Fish Counting in OpenCV using Video Analyses Algorithm for Size 12 Nile Tilapia (*Oreochromis niloticus*)

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***Abstract*— Most digital image processing methods for fish counting are limited only to clear raw input images. In this paper, we present a detailed correlation analysis between turbidity and accuracy of fish count. The paper is able to provide an accurate number of fishes on fish pens intended for fish dispersals for small scale fisheries and Bureau of Fisheries and Aquatic Resources (BFAR) of the Philippines. This includes fish monitoring and data acquisition. The testing was conducted on the research area provided by BFAR Region IV-A located in Brgy. Bambang Los Baños Laguna, Philippines. The calibration and testing period of the device lasted from December 2018 up to March 2019. The results show no significant difference between manual counting and the device. Thus, the device can be used as an alternative for manual counting.**

Keywords— ***Raspberry Pi, BFAR, Fish Counting, Blind Deconvolution, Adaptive Histogram Equalization, Image processing***

I. INTRODUCTION

The Philippines which comprises of 7641 islands, is the world's second largest archipelagic country and is a major fishing nation. In 2012, According to Food and Agriculture Organization (FAO) of the United Nations, Philippines had a total of 3.1 million tons of fish, crustaceans, mollusks, and other aquatic animals. This indicates that the Philippines ranked among major fish producing country and has a wide variety of aquatic species. Philippines has a large aquatic biodiversity and it boosts the productivity of its ecosystem. However, the traditional sampling method done by the agency in the Philippines suggests sampling of fish species per weight [1]. The weight estimation analysis method makes of use of trawling which can cause irreparable habitat destruction [2]. Having that said, the proposed study offers a non-invasive method of systematic counting without compromising the marine ecosystem.

Since the emergence of digital era, a lot of imaging techniques was developed which includes Digital Image Processing. It is the use of computer to process the image by using different algorithms according to the kind of data output needed for the study. According to a research done by Manasa et al., object counting is one of the important image processing techniques in industrial applications. Using only a single input, the output may include single to multiple parameter according to the algorithm that is used [3]. Thus, the rate of development of imaging techniques that is used to monitor environmental changes evolve rapidly. The field of fish abundance and estimation gains an increasing attention within the field of monitoring the biodiversity of aqua resources [4]. In the paper done by Fabic et al., it was concluded that the fish population is estimated according to its specie, the method of video acquisition is through synthetic video through sources in the internet and was used as raw input [5]. Similarly, a related research indicates a raw input video in counting and tracking underwater fishes on synthetic videos also taken from the internet [6]. Furthermore, researchers also conducted a study with respect to behavioral study of aquatic animals as it tracks and monitor its activities. Hossain et al., made use of a monitoring system that identify fishes in high and low-resolution images, and calculated how accurate the fishes are compared to an established marine life dataset.

The study offers fish population determination using various algorithms that are integrated real-time using a camera. The prototype introduces fish detection through image enhancements, and deblurring which is necessary for fish counting using blob analysis. The study bridges the limitations of other journals such as system portability which will be addressed using an integrated camera connected to the microcontroller. Furthermore, in the previous researches, the difference lies on the raw input video itself where it requires a clear high resolution and unobstructed videos. This paper will bridge and minimize problem concerning the turbidity of water. Lastly, it will be covering a given area as an alternative to a manual sampling done by the Bureau of Fisheries and Aquatic Resources (BFAR).

The research aims to determine the fish count using OpenCV using video analyses algorithm. In order to attain this, the researchers will specifically (a) to create fish counting system using video analyses algorithm: Blind Deconvolution Filter, Adaptive Histogram Equalization, and Blob Analysis while considering different turbidities of water; (b) to develop a statistical analysis database on the fish count accuracy.

The research will aid fishermen and authorities from aquaculture sector by providing a method in counting the number of fishes. This non-invasive method will serve as an alternative for the traditional per weight estimation done in fish farms. The primary beneficiary will be the Bureau of Fisheries and Aquatic Resources (BFAR) and Fisheries Statistics of the Philippines under National Statistics Authority. This will aid when conducting quarterly fish survey correlated on the amount fish dispersals and keeping in check the biodiversity of a certain fishing site.

The research will focus on the number of fishes in water. Furthermore, the research will consider the accuracy of the device at different turbidities of water. Also, this research focuses in a specific fishing site which was done on Bureau of Fisheries and Aquatic Resources (BFAR) located in Brgy. Bambang Los Banos, Laguna, Philippines for the testing site. The sensor that will capture the data will be a camera compatible for the microcontroller, while the microcontroller that will be used to run the program will be Raspberry Pi. The carrier of the device will be fixed in an area. The whole calibration and testing period lasted from December 2018 up to March 2019.

II. METHODOLOGY

In this part of the research paper, the process that have taken place will be discussed. The research focuses on capturing video frames of fishes underwater on a specific location in an uncontrolled environment and then processing the frame to be able to tally the total amount of fishes present. In relation to this, a calibration test will be done in a site. In addition, raspberry pi will be used as the main processing unit and a waterproof camera will be used to capture the video frame. Additionally, the researchers will incorporate the use of Python Coding to produce a code that will display the processed image and the number of fishes in the processed

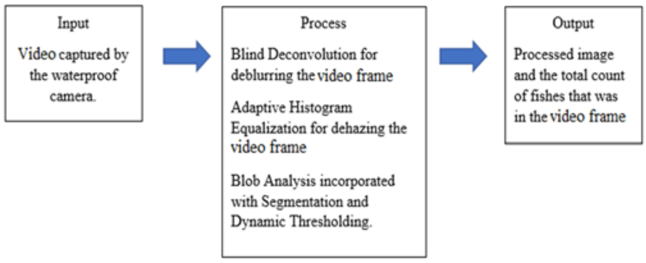

image.

A. Conceptual Framework

Fig. 1. Block Diagram

Figure 1 shows the conceptual framework of the proposed model. At first the waterproof RPI camera will be connected to the Raspberry Pi and the fish counting program will be performed in Python Programming. After processing, the processed frame and the total tally of fishes will be displayed on the monitor.

B. Video Acquisition

In this process, it is intended to capture the video using the waterproof camera. The video frame or the still image will then be converted to an RGB color space format.

C. Process Flow Diagram

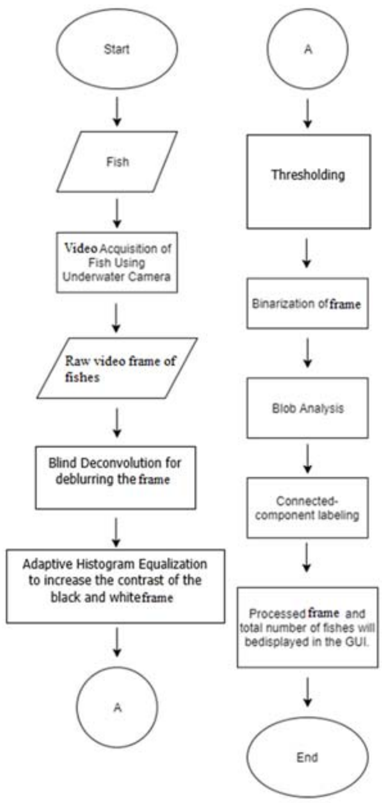

Fig. 2. Flow Diagram

In this part of the research, the process flow will be discussed. In the research, the main object of interest is the population of fish. Thus, in this process, the video acquisition of the fishes underwater will be the first procedure. After, video acquisition, the raw video frame files will be processed by the Raspberry Pi. It will go under go the process of Blind Deconvolution Filter to deblur the frame, if necessary. Similarly, after filtering, the processed image will undergo a process of thresholding. This is the process of converting the colorized image into black white image format. After converting the frame into black and white, it will undergo the process of Adaptive Histogram Equalization. This is to increase the contrast of the frame. Increasing the contrast helps in distinguishing the properties of the image. The next step will be the binarization of the image. All the low contrast part of the image will have a binary value of 0 and all the high contrast part of the frame will have the value of 1. The next step is Blob Analysis. In Blob Analysis, the fish blobs will be detected using the connected component labeling. All the pixels that have the same value and is interconnected will be counted as 1 by the system [7]. Finally, the estimated total number of fishes will be displayed in the graphical user interface created in Python.

D. Filtering Process

The Filtering process shows the results of algorithms used as stated from the process flow diagram into video frames of fishes.

Fig. 3. Original Image

Figure 3 shows the original input raw video frame prior to the processing and algorithms used.

Fig. 4. Blind Deconvolution Filter

Figure 4 shows the result of the video frame upon using blind deconvolution filter which enhanced the blurriness as compared to the original video frame.

Fig. 5. Adaptive Histogram Equalization Filter

Figure 5 shows the result of the video frame upon using adaptive histogram equalization filter on the image after the blind deconvolution process.

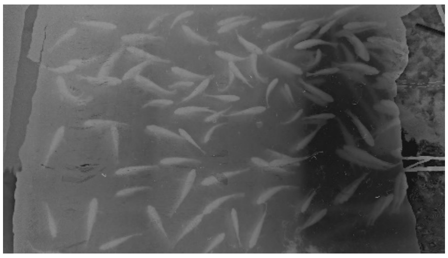

Fig. 6. Binary Image

Figure 6 shows the binary image on the blob analysis algorithm which converts the video frame from colored to black and white.

Fig. 7. Video Output on the Raspberry Pi

Figure 7 shows the output of the device which makes used of the binary image to count the number of blobs and outputs the colored data on the GUI of the device.

TABLE I. CALIBRATION TABLE

Sample	**Fish count without image enhancement (# of fishes)**	**Fish count with image enhancement (# of fishes)**	**True Number of Fishes (# of fishes)**
1	6	11	15
2	4	12	15
3	5	7	15
4	6	11	15
5	6	12	15
6	4	14	15
7	2	13	15
8	11	15	15
9	2	15	15
10	3	16	15

Table I shows the result of the calibration on the number of fish count without image enhancement algorithm used and with image enhancement algorithm filters used.

III. RESULTS AND DISCUSSION

A. Testing

The setup that will be used in a Controlled Testing is in Figure 39. The fish will be Goldfish. It is a freshwater fish with the specific name of *Carassius auratus*. The manual count of fish will be compared to the machine count for the corresponding.

Fig. 8. Gold Fish

Figure 8 shows the fish that is used for the calibration process of the device.

TABLE II. TURBIDITY THRESHOLD

Fish Count	**Actual Count**	**Percent Error**	**Turbidity (centimeters)**	**NTU**
25	25	0	41	14
25	25	0	29	24
25	25	0	22	35
22	25	12	12	90
21	25	16	10	120
20	25	20	8.5	150
19	25	24	7	185

Table II represents the threshold in turbidity of which the device properly counts the number of fishes. The threshold in this testing is about 90 NTU.

TABLE III. TESTING DATA

Year	Month	Date	Fish Count	Miscount
2018	12	2	8	+1
2018	12	2	8	+1
2018	12	2	7	0
2018	12	2	8	+1
2018	12	2	8	+1
2018	12	2	8	+1
2018	12	2	7	0
2018	12	2	7	0
2018	12	2	7	0
2018	12	2	7	0

Table III represents the fish count on the testing and the miscount of the number of fish. The original number of fish in the aquarium is seven fishes. The miscount column was processed after the testing.

B. Site Testing

After a successful system testing, the research will now proceed to the site testing. This part will verify if the system calibrations are done correctly. Like the testing in an aquarium, there will be two tests will be implemented. This is to tally the number of fishes. The same process implemented will be done except that the calibration is now active on the system. The fishes used were size 12 tilapia samples which is equivalent to 5 grams or more in mass. The fishes were chosen by BFAR Region IV-A and was allotted for this specific research

Fig. 9. Fish Count Testing Frame 1

Figure 9 shows the output of the device on the fish count of the first frame of the testing.

TABLE IV. SITE TESTING DATA

Year	Month	Date	Fish Count	Miscount
2019	2	14	46	-2
2019	2	14	50	0
2019	2	14	49	-1
2019	2	14	49	-1
2019	2	14	47	-3
2019	2	14	50	0
2019	2	14	48	-2
2019	2	14	50	0
2019	2	14	49	-1
2019	2	14	47	-3

Table IV represents the fish count on the testing and the miscount of the number of fishes. The miscount column was processed after the testing. The original count is 50 fishes all in all.

TABLE V. AVERAGE MISCOUNT ON A GIVEN TURBIDITY (50 FISHES)

Date	Average Miscount	Turbidity (meters)	NTU
02/14/19	1.13	1	24
02/15/19	1.59	0.7	40
02/18/19	2.02	0.5	65
02/20/19	2.33	0.4	100
02/22/19	2.74	0.3	150

Table V shows the average miscount on the date of testing with 50 fishes as population. It also shows the turbidity of the water on the testing date.

TABLE VI. AVERAGE MISCOUNT ON A GIVEN TURBIDITY (95 FISHES)

Date	Average Miscount	Turbidity (meters)	NTU
02/26/19	2.08	0.9	30
02/28/19	3.11	0.7	40
03/02/19	3.57	0.4	100
03/04/19	4.05	0.3	150

03/05/19	4.31	0.2	185

Table VI shows the average miscount on the date of testing with 90 fishes as population. It also shows the turbidity of the water on the testing date.

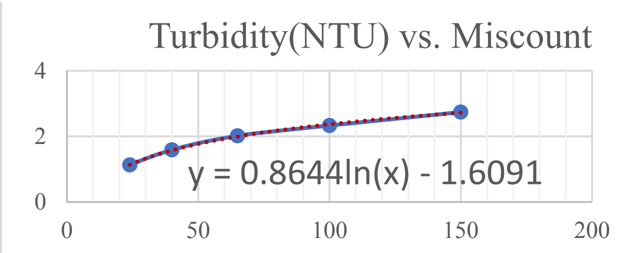

Fig. 10. Line Graph for the turbidity vs Average Miscounts of Table V

Figure 10 shows the inverse proportionality between the turbidity and average miscounts. The figure also shows the logarithmic regression formula of the line which shows the mathematical relationship of the turbidity and the miscounts.

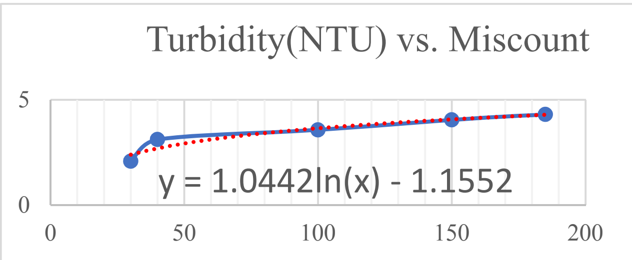

Fig. 11. Line Graph for the turbidity vs Average Miscounts of Table VI.

Figure 11 shows the inverse proportionality between the turbidity and average miscounts. The figure also shows the logarithmic regression formula of the line which shows the mathematical relationship of the turbidity and the miscounts.

C. Statistical Analysis

Statistical Test or Confirmatory Data Analysis calculates the probability of finding the observed data. In addition, it provides grounds for making the quantitative decisions about the null hypothesis created. For this study, the statistical test to be used will be Two Sample t-test assuming unequal variances. This test will verify if the total mean of the experimental values of the trials are equal to the total mean of the actual value.

For the breeding the site, the null hypothesis will be,

Ho: The mean number of fishes manually counted is equal to the mean number of fishes counted by the machine.

$$\text{Ho: } \mu\text{machine} = \mu\text{actual} \tag{1}$$

For the alternative hypothesis,

Ha: The mean number of fishes manually counted is not equal to the mean number of fishes counted by the machine.

$$\text{Ha: } \mu\text{machine} \neq \mu\text{actual} \tag{2}$$

TABLE VII. T-TEST FOR TESTING DATA

Evidence			
	Sample1	Sample2	
Size	17	17	*n*
Mean	11.0588	12.2941	*x-bar*
Std. Deviation	3.64813	3.8853	*s*

Test Statistic	-0.9557	*t*	
df	31		
			At an a of
Null Hypothesis		***p*-value**	5%
H_0: m_1 - m_2 =	**0**	**0.3466**	**ACCEPT Ho**
H_0: m_1 - m_2 >=	0	0.1733	
H_0: m_1 - m_2 <=	0	0.8267	

Confidence Interval for difference in Population Means									
1 - a	**Confidence Interval**								
95%	-1.23	±	2.64	=	[	-3.87	,	1.40	]

For Table VII, the fish count that the device was hypothesized that there is no significance difference from the manual fish count. Since the p- value is in between the range of the confidence interval, the null hypothesis is accepted meaning that the measured data from the device has no significant difference from the actual count assuming population variance are unequal.

D. Test for Accuracy

For testing of accuracy, the percent error is calculated using the formula:

$$\%\,ERROR = \left|\frac{measured - accepted}{accepted}\right| x100 \tag{3}$$

TABLE VIII. PERCENT ERROR AND ACCURACY

Day	**Average**	**Actual count**	**Percent Error (%)**	**Accuracy (%)**
1	48.87	50	2.26	97.74
2	48.41	50	3.18	96.82

3	47.98	50	4.03	95.97
4	47.67	50	4.66	95.34
5	47.26	50	5.48	94.52
6	87.92	90	2.31	97.69
7	86.89	90	3.46	96.54
8	86.43	90	3.97	96.03
9	85.95	90	4.50	95.50
10	85.69	90	4.79	95.21

For Table VIII, the percent error and accuracy are calculated. As seen in the graph day 1table xi to day 7 exhibits a high accuracy with accuracy greater than 94%. Lastly, the accuracy on the last day has the lowest since it has also the lowest turbidity.

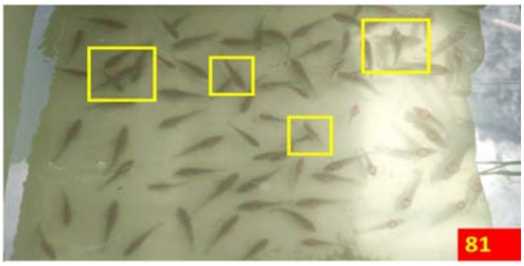

Fig. 12. Video Frame with Miscounted Fishes due to overlapping of fishes.

Fig. 13. Video Frame with Miscounted Fishes to reflection of light.

In Figure 12 and Figure 13, there are miscounted fishes in a frame due to the reflection of sunlight and the overlapping of fishes. For the reflection of sunlight, the prototype will not be able to see and count the fishes reflected. And for the overlapping of fishes, the prototype will count the fishes as one resulting to a miscount.

IV. Conclusion

Given that all objectives are met, the researchers conclude that the prototype can count the number of fishes with minimal error. However, there is a positive correlation between turbidity and number of fishes counted, concluding that at 120 NTU is the maximum threshold for turbidity of water in order to produce accurate results. Given clear water, the prototype would be able to identify and tally the number of fishes accurately. The error produced by the device are mostly from fishes overlapping each other and intolerable reflection of sunlight.

As seen in Table VII, the null hypothesis is accepted where both means are said to be equal or there is no significant difference between manual counting and the device used. Thus, the data gathered is not significantly greater than to the actual value. Also, the percent error shown in Table VIII has the highest value of 5.48%.

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