Design of Biofouling Level Classification System Using Haar-Cascade Classifier And Local Binary Pattern Histogram

Yuning Widiarti [1], Fasa Imana Faumi [2]

[1] Marine Electrical Engineering Shipbuilding Institute of Polytechnic Surabaya, Surabaya, Indonesia
[2] Automation Engineering Shipbuilding Institute of Polytechnic Surabaya, Surabaya, Indonesia
yuning.widiarti@ppns.ac.id, fasaimana15@student.ppns.ac.id

Abstract. The shipbuilding industry still faces challenges and problems. One of them is biofouling on ships, a major problem that can lead to increased fuel consumption and a higher risk of spreading invasive species. The shipbuilding industry is a strategic and competitive domestic industry that deserves to be developed. Biofouling consists of five levels ranging from 0-100% fouling on the ship's hull. Therefore, the countermeasures carried out so that the process of fouling the ship's hull by biofouling is not too severe is the creation of a system to identify fouling on the ship's hull. Based on these problems, in this study, the researchers classified the level of biofouling on the hull using the Haar Cascade Classifier method and the Local Binary Pattern Histogram where the system input was in the form of biofouling images and the system output was in the form of levels of biofouling images that were inspected. This design is applied to the ROV which is equipped with a servo motor on the camera so that it can move in the direction of the yaw axis and pitch axis which can be controlled using a joystick. In this study, it was found that the accuracy of success using the Haar Cascade Classifier reached 90% while using the Local Binary Pattern Histogram obtained an accuracy of 86%. The accuracy of the Haar Cascade Classifier and LBPH methods which have been integrated with the GUI (Graphical User Interface) shows that each level has a different number of pixels.

Keywords: Biofoulin, Jetson Nano, ROV, Haar Cascade, Local Binary Pattern, Classification.

1 Introduction

Colonization of fouling organisms on marine structures has long been a common problem faced by the shipping industry. In general, ships moving on the surface of the water experience biological contamination caused by biofouling which hinders the ship from sailing. Marine biofouling is the colonization and unwanted growth of marine organisms on submerged artificial structures [1]. The process of forming a biofouling community is through a process in which colonization on a surface occurs as a result of succession with several stages. At first, a film is formed biochemically on a clean surface, followed

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by micro- sticking or microfouling (colonization of bacteria and diatoms) until the final stage is macrofouling [2].

Based on these problems, this research proposes the Haar Cascade Classifier method to identify the type of biofouling on ship hulls and classify biofouling levels using the Local Binary Pattern (LBP). Images (images) of fouling on the ship's hull were taken using a Remotely Operated Vehicle (ROV) that has been equipped with a full HD camera. Furthermore, the Haar Cascade Classifier and LBP histogram will classify the type and density of fouling based on the image obtained for offline fouling detection using Jetson Nano as a data processor. The advantage of this method is that it has a very fast computation because it only depends on the number of pixels in a square, not every pixel value of an image. Then combined with the LBP method which is a simple method, but efficient in representing texture features. The LBP operator consists of only a few neighboring pixels with uncomplicated calculation operations. In addition, LBP is a gray-scale invariant method, or not affected by uneven lighting in the image, because LBP describes texture locally [3].

2 Research Literature

The process of taking biofouling images in this study uses a Remotely Operated Vehicle (ROV) so that it is more flexible, especially in areas that are difficult to reach. For technology development in the docking process, using an ROV for biofouling detection is very useful because it saves time and money. In this research, the microcontroller used is the Jetson Nano because it is considered more compatible in its implementation. The system for detecting and classifying the level of fouling on the hull through computer vision combines two methods, namely the Haar Cascade Classifier and the Local Binary Pattern Histogram (LBPH).

2.1 Biofouling

The presence of biofouling on ships can cause economic problems such as operational problems [4]. The presence of biota attached to the hull of a ship that has been sailing for 6 to 8 months can cause the ship's speed to decrease by up to 50% so that fuel consumption increases by up to 40%. Lack of ship speed results in delays in sailing time for 10-15% of the total sailing time [5]. The presence of biota attached to the bottom or hull of the ship also accelerates engine damage and the loss of around one month of time every year for docking. Figure 1 is the Biofouling propagation process.

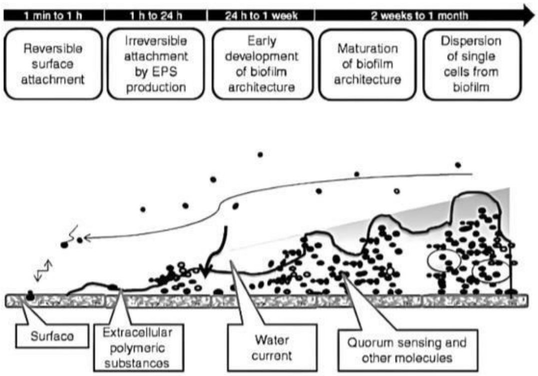


Fig. 1. Biofouling Process

2.2 ROV (Remotely Operated Vehicle)

An underwater robot often called ROV (Remotely Operated Vehicle) is a type of underwater robot that is classified as a type of moving robot with applications intended to carry out activities underwater. In operation, the ROV can be controlled by the operator because it is supported by a control device (remote control). An empty ROV is a mini-submarine with a core cable harness that carries electrical power, sensor data, and control commands. The pilot or operator works remotely but remains in control of the vehicle (the ROV itself). ROVs are used primarily in offshore oil and gas operations for a variety of inspection and manipulation tasks and have largely replaced divers in a wide variety of industrial jobs. ROV is equipped with certain equipment or sensors such as video cameras, transponders, compasses, odometers, bathy (depth data), and others depending on the needs and objectives of the survey. Most ROVs are equipped with video cameras and lights. Its capabilities can be increased by adding sonar, magnetometers, photo cameras, manipulators or robotic arms, water samplers, and tools for measuring water clarity, light penetration, and temperature [6].

Fig. 2. Remotely Operated Vehicle

2.3 Haar CascadeClassifier

Haar cascade is an effective object detection method proposed by Paul Viola. This method uses a machine learning approach where a cascade function is trained from many positive images and negative images. This image is used to detect objects in other images. This method uses haar-like features where training needs to be carried out first to obtain a decision tree called a cascade classifier to determine whether or not an object is present in each frame processed.

- Haar-like feature

Haar Feature is a feature that is based on Haar Wavelet. The Haar wavelet is a single square wave (one high and one low interval). For two dimensions, one light and one dark. Furthermore, box combinations are used for better detection of visual objects. Each Haar-like feature consists of a combination of black and white boxes [7].

Fig. 3. Haar Like Future

F(x) = sum black rectangle - sum white rectangle (1)

The presence of the Haar feature is determined by subtracting the average pixel in the dark area from the average pixel in the light area. If the value of the difference is above the threshold value, then it can be said that the feature exists. The value of the Haar-like feature is the difference between the number of gray-level pixel values in the black box area and the white box area. where boxes on Haar-like features can be calculated quickly using an "integral image" [7].

- Integral Image

Integral Image is used to efficiently determine the presence or absence of hundreds of Haar features in an image and at different scales.

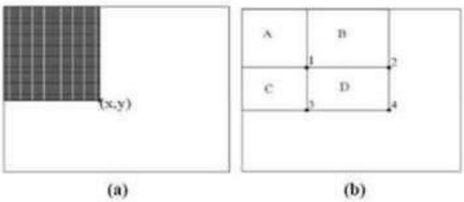


Fig. 4. Integral Image

- Cascade Classifier

The Cascade classifier method is a multilevel classification that functions to filter undetected images, using a classifier that has been trained by 0the AdaBoost algorithm at the classification level. If any input from a sub-window fails during the initial classification process, it will be immediately rejected and the next classification process will not be carried out, however, if the sub-window can pass all classification filters then it can be considered that the feature is the object you want to classify.

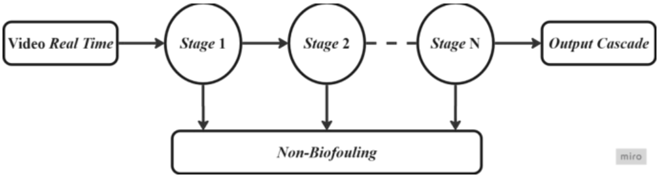


Fig. 5. Cascade Clasifier

2.4 Local Binary Pattern Histogram

Local Binary Pattern Histogram is a texture analysis method that uses statistical and structural models. LBP was first introduced by Timo Ojala. The LBP operator uses a comparison of the gray values of neighboring pixels [HYPERLINK \l "Oja02" 3]. The basic 3x3 LBP operator uses 8 neighboring pixels g_p from a central pixel g_c. The nth neighboring pixel is thresholded using the gray value of the middle pixel as shown in the equation and the thresholding function s(x) as shown in the equation below. The binary code resulting from the LBP operator for neighboring pixels will be used to represent the features of the center pixel of the IC.

$$\mathrm{LBP(x,y)} = \sum_{i=0}^{P-1} s(g_p - g_c) \times 2^i \qquad (2)$$

$$S(x) = \begin{cases} 1, if\ x \geq 0 \\ 0, if\ x < 0 \end{cases}$$

Information:

- x and y : Coordinates of the central pixel
- gc : Central pixel intensity value.
- Gp : The intensity value of the p-th neighboring pixel
- s(x) : Function that returns 1 if x ≥ 0 and 0 otherwise.
- P : Number of neighboring pixels considered in the circle local connections (8 for a 3x3 window).

2.5 Jetson Nano

NVIDIA Jetson Nano Developer Kit is an Artificial Intelligence development kit that can be used to run various modern AI loads with good performance. The NVIDIA Jetson Nano Developer Kit uses micro USB and is equipped with many I/O pins, from GPIO to CSI. NVIDIA Jetson Nano Developer Kit is also supported by NVIDIA Jet-Pack, which includes Board Support Package, Linux OS, NVDIA CUDA, cuDNN, and TensorRT for deep learning, computer vision, GPU computing, multimedia processing.

Fig. 6. Jetson Nano

2.6 Webcam

The Logitech C920 webcam is the focus of research in this final project, where its function is to take biofouling images which will later be processed using the Haar Cascade Classifier and also the Local Binary Pattern Histogram. The PCB dimensions of this camera module are 32mm x 32mm, and the mounting hole spacing is 28mm x 28mm. This camera module has a total weight of 17 grams and for the cableless period it is 13.5 grams.

Fig. 7. Webcam Logitech C920

3 Result

3.1 Data Flow Diagram

This research method will explain and describe the steps taken by researchers to achieve the objectives of this research. Figure 3 will explain the architecture of the system using the Haar Cascade Classifier and LBPH methods for real-time detection of biofouling levels.

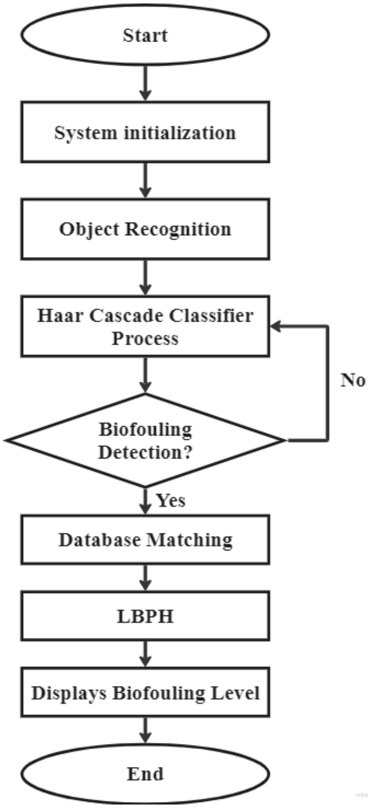


Fig. 8. Flow Diagram

Design system workflow in this research starts with initializing the system, what is done is to detect the desired data and input, such as objects captured by the camera. Biofouling photos that have been studied will be matched with the detection results from the camera, then several images in the database are then carried out by the Haar Cascade process, then the histogram values that have been extracted from the image are matched using the Local Binary Pattern Histogram equation. Table 1 shows the levels used in this research as follows.

Table 1. Level of Fouling (LoF) rank scale with Descriptions of each LoF

Level	**Deskripsi**	**Estimasi Visual Penutupan *Fouling***
1	No Fouling detected Biofouling only, no macrofouling	0%
2	Light fouling. The ship's hull is covered in biofouling and there are 1-2 layers of very small macro-fouling (only one taxon)	1-5%

3	Quite a big mess. There is biofouling, macrofouling as well as layers of one or several different taxa	6-15%
4	The fouling is quite extensive. Several biofoulings and fouling groups are consisting of more than 1 fouling taxon.	16-40%
5	Very heavy fouling. There is a diverse collection of fouling that covers most of the ship's hull.	41-100%

3.2 System Design

There are two system inputs including camera input which functions to capture objects and images from biofouling which is connected to the Jetson Nano which is then controlled using No machine so that it can be displayed on the device to display the GUI (Graphical User Interface) that has been designed. The second input is the Joystick which functions to control the ROV, starting from the movement of the thruster and servo motor. The joystick in this research uses a wireless joystick, making it easier to move the ROV. The ESP32 will receive the Joystick signal which is then sent to the Jetson Nano.

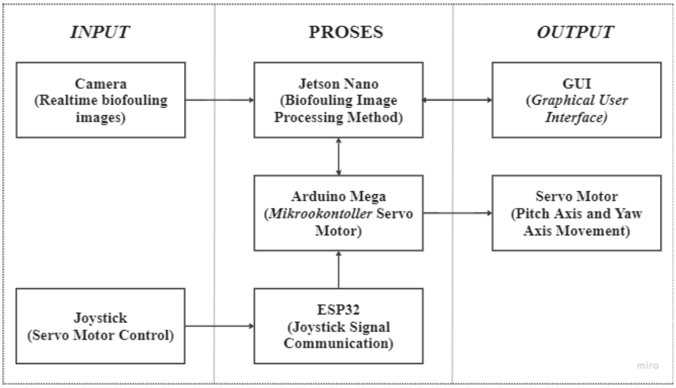


Fig. 9. System Block Diagram

The ROV (Remotely Operated Vehicle) hardware that has been designed and assembled can be seen in Figure 10 as follows.

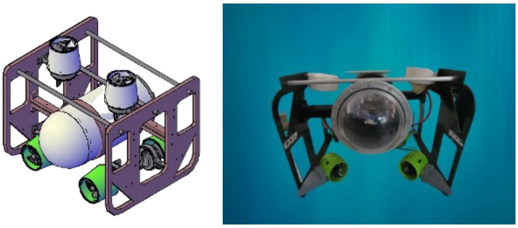


Fig. 10. ROV (Remotely Operated Vehicle)

In this research, the GUI (Graphical User Interface) was created using the Tkinter and OpenCV libraries to access the camera and process frames.

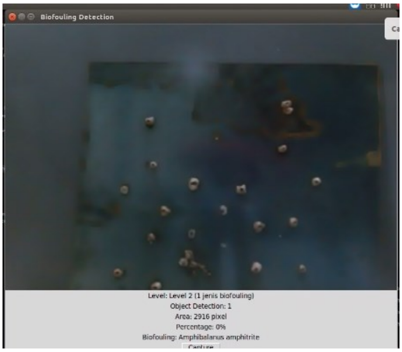


Fig. 11. Implementation of Graphical User Interface (GUI) Display

3.3 Method Processing Stages

- Dataset Implementation

The dataset used in this research is 250 with a division of 80% for system testing and 20% for testing. After dividing the dataset, an image extraction process is carried out to identify important information contained in biofouling. then the results of biofouling recognition will be more accurate.

Table 2. Dataset Distribution

Dataset 250	
Data *Training*	Data *Test*
80% = 200 Data *Training*	20% = 50 Data *Test*

- Haar Cascade Clasifier

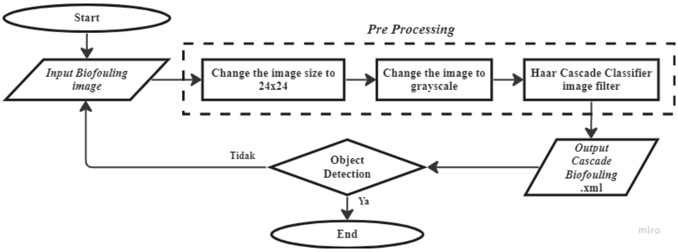


Fig. 12. Diagram Flow Haar Cascade Clasifier

The biofouling images that have been collected with positive data and negative data are then stored in one folder called Biofouling and then trained using the Cascade Trainer GUI application. After training is carried out, it will produce a file called *xml which will later be used for training on biofouling types using the Local Binary Pattern Histogram method, the results of the training will be automatically saved in the Biofouling folder

- LBPH

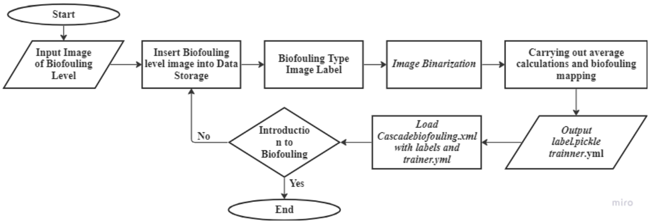


Fig. 13. Diagram Flow Local Binary Pattern Histogram

Image feature extraction process with a window size of 3×3 pixels. After obtaining the decimal value from each binary calculation on all pixels, the final process is to create a histogram of all the decimal values that have been previously generated.

3.4 Result and Discussion

- Servo Motor Test Data

The results of testing the movement of the servo motor yaw axis and pitch axis according to the servo performance angle used using an oscilloscope with PWM input can be seen in the following table.

Table 3. Servo Angle Test Data

PWM	***Duty cycle* (%)**	**Angle Measurement Using Arcs (^{0})**	**Calculation Angle(^{0})**	***Error* (%)**
99	38,8	71	70	0,014

106	41,6	76	75	0,013
113	44,5	80	80	0

- Biofouling Test Data Using Haar Cascade Clasifier

Fig. 14. Detection Biofouling Using Haar Cascade Clasifier

The results of testing each biofouling image have the percentage accuracy calculation for the Haar Cascade algorithm as follows:

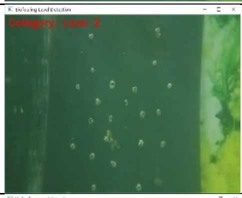
$$\text{Accuracy} = \frac{\text{number of successful images}}{\text{all data}} \times 100\% \qquad (3)$$

Accuracy = 45/50 x 100%

Accuracy = 90%

Based on the results obtained, the level of accuracy using the Haar Cascade classifier method is 90%.

Table 4. Biofouling Test Data Using LBPH

No	Citra Biofouling	Keterangan	Level
1		Succeed	Rank 1
2		Succeed	Rank 2
3		Succeed	Rank 3

4		Succeed	Rank 4
5		Succeed	Rank 5

The results of each image have a calculated percentage for the LBPH algorithm as follows:

$$\text{Accuracy} = \frac{\text{number of successful images}}{\text{all data}} \times 100\%$$

Accuracy = 43/50 x 100%

Accuracy = 86%

Based on the results obtained, the level of accuracy using the Local Binary Pattern Histogram method is 86%.

- Biofouling Test Data At Various Levels Using Haar Cascade Clasifier and LBPH

In testing specimens for biofouling contamination at levels 1 to level 5. This test involves applying the Haar and LBPH methods to identify and measure the level of biofouling contamination at levels 1 to level 5 using a real-time GUI. These fouling specimens represent low to high levels of fouling, and testing is performed by entering the image into the system via the GUI. This process tests the system's ability to recognize and classify areas with levels of contamination. The results of this test will provide information about the two detection methods in detecting biofouling pollution starting from the level, pixel, and percentage of fouling that occurs, which is very important for prevention and monitoring steps in biofouling pollution. In the following table are the test results using the GUI that has been created

Table 4. Biofouling Test Data at Various Levels

Level 1	Level 2	Level 3	Level 4	Level 5
0	576	11304	30000	30934
0	3034	10701	23435	34934
0	2704	6497	33563	32875
0	961	8609	23563	36732
0	1444	9640	8105	26723
0	841	9533	21393	56328

0	729	8480	21393	36732
0	900	8465	9182	26723
0	900	8100	14541	32934
0	784	7592	13317	34934

- Graph of the Number of Biofouling Pixels

Based on the results of tests that have been carried out starting from testing specimens for biofouling level 1 to level 5. This test involves the application of the Haar and LBPH methods to identify and measure the level of biofouling contamination at level 1 using a real-time GUI. The results of this test will provide information about the two detection methods in detecting biofouling contamination at the initial level starting from the level, pixel and percentage of fouling that occurs, which is very important for prevention and monitoring steps in biofouling pollution. The following is a graphic image of the number of biofouling pixels starting from level 1 to level 5 which is shown in

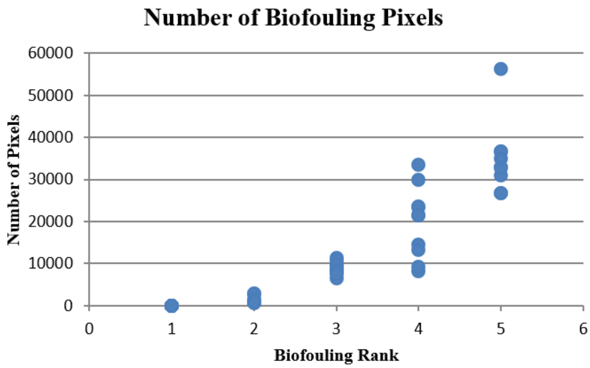


Fig. 15. Graph of the Number of Biofouling Pixels

Based on the graph above, which is the result of a total of 50 (fifty) tests with 10 (ten) tests on each level of biofouling using a comparison of the level and number of pixels produced. Based on this graph, it can be seen that the number of pixel values produced at each level of biofouling has different pixel values

4 Conclusion

Based on the research that has been carried out, testing using the Haar Cascade Classifier method was carried out 50 times. It has a success rate of 90% and for testing using the LBPH method, 50 trials were carried out. Has a success rate of 86% and failure rate of 14%. Meanwhile, in biofouling detection using the Haar Cascade Classifier and LBPH method which has been integrated with the GUI, the results obtained were that the number of pixel values produced in each biofouling image had a different value with the magnitude of the biofouling contamination rank.

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