Shrimp growth monitoring system using image processing techniques

Rex Paolo C. Gamara, Camille Tabalanza, Tim V. Cruz, Jennie Lou C. Tindugan, and Pocholo James M. Loresco

Abstract*—All over the world, the aquaculture industry is very profitable, especially the shrimp farming industry. The various species of shrimps cultivated are considered as the most vital seafood product traded internationally. The better management practices (BMPs) implementation in combination with feed management and growth pattern monitoring achieves farming profitability. Currently, most Filipino farmers assess whether the shrimps reached the marketable size by estimating the length and weight without using measuring tools such as caliper and weighing scale. However, the use of these tools on a large population is a tedious and challenging task in terms of data recording and analysis. For the feed given, farmers usually approximate the amount without any tool; this could lead to underfeeding, resulting in lower growth rate, and overfeeding resulting in habitat pollution. This paper discussed an approach in developing a shrimp growth monitoring system capable of measuring the growth parameters and calculating the optimal feed amount based on the real-time images of live shrimp samples. The system utilizes a specialized conveyor belt and camera controlled by an Arduino microcontroller for image acquisition. The acquired images are sent to the computer for image processing-based measurements using Artificial Neural Network (ANN). The output is presented using the system Graphical User Interface (GUI). The system was tested and reached an average accuracy of above 96% for length and above 94% for weight measurement. Based on the results obtained, an image processing approach for shrimp growth monitoring can be effectively utilized. Future works include the integration of a cloud-based data acquisition system for more effortless data transfer and analysis.

Keywords*—*shrimp, growth monitoring system, length, weight, image processing, growth parameters

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I. INTRODUCTION

Over the years, aquaculture production in the Philippines has been successfully cultivated. The successful aquaculture cultivation resulted in a positive economic impact in terms of revenue. According to the Food and Agriculture Organization of the United Nations (FAO), there are seven dominant aquaculture species in the country, which are carp, tilapia, seaweed, mussels, milkfish, oyster, and shrimp [1]. According to the report published by the Philippine Statistics Authority (PSA) in 2019, the country's aquaculture production is valued more than 100 billion pesos [2]. The implementation of better management practices (BMPs) is necessary to ensure shrimp farming profitability. The application of BMP involves feed management and growth monitoring. It results in 17.6% lower production cost/crop and 21.5% higher cost of production/crop. [3-5].

The body weight and length are the essential biological indicators and specifications in shrimp growth and maturity. These markers are typically recorded for the culture management of shrimp farming. These indicators are used for the computations of different shrimp parameters such as apparent feed conversion ratio (FCR), harvest weight, growth rate, and productivity. In several shrimp farms, conventional tools such as ruler, slide caliper, and weighing are used for length and weight measurement. However, these tools resulted in a tedious task for aquaculturists and farmers, mainly when dealing with a large number of samples. Furthermore, data analysis for the gathered measurements is very challenging to accomplish manually [6-11].

Primarily, shrimp growth highly depends on the feed quality and quantity taken by the species. In the Philippines, shrimp farmers typically estimate the feed amount. They do not use any tool to measure how much feed is needed since it is impossible to observe shrimp species in ponds visually. The actual feeding rate for shrimps should be based on the accurate measure of average weight and the total population of the species in the pond. The average weight of the shrimps can be obtained directly from weighing or measuring the length of the shrimp samples. The proper amount of feed given is very crucial because of the underfeeding and overfeeding risks. The underfeeding risk occurs when a fixed/constant biomass percentage is given to the species, while overfeeding risk occurs when excessive feed is provided, triggering habitat pollution. [12-15].

Based on the data and facts gathered, the researchers of the project developed a system that approximates the growth parameters of the shrimps using image processing utilizing Artificial Neural Networks (ANN). The system approximates the length, then calculates the absolute weight gain, absolute length gain, specific growth rate, AFCR, and condition factor. Moreover, the system determines the feed type and feed amount for optimal shrimp feed management.

This paper comprises of six sections structured as follows. The first section introduces the background of the study, the existing problems, and the proposed solution. The second part deals with the detailed discussion of the proposed framework. The third and fourth chapters are designated for the discussion of the image processing techniques and prototype used. The fifth chapter presents the data and results gathered with the statistical treatment employed. Finally, the sixth section provides the conclusions and recommendations of the study.

II. PROPOSED FRAMEWORK

Figure 1 shows the proposed framework of the study. The input of the system is the harvested shrimp samples. The samples are placed individually on the image acquisition hardware, which is equipped with a camera and a specialized conveyor belt, as presented in Figure 2. The acquired shrimp images will be transferred to the computer using a USB connection.

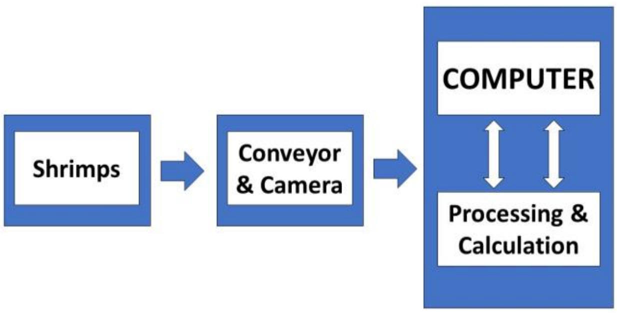

Fig. 1. Proposed Framework

The computer runs the OpenCV software, which launches the system Graphical User Interface (GUI), which requires initial information before the image acquisition. The software reads the data then receives data from the image acquisition hardware. Then, the system performs the pixel-based measurement of the shrimp samples.

The GUI, as shown in Figure 3, provides a real-time view of the image acquisition process. Upon completion of the image acquisition process, the GUI displays all the calculated values for the shrimp growth parameters. The acquired measurements are stored in a database using the Microsoft Excel program.

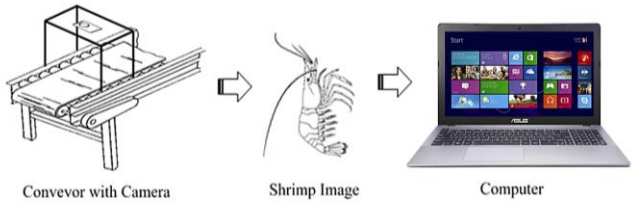

Fig. 2. Image Acquisition Hardware Diagram

The following are the key components of the proposed framework:

- *Conveyor Belt:* the specialized conveyor belt ensures that the live shrimp samples stay in place for the image acquisition. Also, it allows the shrimp samples to be transported throughout the process.
- *Camera:* the camera serves as a transducer to gather image samples of the shrimps. This device is the critical equipment for the image processing implementation of the measurement.

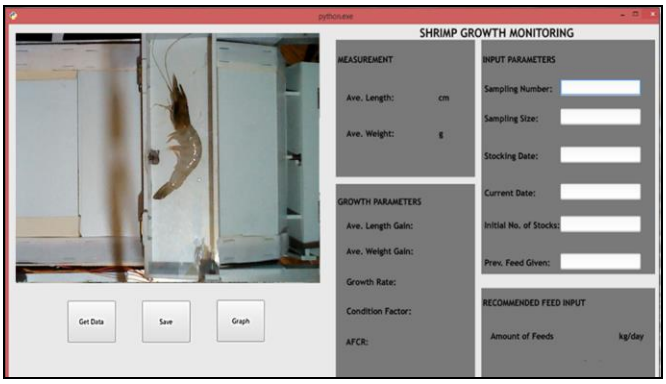

Fig. 3. System Graphical User Interface (GUI)

- *Computer:* The computer provided the processing required for data transfer, storage, and presentation. Furthermore, the image processing algorithm runs with the software installed on the device.
- *Arduino Microcontroller:* The microcontroller controlled the motor for conveyor belt operation and handled the data transfer flow of the image acquisition process.

III. IMAGE PROCESSING TECHNIQUES

The researchers used Python as the programming language for the development of the image processing algorithm. The overview of the image processing techniques is shown in Figure 4. The algorithm utilizes image color space-changing, image filtering, edge detection, image dilation, image thresholding, and image contour. The images used by the researchers to test and calibrate the algorithm of the system involves actual shrimp samples of the same species as Litopenaeus vannamei.

The first stage involves image pre-processing. In this stage, the shrimp images undergo initial image processing to enhance the quality of the image acquired. It is considered as the primary step before the images undergo higher-level processing. In the study, the pre-processing techniques involve are image grayscale and Gaussian De-Noising.

The second stage involves image segmentation. In this stage, the pre-processed shrimp images undergo higher-level processing to specify which regions are useful for the image processing application. In this study, the Canny edge detection and image thresholding were utilized.

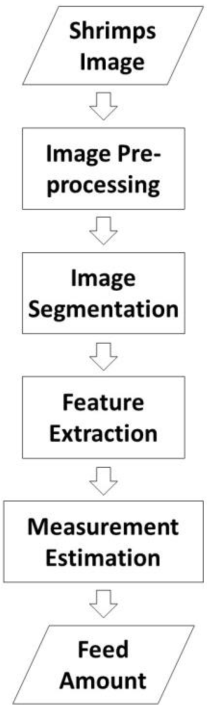

Fig. 4. Overview of Image Processing

The final stage involves image feature extraction. In this stage, the segmented image is processed further to determine the specific image parameter needed to complete the objective of the study. The processes used in the study involves image dilation and contour analysis. The key parameter obtained is the pixel area covered by the shrimp. This information is utilized for training the system with multiple initial shrimp samples to create a model. The implementation of the main stages is depicted in Figure 5. The image processing primary operations performed include grayscale pre-processing, various morphological processes, including binarization, thresholding, filtering, and edge detection to extract the region of interest (ROI).

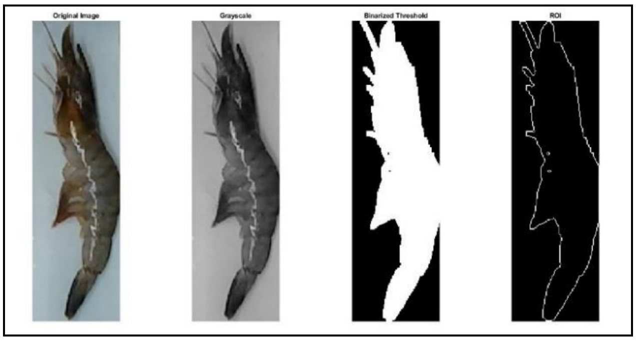

Fig. 5. Implementation of Image Processing

IV. PC-BASED PROTOTYPE DESIGN AND ARCHITECTURE

The growth monitoring and feed-type classification system is integrated with a graphical user interface, see Figure 3. The interface is divided into two main parts: the input parameters and the output parameters calculated by the system. The real-time video feed was also displayed in the GUI as the process commences.

The operation of the prototype is described as follows: First, the farmer/aquaculturist provides the input information. Then, by pressing the 'Get Data' button, the conveyor belt will start to operate. As it works, the servo motor will be activated simultaneously to open the specialized conveyor belt automatically, and the proximity sensor will trigger the stop operation so that the farmer can place individual shrimp easily. After the process, the system will immediately display the calculated parameters. The farmer then presses the 'Save' button to store all the information on the flat-file database powered by Microsoft Excel™. Figure 6 shows the specialized features prototype.

Fig. 6. Actual Prototype

V. DATA AND RESULTS

Figure 7 shows the testing site for the prototype located in Brgy. Abiawin, Infanta, Quezon, Philippines. The Office of the Municipal Agriculturist under the municipal government of Infanta, Quezon, supervised the testing procedures.

Fig. 7. Testing Location

The testing process commenced for 35 days, subdivided into ten trials. Every trial, there are 25 live shrimps cultivated from the farm, which served as the input of the system. After the process, the actual length was measured using a ruler, and the actual weight was measure using a digital weighing scale. The actual values are manually recorded; these values are the expected values for the statistical analysis.

The average length and weight of the shrimp batch measurement underwent accuracy testing. The following equations were utilized.

$$A = (1 - E) \times 100\% \,, \tag{1}$$

$$E = \frac{O - E}{E} \,, \tag{2}$$

Where O represents the observed values (from the prototype measurement), and E represents the expected values (from the manual measurement). Table I and Table II depicts the summary of the accuracy calculation for the weight (in grams) and length (in centimeters), respectively.

TABLE I. ACCURACY TABLE FOR WEIGHT (BATCH)

Expected Value	Observed Value	Percent Accuracy
6.56	7.21	90.09
8.28	9.18	89.13
14.16	15.32	91.81
22.52	23.08	97.51
25.32	26.12	96.84
25.60	27.16	93.91
29.20	29.44	99.18
29.56	30.56	96.62
29.92	31.80	93.72
	Average:	**94.04**

TABLE III. ACCURACY TABLE FOR LENGTH (BATCH)

Expected Value	Observed Value	Percent Accuracy
9.76	10.22	95.29
10.48	11.12	93.89
12.76	13.30	95.77
15.64	14.40	92.07
16.56	17.20	96.14
15.76	15.56	98.73
16.64	16.84	98.80
16.32	17.12	95.10
16.80	16.38	97.50
	Average:	**96.10**

The individual length and weight shrimp measurement also underwent accuracy testing. The Chi-Square Test was utilized to test the null hypothesis H_O: "There is no significant difference between the expected and observed values.". The expected values (E) are based on the manual measurements obtained while observed values (O) are based on the measurements obtained using the image processing algorithm. The test statistic for the Chi-Square Test was calculated using equation 3.

$$\chi^2 = \sum \frac{(O - E)^2}{E} \,, \tag{3}$$

	Level of Significance α								
df	0.200	0.100	0.075	0.050	0.025	0.010	0.005	0.001	0.0005
19	23.900	27.204	28.458	30.144	32.852	36.191	38.582	43.821	45.974
20	25.038	28.412	29.692	31.410	34.170	37.566	39.997	45.315	47.501
21	26.171	29.615	30.920	32.671	35.479	38.932	41.401	46.798	49.013
22	27.301	30.813	32.142	33.924	36.781	40.289	42.796	48.269	50.512
23	28.429	32.007	33.360	35.172	38.076	41.639	44.182	49.729	52.002
24	29.553	33.196	34.572	36.415	39.364	42.980	45.559	51.180	53.480
25	30.675	34.382	35.780	37.653	40.646	44.314	46.928	52.620	54.950
26	31.795	35.563	36.984	38.885	41.923	45.642	48.290	54.053	56.409
27	32.912	36.741	38.184	40.113	43.195	46.963	49.645	55.477	57.860
28	34.027	37.916	39.380	41.337	44.461	48.278	50.994	56.894	59.302
29	35.139	39.087	40.573	42.557	45.722	49.588	52.336	58.302	60.738
30	36.250	40.256	41.762	43.773	46.979	50.892	53.672	59.704	62.164

Fig. 8. Chi-square Table

The decision rule was based on the critical value specified on the Chi-Square table shown in Figure 8. The critical value was set to 39.09, based on the degrees of freedom value of 29 and the level of confidence of 90%.

The null hypothesis is rejected if the Chi-Square test statistic exceeds the critical value and is accepted if the Chi-Square test statistic is less than the critical value. The calculations of the Chi-Square Test Statistic for all parameters are performed using Microsoft Excel™. Table 3 and Table 4 shows the calculation of the Chi-Square test statistic for length and weight.

TABLE IIIII. ACCURACY TABLE FOR WEIGHT (INDIVIDUAL)

Observed Value	**Expected Value**	χ^2
30.25	31	0.0181
26.23	26	0.0020
29.81	29	0.0226
28.94	29	0.0001
32.88	32	0.0242
24.79	25	0.0018
30.12	30	0.0005
27.12	26	0.0482
36.85	36	0.0201
30.74	31	0.0022
28.15	28	0.0008
33.13	32	0.0399
30.19	31	0.0212
24.51	23	0.0991
28.97	30	0.0354
25.13	24	0.0532
27.65	27	0.0156
27.44	26	0.0798
32.56	33	0.0059
31.65	29	0.2422
25.11	23	0.1936
28.61	28	0.0133
33.31	32	0.0536
28.41	26	0.2234
29.84	28	0.1209
31.21	29	0.1684
24.93	26	0.0440
28.69	28	0.0170
27.75	25	0.3025
29.12	29	0.0005
	Total:	**1.8701**

TABLE IVV. ACCURACY TABLE FOR LENGTH (INDIVIDUAL)

Observed Value	**Expected Value**	χ^2
16.43	16	0.0116
14.55	15	0.0135
15.12	16	0.0484
16.25	16	0.0039
18.14	17	0.0764
15.17	16	0.0431
17.14	17	0.0012
16.97	16	0.0588
17.32	17	0.0060
18.19	17	0.0833
18.54	17	0.1395
17.71	17	0.0297
16.16	17	0.0415
15.23	16	0.0371
17.84	17	0.0415
17.59	16	0.1580
18.18	17	0.0819
16.31	17	0.0280
19.41	18	0.1105
15.17	17	0.1970
17.55	16	0.1502
17.49	17	0.0141
17.83	17	0.0405
15.07	16	0.0541
16.81	17	0.0021
14.96	16	0.0676
17.24	16	0.0961
17.32	17	0.0060
15.73	16	0.0046
18.11	17	0.0725
	Total:	**1.7185**

Table III and Table IV show that the Chi-Square test statistic for weight and length is 1.8701 and 1.7185, respectively. The null hypothesis is accepted for the parameters because each value of the Chi-Square test statistic is less than the critical value of 39.09. This shows that there is no significant difference between the observed and expected values for the parameters above with a 90% confidence level.

VI. CONCLUSIONS & RECOMMENDATIONS

The development of the shrimp growth monitoring system using ANN applications provided an effective and innovative tool for shrimp farming management. The system was able to measure the shrimp length accurately and weight, to instantly calculate essential growth parameters, and to effectively recommend the feed type and amount for optimal shrimp feed management.

The system developed was tested and reached an average accuracy of above 94% and above 96% for weight and length batch measurement, respectively. Also, the individual measurements yield an accuracy based on a 90% confidence interval for the Chi-Square test. Based on the results obtained, an image processing approach for shrimp growth monitoring can be effectively utilized.

Future works include the integration of a cloud-based data acquisition system for easier data transfer and analysis.

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