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Benthic Habitat Mapping from Seabed Images using Ensemble of Color, Texture, and Edge Features*

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Abstract

In this paper we present a novel approach to produce benthic habitat maps from sea floor images in Derwent estuary. We have developed a step–by–step segmentation method to separate sea–grass, sand, and rock from the sea floor image. The sea–grass was separated first using color filtering. The remaining image was classified into rock and sand based on color, texture, and edge features. The features were fed into an ensemble classifier to produce better classification results. The base classifiers in the ensemble were made complementary by changing the weight (i.e. cost of misclassification) of the classes. The habitat maps were produced for three regions in Derwent estuary. Experimental results demonstrate that the proposed method can indentify different objects and produce habitat maps from the sea–floor images with very high accuracy.

Keywords: Benthic habitat mapping, ensemble classifier, image classification

1. Introduction

The term benthic refers to anything sitting under a body of water. The organisms (e.g. animals and plants) that live on the bottom are called the benthos. The habitat map presents how the different organisms are distributed on the seabed. Habitat maps are normally produced on near shore and estuary areas. This is primarily due to the fact that these areas are very important to preserve and manage. These areas are also shallow and it's relatively easier to obtain data on the sea floor to produce the map. Benthic habitat maps are commonly used by policy makers, estuary managers, and researchers to make informed decisions to protect the nation's fragile shallow-water coastal areas.

Habitat maps are normally produced based on video data collected by divers. Domain experts then observe the images and produce habitat maps based on their observation. The process is time consuming and thus frequent production of habitat maps is rarely observed. For example, in the Derwent estuary (the region of interest in this research) habitat maps were last produced in 2008 [1]. Automation of the habitat map production involves two steps – (i) the data collection process and (ii) habitat map production process. Image/spectrometer data on the seafloor habitats can be collected by an Autonomous Underwater Vehicle (AUV). AUV is normally equipped with cameras that can be used to capture images of the sea floor. The habitat map production process can be automated by using image processing algorithms or by signal processing algorithms (for spectrometer readings). Altogether the automation will reduce human effort and can increase the frequency of habitat map production.

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A number of works are observed in the literature [2]–[14] that automates the habitat map production process from aerial imagery, underwater photos, acoustic surveys, and data gathered from sediment samples. Depending on the area under consideration the segmentation algorithm, feature extraction process and the classification process varies. The area under consideration in this research is Derwent estuary. To the best of our knowledge no previous attempts were taken in this region for the automation of habitat map production process. In this paper we present a novel image processing and classification based approach. A step–by–step segmentation approach is developed to separate the sea floor objects in the image. A number of features including color, texture, and object edge structure are computed from the image regions. A set of classifiers are then trained on these feature sets and combined in ensemble architecture [15][16][17]. The proportion of objects in each image obtained by the proposed method populates a habitat map. The objects of interest in the particular area of Derwent estuary were sea–grass, sand and rock. The proposed method detects them with high accuracy as evidenced from the experimental results.

2. Related Works

Construction of benthic habitat maps are automated by processing images obtained by spectral imaging, remotely sensed data, or by AUVs. Image classification methods in use today include supervised classification and unsupervised classification. The technique presented in this paper is an ensemble supervised classification system. With supervised classification systems, examples of end-members (i.e., sand, sea-grass) are identified by human experts. These samples are used to develop a characterization of each end-member class. The characteristics of the end-member classes are then used as inputs to the classification system(s).

A number of approaches are observed in the literature to produce habitat from remotely sensed data. In [1] habitat map was produced for an area off the northwest coast of Roatan Island, Honduras, using high-resolution multispectral IKONOS data. Atmospheric and water column corrections were applied to the imagery to make the method robust. Habitat maps were produced for seagrass, coral, and sand-dominated areas. In [3] spatial and temporal dynamics of submerged aquatic vegetation cover were studied in the seagrass-dominated area of Chwaka Bay, Zanzibar (Tanzania) by using satellite remote sensing. The study presented in [4] present reviews the theoretical background and possible applications of remote sensing techniques to the study of aquatic vegetation. The research work in [5] assessed the accuracy of commonly available airborne hyper-spectral and satellite multi-spectral image data sets for mapping seagrass species in the Eastern Banks in Moreton Bay, Australia.

An autonomous benthic habitat mapping algorithm is presented in [6] that enables real-time on-board classification of images gathered by an AUV, with the ability to classify aquatic vegetation at a resolution approaching the species level. The paper in [7] describes a novel technique to train, process, and classify images collected onboard an AUV used in relatively shallow waters with poor visibility and non-uniform lighting. The approach utilizes Förstner feature detectors and Laws texture energy masks for image characterization, and a bag of words approach for feature recognition. The research in [8] uses Local Binary Patterns (LBP) as a method for texture-based identification of Crown-Of-Thorns Starfish from images taken on the Great Barrier Reef. A texture recognition based method for segmenting kelp is presented in [9]. The images were collected in highly dynamic shallow water environments of Marmion Reef, near Perth, Western Australia.

A novel shape recognition algorithm was developed in [10] to autonomously classify the Northern Pacific Sea Star from benthic images captured in the Derwent estuary, Tasmania. Unsupervised methods to classify objects on sea floor images using Gaussian Mixture models and Dirichlet process mixture models were presented in [11] and [12]. The use of color as segmentation criteria in RGB images has been evaluated and found to produce reasonable results [13]. Previous benthic terrain classification techniques have relied on analysis and interpretation of multibeam bathymetry, combined with some kind of visually survey data (e.g., transect videos) to make qualitative and quantitative inferences [14].

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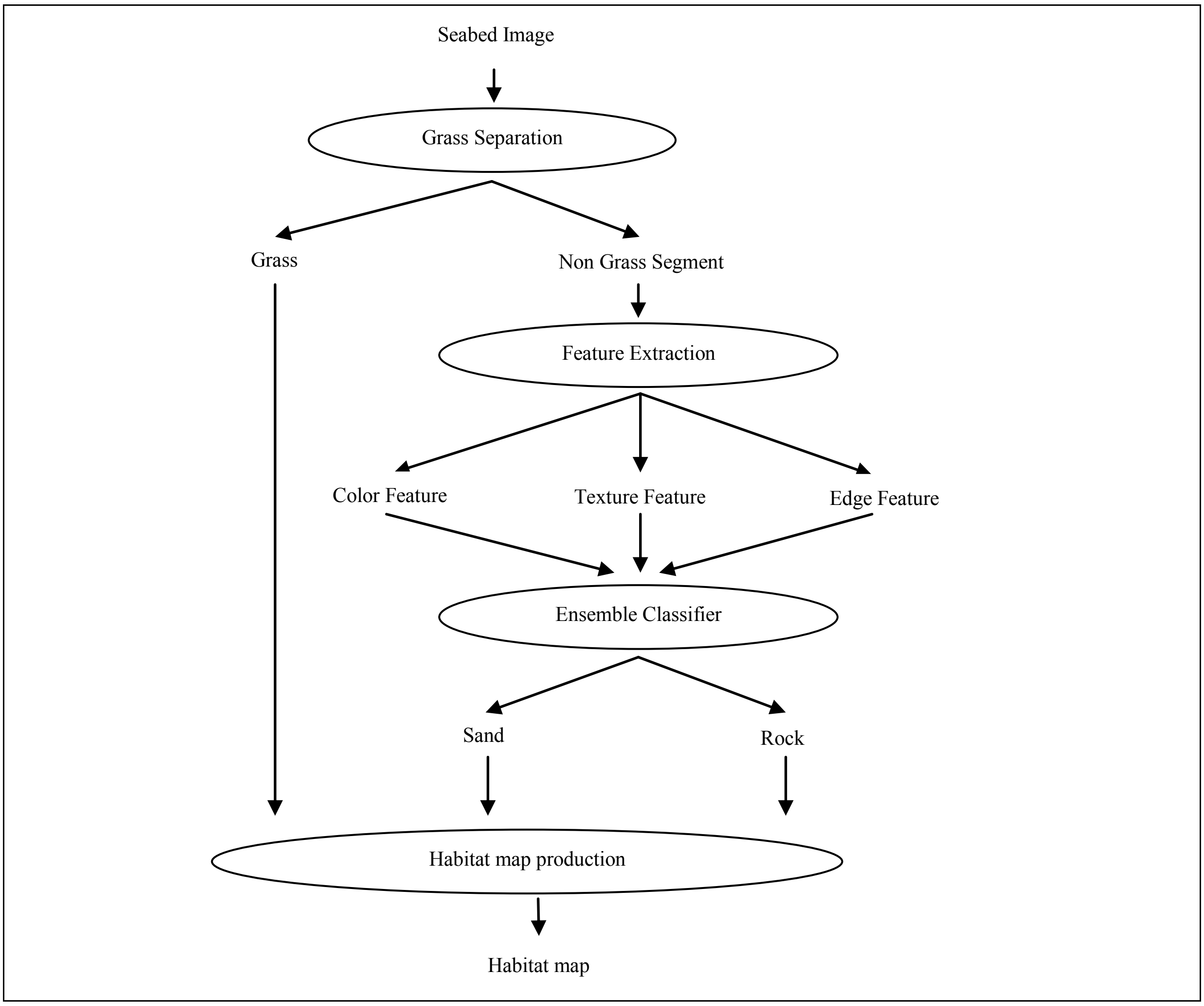

Fig. 1. Habitat map production framework through identification of grass, rock and sand from seabed images using ensemble of color, texture, and edge features.

The existing research reveals that the image processing techniques and features vary depending on the area under consideration. In this particular research we analyze images obtained from Derwent Estuary in Tasmania by an AUV called Starbug [6]. In this research we combine a set of color, texture and edge features in an ensemble classification framework to identify the presence of different objects on the sea floor and produce the habitat map.

3. Proposed Method

The particular region of interest on the seabed contains three different types of objects: sea–grass, rock, and sand. The sea–grass has clear distinctive feature in terms of color (light green). Although sand has signature texture feature, rocks are comparatively problematic. This is due to the fact that rocks exist in different colors and in some scenarios the texture is very similar to sand. The rocks however have significant edges whereas sand does not. Considering these facts we propose the following framework (Fig. 1) to differentiate between grass, rock, and sand from a seabed image and produce habitat maps. The different steps of the proposed framework are presented next.

3.1. *Grass Separation*

The grass object is relatively easy to separate as it has a unique light green color. We have utilized the HSV color space to extract the grass region. We used the

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following color range on H(Hue) and S(Saturation) channel to filter the grass region:

$$0.15<H<0.30 \text{ and } S>0.10 \quad (1)$$

The range was set by trial–and–error on the training images. Fig. 2 represents the outcome of the filtering process on some images. If applied on rock images the outcome of the filtering process is empty as the images do not contain any grass. The other two images contain grass and the filtering process can extract them. The non–grass region of the image is utilized by the following steps to differentiate between sand and rock.

3.2. *Rock and Sand Classification*

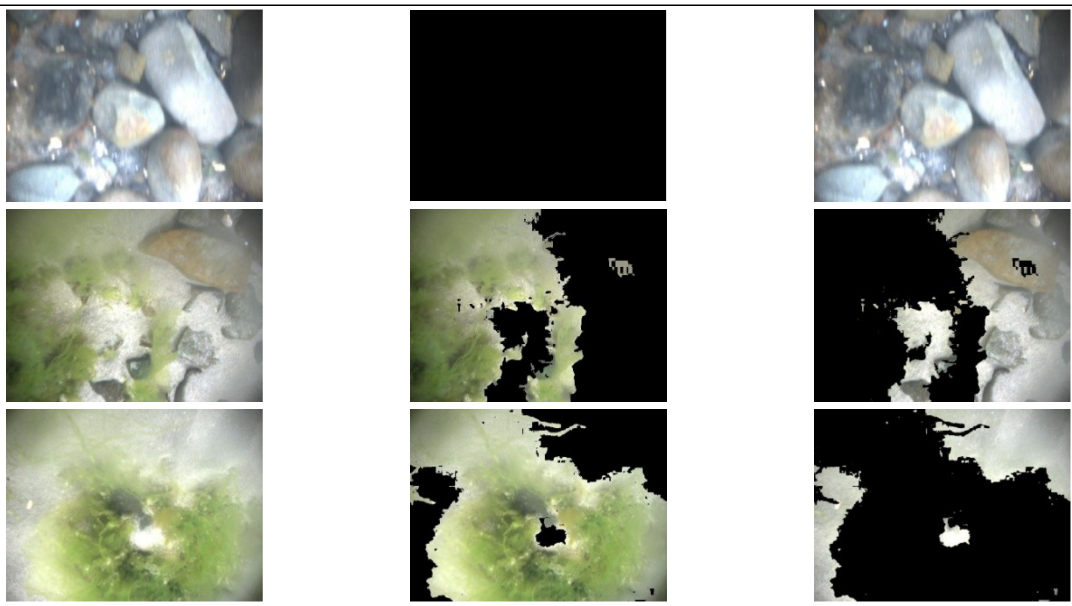
The non–grass region extracted from the previous step contains rock and sand. The rocks are observed to have different colors. Sand has a unique texture. But in some occasions the surface texture of rocks are very similar to sands. There exist strong edges in rocks. We thus have obtained three different features from the non–grass region of the image: color, texture, and edge feature. We developed an ensemble classifier generation method using a complementary training method on these features. The feature extraction and ensemble classifier generation methods are presented next.

3.2.1 Color Feature

Given a sub–image, we have utilized the H channel of the HSV image to compute the color histogram. The reason for not using the S and V channel is to make the feature lighting condition invariant. We have used 11 bins to compute the histograms in the experiments. The extracted color features from the representative rock and sand images are presented in Fig. 3. It can be observed that the probability of certain bins peak in rocks. The probability of the bins is lower in sand images with no bias towards specific color bin.

3.2.2 Texture Feature

We have computed co–occurrence matrix on the H channel of the HSV image to compute the texture feature. We have quantized H values into 11 bins. The co–occurrence statistics compute the occurrence frequency of a pair of H bins (i,j) over the non–grass image. Given eleven H bins it computes a matrix of dimension 11×11=121. The co–occurrence matrix obtained from the representative sand and rock images in a vector form are presented in Fig. 4. Note that co–occurrence based texture feature in sand is significantly different from rock images.



(a) Original Image (b) Sea–grass Region (c) Non–grass Region

Fig. 2. Grass region extraction outcomes from seabed images.

(a) Sand (b) Rock

Fig. 3. Color feature extraction– H histogram

(a) Sand (b) Rock

Fig. 4. Texture Feature: Co–occurrence of H values

3.2.3 Edge Feature

Fig. 5 shows the edge structures while edges are computed from the representative rock and sand images. There is significant difference between the edge structure of sand and rock images. The rock images show the presence of strong and long edges. The edges obtained from sand images are not strong and spans small areas. We computed the frequency domain response of the edge images using Discrete Cosine Transform (DCT). The outcome of the DCT in 50 quantized bins is presented in Fig. 5. Note that the frequency response peaks at different positions for sand and rock images.

3.2.4 Ensemble Generation

We have generated an ensemble of classifiers utilizing the above three features. An ensemble performs better than its base counterparts if their training process is complementary in nature [15][16]. We obtain diversity among the base classifiers by manipulating the cost function associated with each class (i.e. rock and sand). Table 1 highlights the class weighting strategy for the different features. The different class weightings for different features ensure complementary training process among the base classifiers that improves the diversity in the ensemble classifier. Experimental results demonstrate the effectiveness of this training strategy.

4. Experimental Results and Discussion

We have deployed Starbug under the Derwent estuary to capture images in three different regions. We have obtained videos with a total of 36 images from region one, 70 images from region two, 134 images from regions three. The regions contain mostly rock, sand and sea grass. The images in the first half of the video in each region were used for training and the images in the second half were used for testing. We have used libsvm implementation of SVM [18] to train on the features. Parameters can be supplied to assign the costs of misclassification in libsvm that is required for generating the ensemble classifier in the proposed method. All the experiments were conducted in MATLAB.

Table 2 presents the best test set accuracies obtained by the individual classifiers and the true positive rate of both the sand and the rock class. The maximum accuracy is 92.54%. This leaves space for improvement by using an ensemble classifier. Table 3 shows the parameters used for training the base classifiers in the ensemble to separate rock and sand. SVM was trained on the color feature with equal weights (0.5 to sand and

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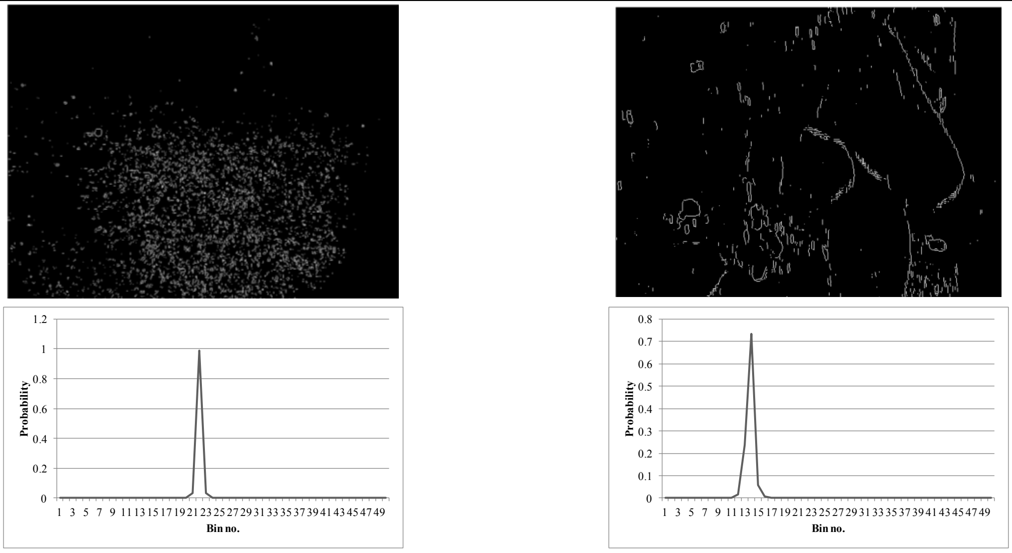
0.5 to rock) to both classes. Higher weight was given to rock (5) than sand (0.5) while training SVM on texture feature. SVM was trained on edge features with higher weight given to sand (5) and lower weight given to rock (0.5).



(a) Sand (b) Rock

Fig. 5. Edge Feature– *top row*: edge structure and *bottom row*: DCT of edge image.

Table 1: Class weighting (i.e. cost of misclassification) strategy for different features to obtain diversity among the base classifiers in the ensemble.

Feature	**Class Weighting Strategy**
Color	Equal weight for both class
Texture	Higher weight for Rock
Edge	Higher weight for Sand

Table 2. Maximum test set accuracies obtained by the individual classifiers

	Color Feature	**Texture Feature**	**Edge Feature**
Sand	93.75	93.75	65.42
Rock	91.43	91.43	91.42
Total Accuracy	92.54	92.54	79.10

Table 3. Parameter Setting for the SVM classifier: g and weight (cost of misclassification)

	Color Feature	**Texture Feature**	**Edge Feature**
g	10	12	0.3
$\text{Weight}_{\text{Sand}}$	0.5	0.5	5
$\text{Weight}_{\text{Rock}}$	0.5	5	0.5

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The ensemble classifier accuracies are presented in Table 4. In the proposed ensemble classifier, the class predicted by majority of the base classifiers is considered as the verdict of the ensemble classifier. The performance of the ensemble classifier is (97.01–92.54)=4.47% better than the best performing individual classifier. Also note that the base classifier corresponding to texture feature in the ensemble obtains very low accuracy (50%) on the sand class. However, as the base classifiers are trained in a complementary fashion the remaining two base classifiers covers it up and results in overall ensemble accuracy of 97.01%. Fig. 6 presents some of the outcomes of the test images. The percentage of area coverage by sea–grass, rock, and sand were obtained from the segmented images in each of the three regions. As the Starbug did not provide any trajectory information we are unable to show the habitat maps on a spatial graph. Fig. 7, Fig. 8, and Fig. 9 shows the percentage of sea–grass, rock, and sand in the three regions. Region one and two is mostly rocky with small presence of sea–grass. Region three is however rich in terms of sea grass. The area is also sandy with scattered presence of rocks.

The solution to the habitat mapping problem depends on the area of study and kind of habitats expected. A more robust approach is unsupervised learning. But in some occasions the marine scientists look for habitats of specific kind that meets some characteristics. This approach is suitable for that. Most of the works that approach this problem are from remote satellite images [2]–[5]. Only one study was undertaken so far on the same set of images in [6]. The paper mentioned two alternative approaches namely spectrum response based and image processing based to solve the problem. No accuracies were mentioned in the paper and we thus can't provide a straight-forward comparison of the approaches in terms of accuracies.

Table 4. Maximum test set accuracies obtained by the ensemble and corresponding base individual classifiers.

	Color Feature	**Texture Feature**	**Edge Feature**	**Ensemble**
Sand	93.75	50	78.13	93.75
Rock	91.43	100	88.57	100
Total accuracy	92.54	76.12	83.58	97.01

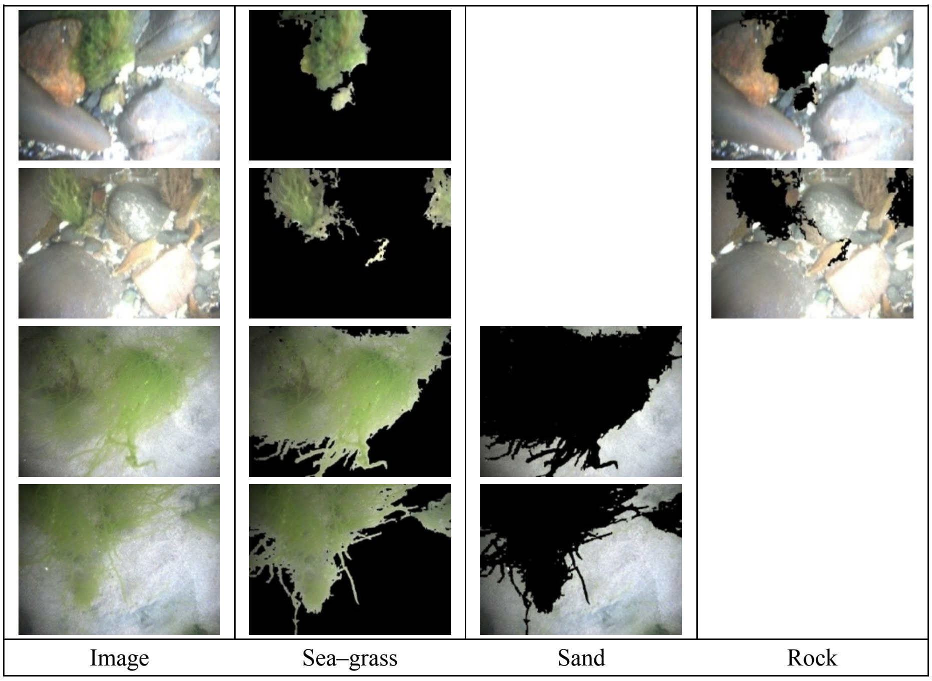

Fig. 6. Separation of test image into sea–grass, sand and rock

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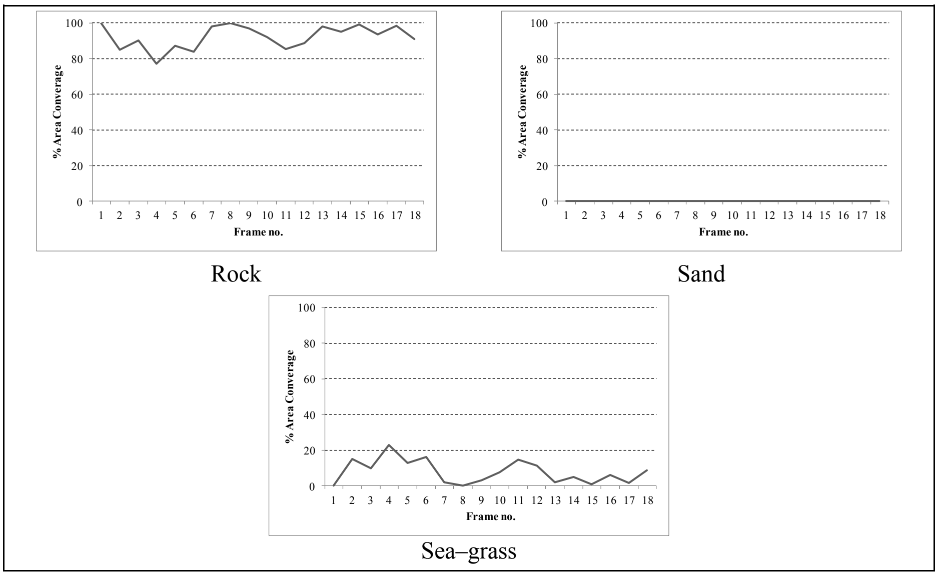

Fig. 7. Habitat map of Region one

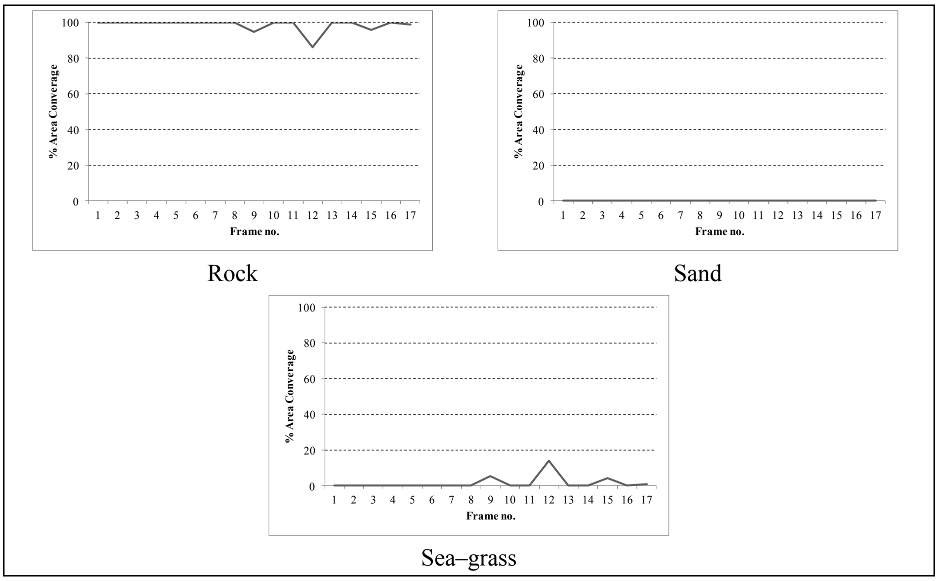

Fig. 8. Habitat map of Region two

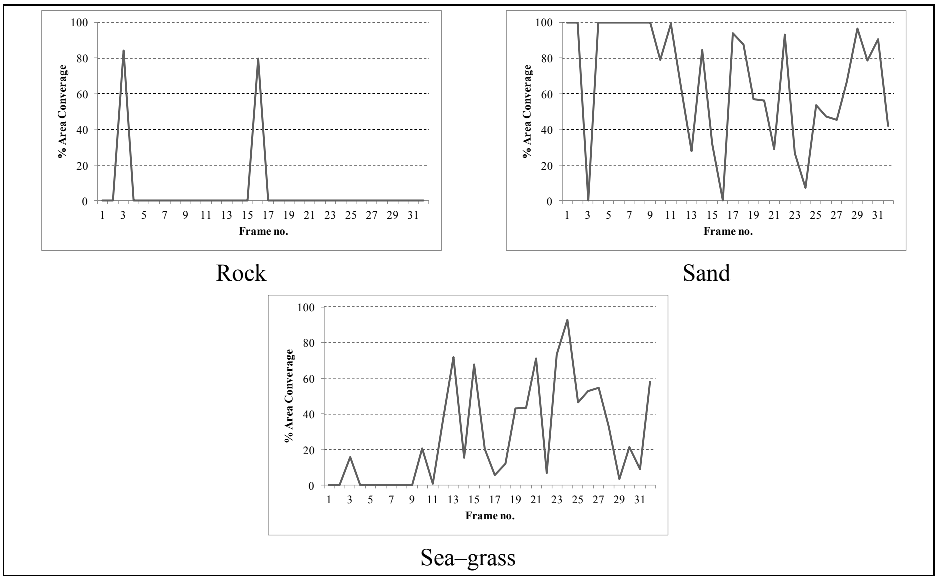

Fig. 9. Habitat map of Region three

5. Conclusions

In this paper we have presented a novel approach to produce benthic habitat maps from sea floor images obtained from Derwent estuary. We have utilized a step–by–step approach to separate grass, sand, and rock from the image. The grass was separated using color filtering. Rock and sand were classified using an ensemble of color, texture, and edge features. The base classifiers in the ensemble were made complementary by changing the cost function. The rock and sand were separated with 97.01% accuracy. The habitat maps were produced for three regions with first two being rocky and the third being sandy and rich in sea–grass.

In future we intend to investigate the inclusion of an extended feature set to classify a broader range of objects (e.g. corals) on the sea floor. Another thing that needs attention is the lighting condition. The images we worked with in this research were taken in good and uniform lighting condition. The visibility normally degrades under water and the color cues obtained from the images does not reflect the true color. Lighting condition normalization and color correction are two more areas that need to be investigated in the future. The author would like to acknowledge Andrew Davie from ISSL, CSIRO for providing the data and active feedback on the paper.

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