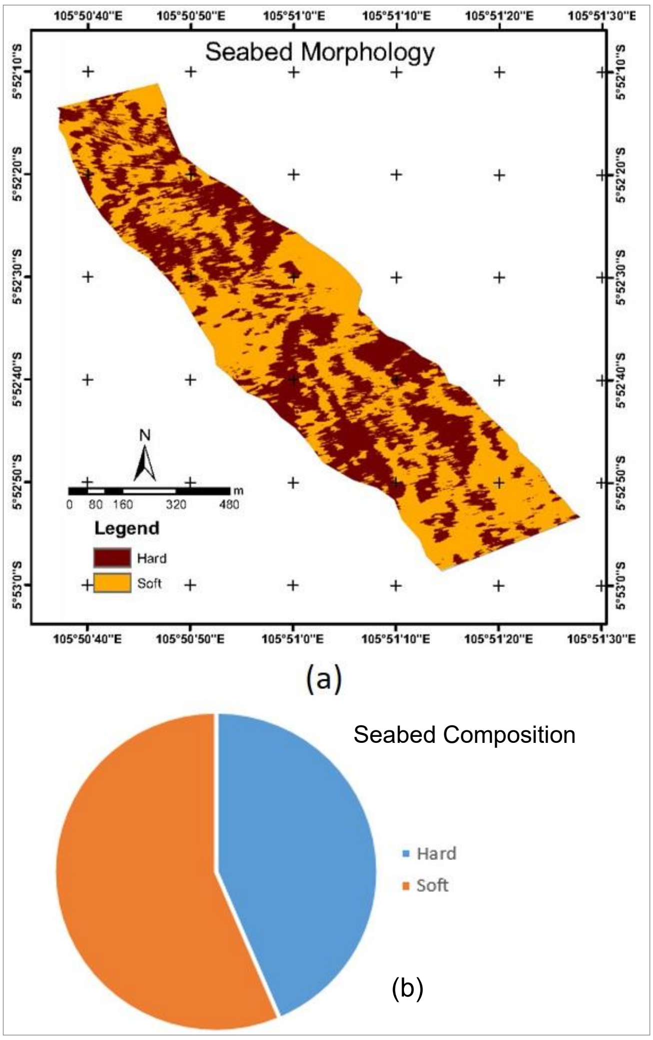

Fig. 8: K-means result of seabed morphology (a), percentage of seabed composition (b)

rock and tuff for the soft seabed. Furthermore, the composition of soft seabed slightly dominant that controlled by current velocity.

Discussion

This study investigates two applications in the use of multibeam products (bathymetry and backscatter) for underwater wreck detection (study case: MV Bahuga Jaya) and seabed morphology depiction. Features extraction was carried out of bathymetry (slope feature) and backscatter (textural features). Support Vector Machine then was examined to classify the textural features and with combination with the slope, it used to detect the wreck location. In addition, a K-means clustering was also used to characterize the seabed morphology by segmenting the backscatter image into two classes (hard and soft).

The result of bathymetry depicts a clear seabed topography with some interesting features (wreck location and seabed channel) that are clearly portrayed. Although in visual, the wreck is easily detected, however, the visual interpretation would be rather helpless in detecting many seabed features (e.g. man-made debris, outcropped rocks etc.). Thus, a more automatic method, such as the one that has been tried in this study is required. The resulted backscatter image has a noise at the nadir of the image (bright line in the centre of the image). This is because the near-vertical angles of incidence (nadir) have a strong variation of backscatter value and need to be removed for further analysis. Detailed explanation of methods in removing angular dependence can be found in several papers (Kloser et al., 2010; Parnum & Gavrilov, 2011).

In this study, the slope feature generally is adequate for detecting the wreck location. However, since there is a steep edge of the channel, it can mix with the detected wreck itself and therefore requires additional features. Vector Ruggedness Measure (VRM) is another morphometric feature that could be examined. The VRM represents seafloor ruggedness (3D orientation variation of grid cells within neighbour pixels) and could depict the variety of slope and aspect (SAPPINGTON et al., 2007). For instance, Pirtle et al. (2015) demonstrated the use of Vector Ruggedness Measure (VRM) to classify the trawlable and untrawlable seabed regions.

The two resulted textures (Variance and Skewness) were chosen for the classification due to their capability to distinguish between the wreck and non-wreck features (terrain). It seems that the Kurtosis feature cannot depict a clear feature of the wreck and it tends to mix with the surroundings. In addition, the brighter tone at the nadir in the Standard Deviation feature is probably due to the effect of non-removed angular dependence in the backscatter image. This effect could lead to non-optimal results in the classification, though the wreck tends to have a noticeable visual appearance with surroundings. However, this study has not tried to examine the use of second-order texture analysis. The second-order texture such as Grey Level Co-occurrence Matrix (GLCM) could be a promising subject. This method has been successfully demonstrated in backscatter classification as proven by Hamilton (2017), Buscombe (2017), and Hamill et al. (2018). Febriawan et al. (2019) also argues that the combination of both first-order and second-order GLCM textures can give a promising result. As alternative to the feature selection above, a Principle Component Analysis of all features is interesting to investigate. However, it was not a part of this study and could be a direction for future research.

Angular dependence also leads to the nadir effect in the SVM classified image. Although the textural features used in the classification could predict the wreck location quite well, a number of miss-classified wreck features exist in the nadir and reduce its accuracy. Removing angular dependence could lead to a smoother result and improve the accuracy assessment. The final detection map shows that the combination of SVM classified image and slope feature has demonstrated that it can lead to a good performance in wreck detection. This research has also verified that SVM could be a promising method in shipwreck detection and classification with limited numbers of training samples with a clear margin of separation between classes (e.g. wreck and non-wreck). However, this method cannot perform conveniently with the noisy data (e.g. side-scan sonar and backscatter imagery) and could lead to some miss-classifications as proven in this study. Thus, other machine learning techniques need to be investigated. Some machine learning methods in archaeological studies such as fuzzy K-means for site maintenance (Malinverni & Fangi, 2009), neural network for archaeological sites formation study (Sharafi et al., 2016), and random forest classification for prospecting archaeological sites (Thabeng et al., 2019). Further study could use those other machine-learning methods in underwater shipwreck investigation.

In general, K-means segmentation used in this study also showed an adequate result to depict the distribution of seabed covers. However, field data samples are mandatory to achieve more reliable results and to reveal other information. For instance, Richards et al. (2016) carried out the in-situ preservation and long-term monitoring for the archaeological shipwreck site. They found that biogeochemistry is an important factor for that process since it could control the degradation of the shipwreck. Thus, further research regarding this topic is required. Richards et al. (2016) also argued that seabed morphology analysis could correlate to shipwreck preservation methods. Seabed features that can be found in the study area consist of a channel, slightly slope, hard and soft seabed characteristics. In general, seabed morphology is controlled by geological activities (e.g. earthquake, fault zone, erosion, and Krakatau eruption). They are implied to sediment grain size and transportation process (e.g. gravity mass flow and suspended sediment). In this study, the wreck site itself lays on the soft seabed and low-medium slope, but is surrounded by both seabed type and low-high slope. Thus, the wreck site may be affected by covered sediment and/or partly moved. This site is also closed to a deep valley and has regional seabed landslide potential (Yudhicara & Budiono, 2008). For that reasons, regular monitoring of the shipwreck site using the same method in this study is required to get comprehensive and continued results.

Conclusion

This study attempted to investigate the use of bathymetry DEM and backscatter image resulted from multibeam swath survey. The combination of Support Vector Machine classification and Slope analysis of the data was carried out to detect the Bahuga Jaya wreck location. Derived from the backscatter image, first-order textural features were used as parameters for the SVM. Based on the texture analysis, the most suitable ones were variance and skewness textures. The backscatter image then was classified into two classes (wreck and non-wreck). Slope analysis was conducted using bathymetry DEM and successfully removed almost all of the non-wreck objects (terrain seafloor) using a slope threshold of 55°. The combination of SVM classification and Slope analysis has been demonstrated as a promising tool for detecting the wreck location.

Additionally, K-means clustering of the backscatter image was conducted to characterize the region into two classes: hard and soft seabed. According to the segmentation result and other research, 56.4% of the area consists of the soft seabed (there were presumably sedimentary rock and tuff), which was influenced by current velocity and sub-aerial erosion. Conversely, 43.6% of the area was hard seabed, probably igneous rock and volcanic rock. Since the wreck was surrounded by the soft seabed and low-high slope, sediment could potentially cover the wreck or could move the wreck's body. Although the K-means clustering showed a potential result, a more accurate outcome could be achieved by applying ground reference samples.

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