Fish Detection in Seagrass Ecosystem using Masked-Otsu in HSV Color Space

Sri Dianing Asri[1], Indra Jaya[2], Agus Buono[3], Sony Hartono Wijaya[4]
Computer Science Department, IPB University, Bogor, Indonesia[1, 3, 4]
Marine Science and Technology Department, IPB University, Bogor, Indonesia[2]

***Abstract*—Seagrass ecosystems are coastal ecosystems with high species diversity, especially fish. Fish diversity determines the abundance of communities based on the number of species. Detection of fish directly (in-situ) and conventionally by catching them requires more energy, costs, and relatively needs time. Therefore a computer vision method is needed that can detect fish well using underwater images. The fish detection model used Masked-Otsu Thresholding, HSV color space with closing techniques in morphological operations. The dataset is in the form of 130 underwater images, divided into 80% training data and 20% testing data. The test results showed a model accuracy value of 0.92, Precision value of 0.84, Sensitivity value of 0.93, and F1 Score of 0.88. With these results, the model could detect fish in the seagrass ecosystem.**

Keywords—Fish Detection; HSV color space; masked-otsu thresholding; morphological operation; seagrass ecosystem

I. Introduction

Seagrass ecosystems are ecosystems in coastal areas with a high diversity of species, especially fish. These varieties are variations in how species interact with each other in their environment. Diversity indices are useful for determining abundance in a community based on the number of species in a location, such as the research of R. Machrizal et al. on the diversity of macrozoobenthos species[1], fish assemblages[2], seahorses species[3], sea cucumber[4]. Detection and classification of fish in seagrass ecosystems are done manually by fishing, photographing, recognizing, and recording in the ledger. This technique is quite good but takes a long time and costs a relatively high amount. Therefore, computer vision techniques and digital image processing will be very helpful.

The underwater environment is more complex than the above-water surface. Sunlight entering the water will undergo absorption and dispersal of light by water media and floating particles in water. The light absorption and dispersal effect results in color distortion, low contrast, and blur in the resulting underwater image[5]. In addition, the difference in attenuation causes the underwater image to be bluish, greenish, or other colors. In addition, the image contains foreground and background caused by the placement of the camera, which is difficult to get close to the observation object. That observation object will be smaller than the background image. Caused bias in the object detection process. It is challenging to make underwater observations using both underwater images and videos.

One solution to separate the background to get the desired object is to use an image segmentation technique based on RoI (Region of Interest). One of the RoI segmentation techniques is the Otsu Thresholding method. The otsu method[6] aims to automatically segment the histogram value of the grayish image in two different regions by entering a threshold value. After the background has been successfully separated, this value is used to detect objects.

Fish detection has been carried out [5][7][8][9] using fish data taken on land, namely by taking photos of fish manually or taking data in an aquarium that has good lighting. In addition, research on fish detection using underwater video was carried out by [10][11]. Retrieving datasets in a limited environment (aquarium) results in a simpler background and foreground. Data collection in the original environment, such as in the seagrass ecosystem, has a more complex background, such as the color of fish objects similar to seagrass leaves or water.

This study used primary data from UTS (Underwater Televisual System) equipment on Beralas Pasir Island, Bintan Regency, Riau Islands, Indonesia. In this study, underwater image data is used, with the area of fish observation objects, seagrass leaves, and transects. Analysis of the underwater image dataset used in this study, it can see that fish objects swimming between seagrass leaves have a color that is almost similar to the color of water or seagrass leaves, that the shape of the fish tends to be smaller (narrow object area) compared to the image background, this makes it difficult to detect it, therefore to remove the background of the underwater image and obtain the detection object, then otsu thresholding is used. The use of HSV color space and morphological operation to obtain a range of HSV values used for area detection of fish objects. This study aims to create a fish detection model associated with seagrass beds on Beralas Pasir Island, Bintan Regency, Riau Islands, Indonesia, using Masked-Otsu in HVS color space. By determining research questions as follows:

R1: How to segmentation of fish objects with an underwater image background using the masked-otsu algorithm.

R2: How to detect fish by applying a range of HSV values and object contours through morphology operation.

II. Related Works

Research on fish detection in seagrass ecosystems has been widely practiced. Most of this research is still done manually, namely by catching fish, being photographed, recognized, and recorded in books. The results have been good, but it requires a lot of time and cost [12][13][14][15][16].

Recently, the use of machine learning and deep learning for fish detection has been widely carried out, and extensive resources and longer time consumption have become considerations in this technique. Meanwhile, digital image processing techniques such as segmentation that can separate the background and foreground with less time consumption can be further developed.

Petrelis Nikos [17] in 2021, utilizing image processing and deep learning techniques to estimate the length, height, and area of fish through fish morphological features and CNN methods, fish objects are visible in shape, and the system built has estimation errors of 1.9% and 13.2%. In 2021, Shoffan Saifullah et al. [7] detected fish through morphological operation and K-Mean segmentation, using photos of fish taken on land so that fish objects were visible, obtaining an SSMI distribution value of 0.9994. Heningtyas research et al. in 2020 [8], using the Expectation Maximization (EM) segmentation algorithm, photos of fish objects taken from an aquarium with good lighting obtained an accuracy of 89.14. Kartika et al. in 2016 [9] classified Koi fish using Naïve Bayes and SVM using K-Fold Cross Validation in HSV space; The Koi Fish image was taken on land, and the study results had a success rate of 0.968. Anggraeny research et al. in 2020 [18] detected fish with the Histogram of Oriented Gradients (HOG) algorithm and AdaBoost-SVM, the accuracy of which was achieved at 0.848. In this Studi, we propose a masked-otsu thresholding segmentation technique to separate objects from the background. The object area is divided into 3, namely the fish, seagrass leaf, and transect areas. After the object is separated from the background, fish detection uses upper and lower HSV color space values and morphological operations with the closing technique. The contribution of this study is to detect fish in complex dynamic environments, namely in seagrass ecosystems, by separating the background of underwater imagery to obtain fish objects.

III. Research Methodology

Broadly speaking, this research consists of several stages, namely: Starting from collecting datasets in the form of underwater images with a size of 620x480 pixels as many as 130 RGB image data, Fig. 1 shows the system flowchart, and Fig. 2 shows the original underwater image.

The original underwater image is cropped at the top to remove the color of the water so that the cropping image is 620x330 pixels. This image is later used to detect fish in a seagrass frame. Furthermore, this dataset will be divided into 2, namely Data Training as much as 80% and Data Testing as much as 20%.

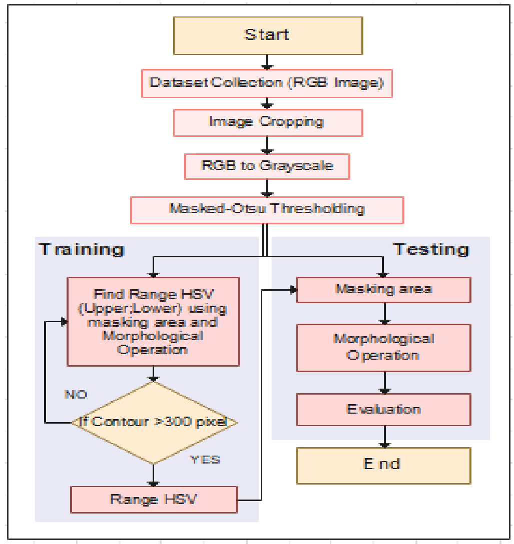

Fig. 1. Research phases.

Fig. 2. Original underwater image.

The third step converted the RGB image to Grayscale. Then, the grayscale image was converted again into a binary image using the Otsu Threshold Method to separate objects (fish) from the background; a threshold value of 120/255 or 0.47 was used.

In the training stage, a search for HSV value range values is performed to detect fish areas, using masking areas and morphological operations. The morphological operation used is a closing operation to close gaps or remove small holes between contours so that it can soften a large object without changing the object significantly.

The equation of the closing operation with the notation A (original image) and B (structuring element) is as follows:

$$A \bullet \boldsymbol{B} = (\boldsymbol{A} \oplus B) \ominus B \qquad (1)$$

Dimension search for detecting objects using the HSV value range is by setting the Upper and Lower values based on the reference object (fish) specified in the thresholding process. The testing stage will be implemented value at range determination is done by paying attention to the area of the object to be detected; if the range is too wide, then unwanted objects will appear; on the other hand, if the range is too narrow, cannot detect the object.

In the testing phase, the masked-otsu threshold result image, given masking, namely the area that is included in the HSV value range that has been obtained previously set as the object dimension. Then the morphological process of closing the area object is carried out; if the contour value is> 300 pixels, it will be marked as fish. The last step is to evaluate by looking for Accuracy, Precision, and Recall values from fish detection models in the seagrass ecosystem. Accuracy, Precision, and Recall using the confusion matrix are as follows:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \tag{2}$$

$$Precison = \frac{TP}{TP+FP} \tag{3}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{4}$$

$$F1\,Score = 2x\frac{Precision\ x\ Sensitivity}{Precision + Sensitivity} \tag{5}$$

Where TP (True Positive) is the number of fish objects successfully detected, TN (True Negative) is the number of non-fish objects (seagrass and transects) detected as non-fish objects, FN (False Negative) if the fish object is not successfully detected as fish. Finally, FP (False Positive) refers to the object that is not fish (seagrass or transect) and is recognized as fish.

IV. Result and Discussion

The data set used in this study is in the form of an underwater image with a size of 640x480 pixels, as many as 130 RGB image data, after cropping the original image's dimensions to 640x330 pixels. Each image is divided into three sample areas: fish, seagrass, and transect. After the dataset is formed, the next step is to cut the top of the image to remove the color of the water so that later this image is used to detect fish in the seagrass frame. Fig. 3 shows the change of the original image to a threshold image with masked-otsu in RGB space.

The dataset is divided into 80% for the training stage, 104 underwater images, 20% for the testing stage, or 26 images. All of these images will be thresholds, then at the image training stage, as many as 104 are used to train the model so that it can detect fish objects; the HSV value range is obtained as follows:

Lower = [74,83,190]

Upper = [88,99,230]

This value is implemented in the data test, after which masking the area for the object's dimensions is included in the HSV value range. Then a closing operation is carried out to close the gap between the contours so that the corresponding object contour is obtained, namely the contour value > 300 pixels marked as fish. While if the contour value <= 300 will be discarded. Fig. 4 shows the fish detection process starts by changing the RGB image from implementing Otsu thresholding to HSV color space, masking area, and operation morphology until the fish object is successfully detected.

At the training stage, the accuracy level is calculated using Equation (2) with 104 underwater image data covering three area objects: Fish, Seagrass, and Transect. The total area used is 314 areas. Based on the experiments, an accuracy of 0.91 or 91% was obtained, which means that the model can correctly predict the area of objects (fish, seagrass, and transects) (Positive).

Meanwhile, at the testing stage, a dataset of 26 underwater images was used. Fig. 5. Show a confusion matrix for testing data.

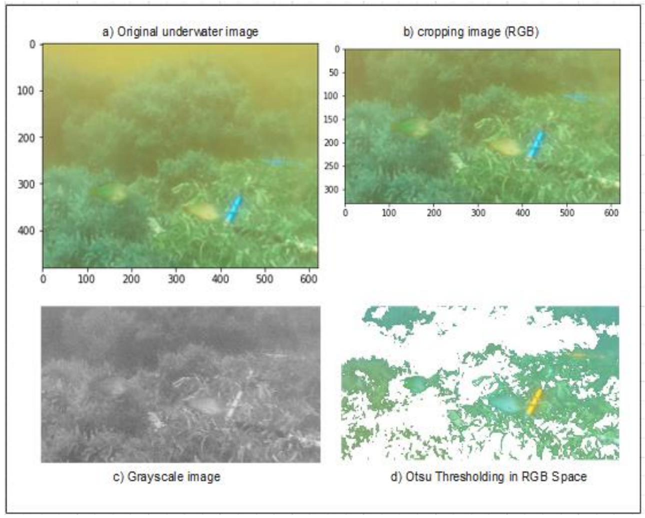

Fig. 3. Change of original Image to threshold image in RGB space.

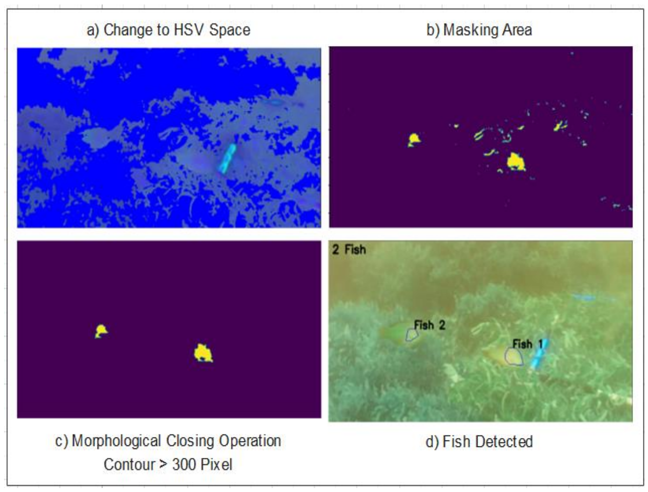

Fig. 4. Fish detection process.

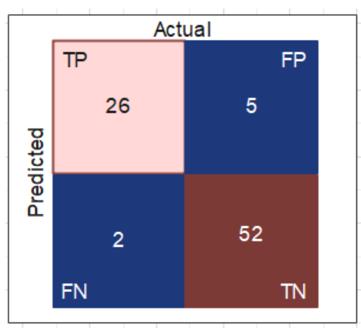

Fig. 5. Confusion Matrix on testing data.

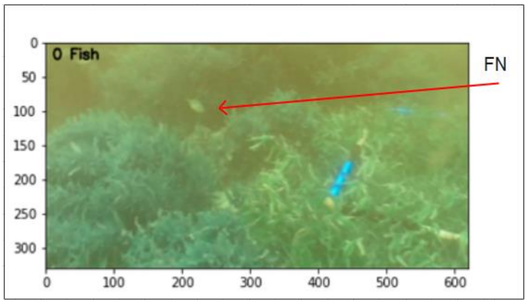

Fig. 6. False Negative (FN) on testing data.

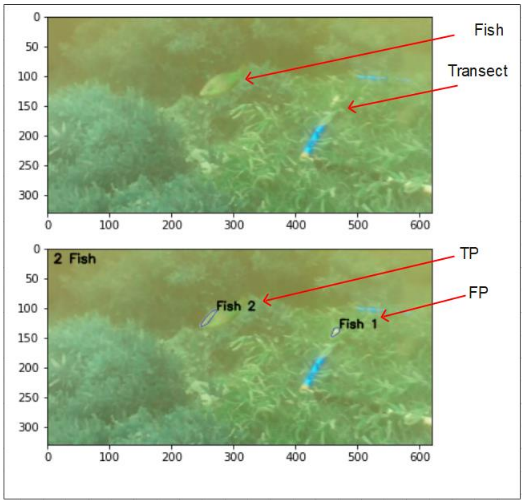

Fig. 7. False Positive (FP) on testing data.

The FN error appears when the model cannot detect the fish object as a fish, as in Fig. 6. Meanwhile, FP occurs because the model states a non-fish object as a fish, where the non-fish object can be seagrass or transect. Fig. 7 shows False Positive.

Based on Table I of the data testing results, there is an increase in the percentage of data testing accuracy values compared to the results of training data experiments by 1%. This increase in accuracy percentage is not significant, so the model created is already optimal. The detection error rate is 0.08 or 8%. This detection error is caused by the presence of FN and FP on the model. The error arises because the area of the fish to be detected is narrow, blurry, and unclear; besides that, the shape and color of the fish are almost the same as the seagrass leaf. Even with ordinary eyes, this fish is difficult to detect.

In addition to the Accuracy value, Table I also shows a Precision value of 0.84 or 84%. This Precision value signifies the reliability of a reliable model for repeated data testing. The sensitivity value is obtained at 0.93 or 93%, which means that the model can detect or give a True value to positive data. Then last is the F1 Score. The F1 Score is 0.88 or 88%, meaning that the model is capable and reliable in detecting fish well.

TABLE I. DETAIL RESULTS OF TESTING DATA

Accuracy	Precision	Sensitivity	F1 Score
0.92	0.84	0.93	0.88

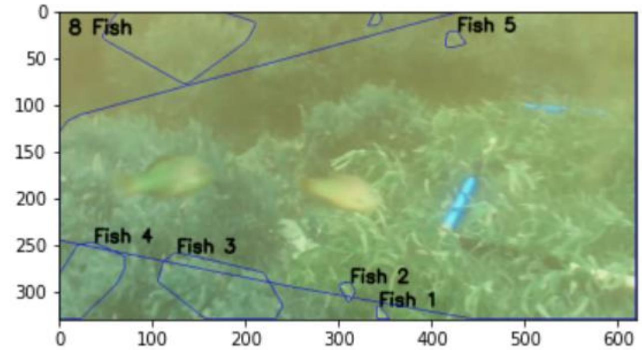

Fig. 8. Fish Detection Model Without HSV.

This study also tried to test fish detection directly, namely from masked Otsu Thresholding directly carried out the morphological process of the operation without using the HSV color space range value. The results are shown in Fig. 8. The picture shows that the detection results could not be better because the error rate that occurs is high, and the detection results are widened.

V. Conclusion

Based on the test results on the testing data, an accuracy value of 0.92 was better than the accuracy of the training data of 0.91. It is not significant, meaning that the model built is optimal for detecting fish. In addition to accuracy, the model gets a Precision value of 0.84 which means it can be relied upon for repeated data testing. The Sensitivity value is 0.93, which means that the model can detect or give a correct value to positive data. Then last is the F1 Score. The F1 Score is worth 0.88, meaning that the model is capable and reliable in detecting fish well.

The test results also showed a misdetection of 8%. The error arises because the area of the fish to be detected needs to be narrower, opaque, and unclear. Besides that, the shape and color of the fish are almost the same as the seagrass leaf. Even with ordinary eyes, this fish is difficult to detect. This cause the resulting underwater image to have low contrast and blur. The next study is to create a fish detection model that can capture small fish dimensions with a fish shape or color almost the same as the color of water and seagrass leaf based on video using the GMM (Gaussian Mixture Model) algorithm and morphological Operation. Using datasets in the form of underwater videos considering fish objects will look moving and can be distinguished from the image background. GMM was chosen because this algorithm effectively separates the background and foreground on the input frame sequence compared to Otsu Thresholding.

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