Development of a Fry Counter Software for Striped Catfish [*Pangasianodon hypophthalmus* (Sauvage)]

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ABSTRACT

A counting software for striped catfish [Pangasianodon hypophthalmus (Sauvage)] fry was developed by using the Vision Development Module of LabVIEW 2010 with computer camera as a sensor. To count overlapping fry, classification algorithm was developed based on support vector machine (SVM), a pattern recognition method. Image sets with fry numbers varying from 100 to 1000 were captured by the camera and features were extracted to distinguish individual fry image.

A total of 1400 sub-images with overlapping fry were randomly selected, and 700 images were used as a training set for the classification algorithm, while the remaining images were used to verify the counting workflow. Results showed that the software is 96.30% accurate. It was verified using live fry samples and yielded an average accuracy of 91.67%. The average counting speeds for sample sizes of 100, 300, 500, and 1000 were 36.7, 37.9, 40.9 and 52.2 seconds, respectively. This indicated that the fry counter using machine vision can be an accurate and fast way to count fry up to 1000 samples and can be used by fry farmers-fisherforks to significantly improve their operation.

Keywords — fry counter, machine vision, striped catfish, pangasius, fry counter software, LabVIEW

INTRODUCTION

In 2017, the Philippines' aquaculture production has reached about 2.2 million metric tons. Since aquaculture production of fishes involves acquisition of fry, there is a huge volume of fry that needs to be quantified. About 40 metric tons of this production is pangasius for that year (PSA, 2018). Pangasius or striped catfish [*Pangasianodon hypophthalmus* (Sauvage)] is one of the largest and most important inland fisheries in the world (see Figure 1). It is considered as an economically important food fish because of its fast growth (FAO, 2010). In the Philippines, counting pangasius fry is similar to the procedures described by Moretti *et al.* (1999). Pangasius cannot be sorted using fine-mesh nets. The fry has no scales such that once in contact with the net, their bodies can easily be damaged leading to bad quality or even death. Counting by weight is not feasible due to size variability. Thus, individual counting is its conventional way of counting. In individual counting, fry are transferred to an immersed part of a net or a large basin with water. The personnel catch small numbers of fish with a container or cup. After a quick count, fry are released into a container for selling or disposal. Counting is often done with the aid of pebbles where a pebble may represent 50 or 100 fishes. These pebbles are counted for the final count of the fishes. This counting procedure has an advantage in accuracy since they are counting every single fry, but it takes time and manpower. Thus, fry counter can be used to improve the counting operation efficiency.

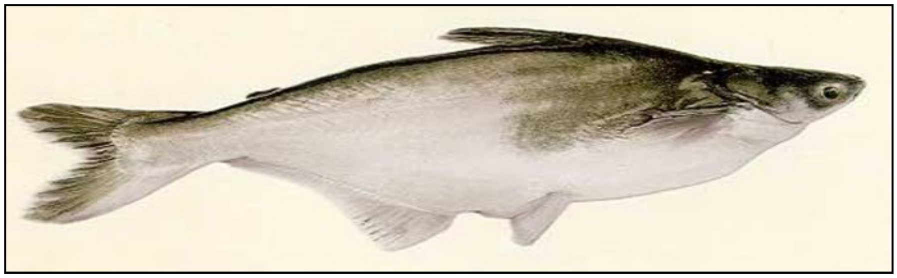

Figure 1. *Pangasianodon hypophthalmus* (Sauvage) (VASEP, 2012)

Reliable automatic fish counters are not available in Philippine market. These fish counters are accurate, have very high capacity of up to 200,000 1g fish per hour, and let the fishes stay in water at all times during counting. However, such equipment is as much as ₱320,000 which is expensive that small scale fry farmers cannot afford. A solution to the problem is the use of a machine vision system for counting fry. Though LabVIEW is an expensive proprietary software, only the developer needs to purchase the license for it to be useful to farmer. Some institution, like UPLB, has a licensed version in which the software can be written. A basic desktop computer which can be used for the software which is about ₱30,000 while the computer camera can be used as the sensor which is only about ₱1,000. Machine vision has been widely used to fisheries research and different aquaculture application. Fish images have been used by Tharwat *et al.* (2018) for fish identification of four common and important fish species. Computer vision has also been used to measure feeding activity of fish in recirculating aquaculture systems (Liu *et al*, 2014). Machine vision has also been investigated in fish measurement such as mass of Jade perch (Viazzi *et al.*, 2015), length of rainbow trout (Miranda and Romero, 2017), and length of zebrafish (Al-Jubouri *et al,* 2017). Duan *et al* (2015) has made a computer vision based automatic counting system for transparent fish eggs. Like other aquaculture operations, machine vision has also been applied to counting fish.

As early as 1995, Newbury *et al.* have utilized photographic images and artificial neural network with back propagation of error feed-forward to count the fish image. This procedure gave 94% correct classification, which outperformed both pixel counting and energy estimation method. Morais *et al.* (2005) studied particle filter-based predictive tracking for robust fish counting. Visual tracking was used underwater to count the fishes *in vivo*. Bayesian filtering technique was applied and enables tracking of objects whose number may vary over time. The proposed approach was successfully validated with real-world video streams, achieving an overall accuracy of as high as 81%.

Another study used a dual camera system for counting and sizing Northern Bluefin Tuna stock during transfer to aquaculture cages, with a semi-automatic tool (Costa *et al.,* 2009). To use these dual underwater cameras, they connected it to a system, synchronized, and powered it via cable to a waterproof transportable computer. The images from the camera were processed using software based on Artificial Neural Networks (ANNs). The total number of tuna was predicted with an error of 2.2%, while the fish size classification error was as low as 3.0%.

Fan and Liu (2013) studied the automation of fry counting using computer vision and back propagation neural network (BPNN) and least squares support vector machine (LS-SVM). The paper mainly focused on geometric feature approach on counting up to 100 overlapping fry from video clips captured using a camera. Results indicated that the best result was achieved with about 98.73% accuracy, by the LS-SVM model. In 2018, Hernández-Ontiveros *et al.* had developed a fish counter for ornamental fishes: guppies and mollies.

This algorithm is based in area and perimeter threshold of the images and has obtained an average counting accuracy of 95.57%.

This study aimed to develop a machine vision system for fry counting of striped catfish [*Pangasianodon hypophthalmus* (Sauvage)] using LabVIEW 2010. It focused on the development of affordable machine vision software appropriate for small scale sellers. Web camera was used as the optical sensor, laptop as the processing system, and LabVIEW as the programming language. Furthermore, up to 1000 small objects are counted at the same time so as to optimize the fry counting operation speed. Specifically, it aimed to (1) determine the classes and number of erosion that can give the optimal classification accuracy for the fry counting software; (2) test the accuracy of the developed counting algorithm; and (3) evaluate the counting speed of the fry counter.

METHODOLOGY

Samples and Image Acquisition

Fish images were acquired with a machine vision system composed of light source, web camera, and a laptop. Light source was from a pair of desk lamp holder with 23-watt, 60-hertz white daylight lamp. A web camera (A4 Tech's PK-810G Anti-glare Web Cam) was oriented with the lens facing downwards toward a counting tray containing live fry. The image resolution was 2560 x 2048 pixels and was taken at the height of 120 cm with a frame rate of 30 fps.

Striped catfish fry with length from 2.5 to 6 cm were used in the study. It was sourced from a local fry seller in Victoria, Laguna. A batch starting from 100 fry, manually counted, was poured into the counting tray. 200 images were obtained and equally divided into two sets. One set of images was used to train the classifier software. The other set of images was used to evaluate the performance of the software. Additional fry were added to the counting tray at increments of 100 repeating the process of image acquisition until the number of fry in counting tray reached 1000.

Computer System

An Intel® Core™ i5-2435M laptop (Apple - MacBook Pro®) with speed of 2.40 GHz each and a RAM of 4.00 GB was used as the main processing unit during the experiment. Several algorithms were written using LabVIEW 2010 to analyze images for counting and size estimation, which were needed in developing the final application (Pangasius Fry Counter).

Data Analysis

Patterned to the approach of Fan and Liu (2013), sampling of data set for classifier is summarized in Figure 2. From training images, sub-images or blobs were extracted which can be an image of overlapping fry or non-fry object. A set of 1400 sub -images were manually categorized into classes of fry count varying from zero to more than six $\{C_0, C_1, \ldots, C_{6+}\}$. Seven sub-image classes were made with 200 samples each. Fry sub-images for each class were divided randomly into two subsets. One subset was used to build the Support Vector Machine (SVM) classification model and the other was used to test the robustness of the model.

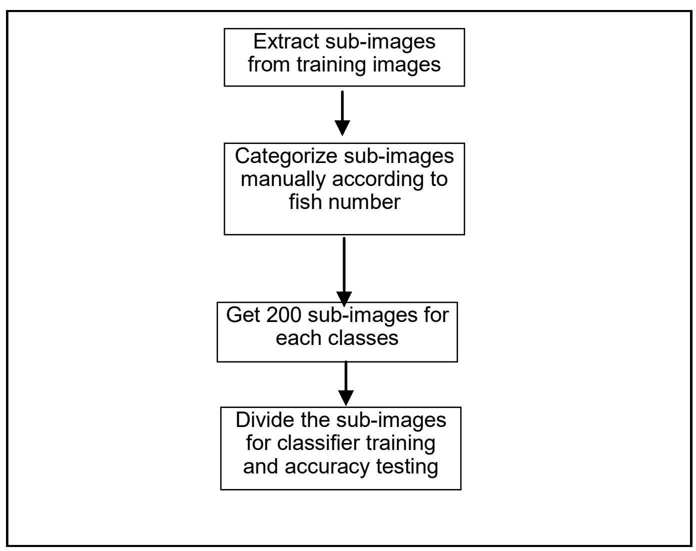

Figure 2. Data selection for classifier

Performance evaluation of the algorithm.

Accuracy rate (AR) was used to characterize the prediction efficiency of the classification algorithm on the individual sub-images; AR was computed using Equation 1, where N_{correct} refers to the number of rightly classified samples of the proposed algorithms, and N_{total} is the total number of samples in the prediction set.

$$AR = \frac{N_{correct}}{N_{total}} \times 100\% \qquad Equation\ 1$$

The metric used for the quantitative evaluation of each class or the nearness of the count to the correct value was the counting accuracy rate (CAR), computed as shown in Equation 2, where N_k represents the sub-images number of class k. In this study, the value of N_k is set at 100, and f_i is the estimated fish count for sample i.

$$\text{CAR} = \frac{\sum_{i=1}^{N_k}(k - |k - f_i|)}{k \times N_k} \times 100\% \qquad Equation\ 2$$

The overall accuracy (OA) of the Pangasius Fry Counter, the main software output of this study, was also measured. This was done by subjecting the software into the prediction set. This particular OA was computed using Equation 3, where F_P represents the fry count return by the software, and N_P represents the actual fry count in the prediction set.

$$\text{OA} = \left(1 - \frac{|N_P - F_P|}{N_P}\right) \times 100\% \qquad Equation\ 3$$

Counting speed analysis

Another parameter that describes the performance of the software is the speed of counting. The software was run and timed for every batch of counting to determine its counting speed. Five trials were done to determine the average processing speed for a certain number of fry samples.

RESULTS AND DISCUSSION

The Pangasius Fry Counter Software

The main output which is a program was named "Pangasius Fry Counter". The application's front panel is shown in Figure 3.

The Counting Workflow

When the "Count" button is clicked, the software application would start the counting workflow. The workflow's flowchart is shown in Figure 4. To provide One hundred (100) images are extracted from the camera to have a higher chance of getting the most number of particles per counting session. Sample background image (Figure 5a) and fry image (Figure 5b) are shown. To minimize noises such as dirty water, tray edges, and fish shadows, part of the counting workflow is preprocessing of images. Built-in functions of Vision Development

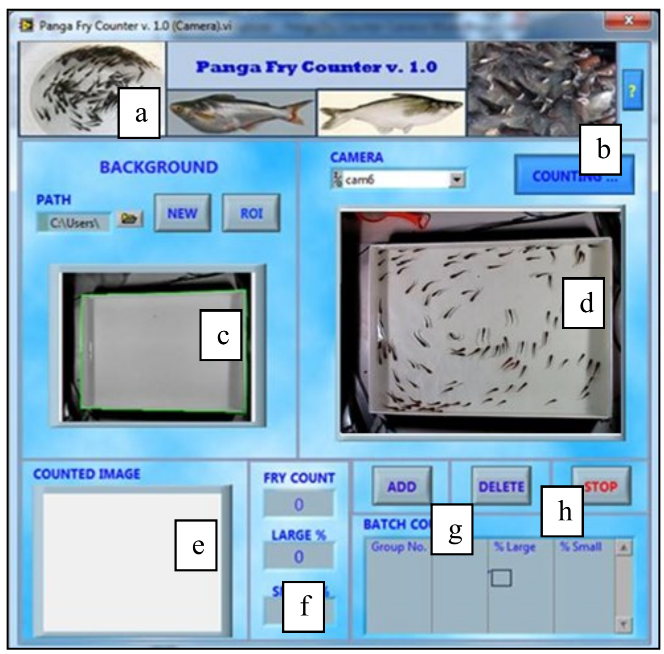

Figure 3. Front panel of the Pangasius Fry Counter Main Window
[Banner image (a); About button (b); Background control window (c) Camera control window (d); Counted image window (e); Result indicators (f); Fry batch control and table indicator (g); Stop button (h)]

Module of LabVIEW 2010 were used to preprocess the images.

Pre-processing (Figure 6) techniques of Fan and Liu (2013) was used in this study. In subtraction (Figure 6a), the background was subtracted from an image. The region of interest (ROI) or the area of the counting tray was then extracted from the resulting image (Figure 6b). Inter-class variance was used as the thresholding method which was done right after (Figure 6c). To remove noise, the images were subjected to median filtering and morphological 'open' operation (Figure 6d). Median filtering was done with a 3 x 3 kernel. Morphological 'open' operation was done. Further small area deletion (Figure 6e) was made with 4 x 4 erosion. Finally, a labeling algorithm (Figure 6f) was made to label the different particles in a binary image.

Among the 100 images extracted from the camera, the one with the greatest number of labels or particles was obtained from the preprocessed image while the rest of the images was deleted to free up memory. It was used to determine the fry count since a greater number of particles means that there is lesser intertwining fry which can lead to greater accuracy in counting. The pre-processed image with the most number of particles was displayed in the "Counted Image" indicator. Every particle in this processed image would be extracted as a sub-image.

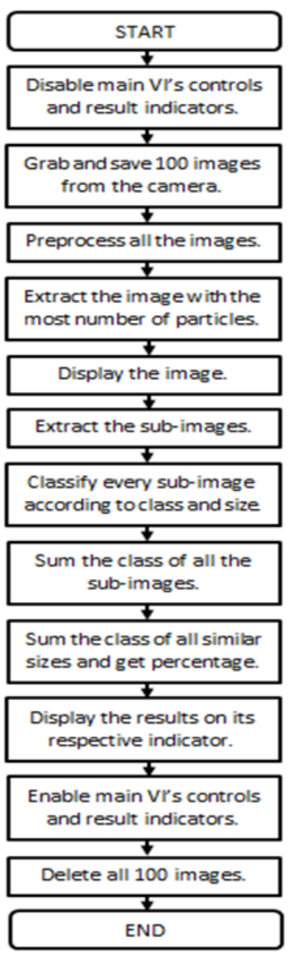

Figure 4. Flowchart for the counting workflow

Figure 5. An example of fry image:
(a) background image and (b) fry image.

Each sub-image would be classified according to class (number of fry). The sub-images class would be summed to determine the fry count.

The Classification Workflow

The classification workflow was designed to recognize one to five joining fry images without the need for separation of more than two joining fry. For this study, four classifier sessions with up to seven different classes were needed to complete the final software application. Classes pertain to the number of joining fry in a single image. The created classifier sessions were trained with Support Vector Machine (SVM). SVM, a pattern recognition method, is also built-in on Vision Development Module of LabVIEW 2010, wherein the type of classifier can be set. In this study, a non-linear classifier was used. According to Heisele (2004), Gaussian have shown excellent performance in many applications after tuning of sigma, thus the kernel of the Kernel Options was set to Gaussian.

It was observed from the training set images that there were so many schools of fry having class of more than six. However, having so many classes for the SVM would make the classification algorithm less accurate than those having only few class. To solve this problem, the class '6+' was chosen. This class would classify sub-images having a number of six or more fry in one particle. When a sub-image is classified as class '6+', it would be subjected into a separation algorithm which is another NI Vision function. This separation algorithm would make the sub-image of class '6+' into a new set of sub-images with number of erosion set. These sub-images would again be subjected to the classifier that do not have the '6+' class.

Classifying training image sets determined the best classifier for a specific case of fry number and the best number of erosion that could be used by the system. This was done by inputting the training image set in the counting algorithm using the two classification algorithms, Classification 0 to 6+ then Classification 0 to 5 (With 0) and Classification 1 to 6+ then Classification 1 to 5 (Without 0), and the counting accuracy was determined. The results are shown in Table 1. The built-in separation algorithm of LabVIEW utilizes the term erosions where the filter size depends. The algorithm separates touching particle containing pixel with width depending on the filter size (National Instruments, 2003). The input number of erosion was only until up to 6 since a value of more than 6 could affect the counting speed of the software. One observation from the training set images was the presence of non-fish particles in the images which could be caused by dirty water, shadow of fry, or reflection of light used. Some of these noises were not

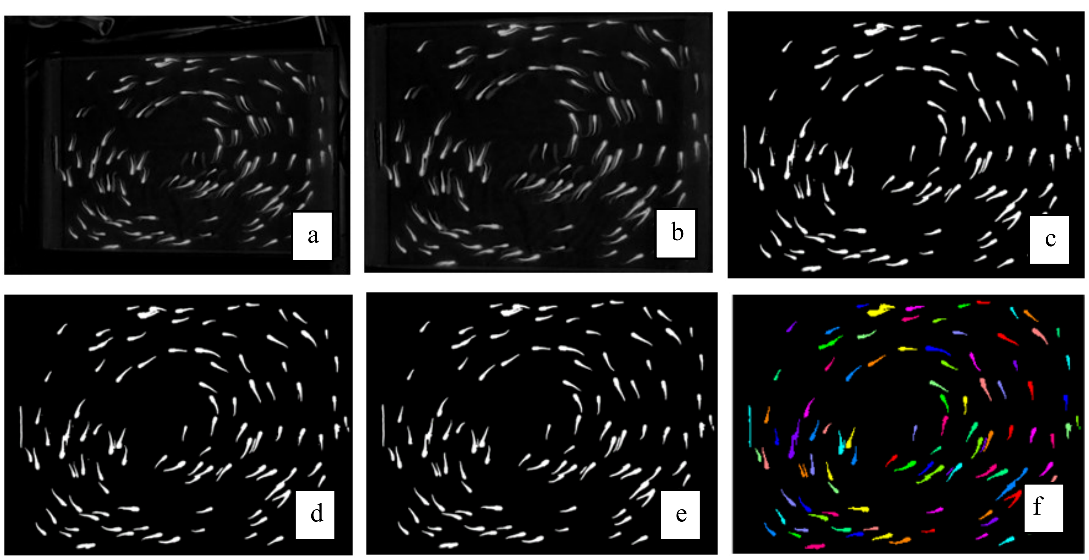

Figure 6. Demonstration of Pre-processing patterned to Fan and Liu (2013): (a) subtracted image, (b) Region of Interest (ROI) extracted image, (c) threshold image, (d) image after median-filtering and morphological 'open' operation, (e) small area deleted image, and (f) labeled image in binary palette form.

Table 1. Counting accuracy for the training image set using the two different classifier sessions at different number of erosion.

CLASS INCLUSION	EROSION	COUNTING ACCURACY FOR TRAINING IMAGE SET									
		100	200	300	400**	500	600**	700**	800**	900**	1000**
With 0	1	87.75	95.00	92.50	97.06a	80.95	77.58c	62.61d	58.81f	44.03e	33.78f
With 0	2	87.75	95.00	93.17	97.75a	82.20	79.25bc	65.46d	62.19ef	47.11de	38.10ef
With 0	3	87.75	94.63	94.58	98.38a	84.95	83.67abc	69.71cd	70.16def	53.69cde	47.40de
With 0	4	87.75	93.88	95.33	97.06a	86.90	84.46abc	73.11cd	74.13cde	60.28cde	53.58cd
With 0	5	87.00	93.38	95.17	96.81ab	87.20	86.25abc	76.14bcd	77.72bcd	62.72bcde	57.00bcd
With 0	6	87.00	93.00	94.33	97.69a	88.50	88.29abc	76.68bcd	79.81abcd	64.53bcd	59.58bc
Without 0	1	80.75	86.25	95.50	95.44ab	87.65	87.25abc	68.61d	62.91ef	49.06de	40.95ef
Without 0	2	80.75	86.25	95.25	94.25ab	89.00	89.96ab	72.25cd	67.44def	53.58cde	46.03de
Without 0	3	82.25	86.50	95.92	92.94abc	91.45	95.00a	77.43bcd	77.91bcd	61.75bcde	56.03cd
Without 0	4	84.25	85.75	94.83	89.88bcd	93.85	89.79ab	84.75abc	90.84ab	71.00abc	68.70b
Without 0	5	83.25	86.25	92.83	87.25cd	94.00	87.46abc	89.96ab	94.50a	80.94ab	82.55a
Without 0	6	80.75	86.25	91.75	83.38d	96.25	85.00abc	93.46a	87.72abc	88.86a	91.83a

** Significant means with ANOVA at 95% level of significance. Means with common letter is not significantly different with Tukey's Honest Significance Difference (HSD) at 5%.

removed during the preprocessing due to its large size, thus the inclusion of Class 0 in the classification workflow.

Table 1 shows that 'With 0' classification algorithm had high accuracy in counting fry of up to 400 samples. For 400 samples, 'With 0' classifications are statistically higher than 'Without 0' classifications. It was expected since at this fry count, the presence of noises or class '0' were predominant. Thus, the 'With 0' classification algorithm would be used for fry samples of up to 400. With respect to the number of erosion, input 1 has been statistically among the highest because at this fry samples, images needed only a few separation as compared to fry image samples with high count. Erosion is a morphological transformation which extracts and alters the structure of particles in an image (National Instruments Corporation, 2010). It filters or smoothens the pixel intensities of an image by noise filtering, uneven background correction, and feature extraction. The higher the value of erosion, the more pixels is affected which can lead to deletion of some parts of the image itself. Table 2 shows the counting accuracy of the chosen classification. It can be noticed that the classification 'With 0', Erosion 1 is statistically effective in measuring up to 400 samples as evident by having the highest accuracy. Thus, it was not used for 500 samples and up.

Table 2. Counting accuracy for the chosen classification.

FRY SAMPLES	CLASSIFICATION	
	'With 0', Erosion 1**	'Without 0', Erosion 6**
100	87.75ab	80.75b
200	95.00a	86.25ab
300	92.50a	91.75ab
400	97.06a	83.38ab
500	80.95bc	96.25a
600	77.58c	85.00ab
700	62.61d	93.46ab
800	58.81d	87.72ab
900	44.03e	88.86ab
1000	33.78f	91.83ab

** Significant means with ANOVA at 95% level of significance. Means with common letter is not significantly different with Tukey's Honest Significance Difference (HSD) at 5%.

It is also observed from Table 1 that the 'Without 0' classification algorithm has statistically higher accuracy in counting fry of 500 and more samples. Again, this was expected since the presence of noises or class '0' could not almost be seen. Thus, the 'Without 0' classification algorithm would be used to classify sub-images in fry samples of more than 400. With respect to the set erosion number, input 6 has statistically consistent for having the highest accuracy among the other erosions values. This shows that a greater erosion was needed for high number of fry samples. Table 2 also shows that 'Without 0' Erosion 6 classification can be statistically effective in measuring fry samples 200 to 400 but this might affect the counting speed since more particles will be needed to be classified for higher erosion values.

Table 3. Accuracy rate (AR) and Counting accuracy rate (CAR) of classes 0 to 6+ classification algorithm.

FRY CLASS	CLASSIFICATION RESULTS FOR CLASSES 0 TO 6+							AR (%)	CAR (%)
	C_0	C_1	C_2	C_3	C_4	C_5	C_{6+}		
C_0	83	11	2	3	1	0	0	83	---
C_1	12	83	5	0	0	0	0	83	83.00
C_2	1	6	63	28	2	0	0	63	80.00
C_3	0	0	28	37	28	7	0	37	76.67
C_4	0	0	8	27	40	25	0	40	83.00
C_5	0	0	4	12	37	43	4	43	83.80
C_{6+}	0	0	0	2	13	37	48	48	---
AVERAGE								**56.71**	**81.29**

Table 4. Accuracy rate (AR) and Counting accuracy rate (CAR) of classes 1 to 6+ classification algorithm.

FRY CLASS	CLASSIFICATION RESULTS FOR CLASSES 1 TO 6+						AR (%)	CAR (%)
	C_1	C_2	C_3	C_4	C_5	C_{6+}		
C_1	95	5	0	0	0	0	95	95.00
C_2	8	64	27	1	0	0	64	81.50
C_3	0	30	34	27	8	1	34	73.67
C_4	0	8	25	39	24	4	39	80.50
C_5	0	8	25	39	24	4	24	74.80
C_{6+}	0	0	1	6	17	76	76	---
AVERAGE							**66.67**	**90.12**

Performance Evaluation of the Algorithm

The accuracy rate (AR) and the counting accuracy rate (CAR) of the two classification algorithms used in Pangasius Fry Counter Software were obtained. The prediction results are shown in Tables 3 and 4. The table entry "---" means that the value could not be computed because its divisor is zero or non-numeric (class 6+).

The average accuracy rate and counting accuracy rate of the classification algorithm that would count about 400 and less fry samples (Classes 0 to 6+) were 56.71% and 81.29% respectively. For the classification algorithm that would count more than 400 fry samples (Classes 1 to 6+), the average accuracy rate and average counting accuracy rate were 55.33% and 81.09% respectively. Fan and Liu (2013), who used Least Square-SVM to train the classifier for the model, obtained better AR (66.67%) and CAR (90.12%). It should be noted, however, that the training and prediction sub-images subjected to the model came from images with only up to 100 fry samples. The probability of more combinations for each class had been increased with fry number, in this case, increasing up to 1000 fry samples, however, the 100 training images wasn't enough to compensate for this. Even then, the value obtained by Fan and Liu (2013) did not seem to be too promising. However, when it was used to count fry in a video, they got a very high counting accuracy rate of 98.73%.

The prediction image sets were subjected to the written software application to determine its overall accuracy (Table 5). The average counting accuracy rate of the software written was 96.30%. The result proves that the software application was accurate in counting pangasius fry. This was also comparable with the results of Fan and Liu (2013) that showed very high accuracy rate despite having low prediction sub-images AR and CAR values.

Counting Speed Analysis

The counting speed of the software while counting the prediction image sets are presented in Table 6. The trend shows that as the number of fry under observation increases, more counting time was needed by the software to finish counting. This was because as the number of particle increases, the number of sub-images that needed to be classified also increases leading to longer processing time.

This counting time did not include the image data gathering time of about 18 seconds, or the time needed for saving a 100 image set. Adding the saving time, the software could count a 1000 fry sample within 52.18 seconds.

The classifier engine used for training the samples was the Support Vector Machine, a built-in function of NI Vision. It was observed from the training image sets that there were a lot of sub-images with fry count of 6 and more. So as not to have lots of classes, a class that lumped these many classes was called “6+” class. This particular class was inputted to a separation algorithm to get the real fry count of the image.

Table 5. Overall accuracy of Pangasius Fry Counter Software when used in Prediction Image Sets.

NUMBER OF FRY SAMPLES	COUNT REGISTERED BY THE SOFTWARE	COUNTING ACCURACY RATE (%)
100	110	90.00
200	204	98.00
300	313	95.67
400	397	99.25
500	507	98.60
600	586	97.67
700	639	91.29
800	856	93.00
900	898	99.78
1000	1003	99.70
AVERAGE		**96.30**

Table 6. The counting time of Pangasius Fry Counter Software when used in Prediction Image Sets.

NUMBER OF FRY SAMPLES	COUNTING TIME (s)					
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Average
100	17.53	18.40	18.42	18.39	17.48	18.05
200	20.61	19.27	18.70	18.84	18.63	19.47
300	20.53	19.32	19.32	19.29	19.25	19.54
400	21.62	20.62	20.75	20.55	20.46	20.80
500	23.52	22.40	22.41	22.21	22.21	22.55
600	24.56	23.09	23.00	23.32	23.16	23.43
700	24.57	23.27	23.33	23.41	23.26	23.57
800	27.70	26.70	26.54	26.72	26.49	26.83
900	31.57	30.56	30.54	30.83	30.79	30.86
1000	35.59	33.90	33.74	33.79	33.87	34.18

SUMMARY AND CONCLUSION

A fry counting software for striped catfish [*Pangasianodon hypophthalmus* (Sauvage)] was developed using a web camera and LabVIEW 2010 with Vision Development Module. Several images of fry batches with 100 up to 1000 pieces were obtained. These images were divided into two sets: training image set, which was used to train the classifier and prediction image set, which was used to determine the accuracy of the written software application.

The overall accuracy rate using the prediction image sets had an average of 96.30%. For counting speed, the counting time increased as the number of particles increased. The average counting speeds for the fry samples were 100 (36.7 sec), 300 (37.9 sec), 500 (40.6 sec), and 1000 (52.2 sec).

With proper communication to institutions with licensed LabVIEW, small scale fry growers can utilize the software for their operations.

RECOMMENDATIONS

It is recommended to add the size measurement feature on the fry counter to profile the size of fry being counted. The hardware component for the written software is also recommended to be developed so as a complete machine vision system for semi- or fully-automated counting will be achieved. Using such system, a proper comparison with the manual operation for counting fry can be done.

LITERATURE CITED

AL-JUBOURI, Q, AL-NUAIMY, W, AL-TAEE, M, YOUNG, I. (2017). An automated vision system for measurement of zebrafish length using low-cost orthogonal web cameras. Aquacultural Engineering 75: 156-162.

COSTA, C., SCARDI, M., VITALINI, V., CATAUDELLA, S. (2009). A dual camera system for counting and sizing Northern Bluefin Tuna (*Thunnus thynnus*; Linnaeus, 1758) stock, during transfer to aquaculture cages, with a semiautomatic Artificial Neural Network tool. Aquaculture 291: 161-167.

DUAN, Y., STIEN, L., THORSEN, A., KARLSEN, Ø., SANDLUND, N. (2015). An automatic counting system for transparent pelagic fish eggs based on computer vision. Aquacultural Engineering 67: 8-13.

FAN, L., LIU, Y. (2013). Automate fry counting using computer vision and multi-class least squares support vector machine. Aquaculture 380-383: 91-98.

FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS (FAO). (2010). Culture aquatic species information programme: *Pangasius hypophthalmus.* FAO Fisheries and Aquaculture Department. Retrieved June 7, 2019 from <http:// www.fao.org/fishery/ culturedspecies/ Pangasius_hypophthalmus/en >.

HEISELE, BERND. (2004). Classification. Lecture notes in Pattern Recognition for Machine Vision. Downloaded from MITOpenCourseware of Massachusetts Institute of Technology. Retrieved June 7, 2019 from <http://ocw.mit.edu/courses/brain-and-cognitive-sciences/9-913-pattern-recognition-for-machine-vision-fall-2004>. LIU, Z, LI, X, FAN, L, LU, H, LIU, L, LIU, Y. 2014. Measuing feeding activity of fi)sh in RAS using computer vision. Aquacultural Engineering 60: 20-27.

HERNÁNDEZ-ONTIVEROS, J., INZUNZA-GONZÁLEZ, E., GARCÍA-GUERRERO, E., LÓPEZ-BONILLA, O., INFANTE-PRIETO, S., CÁRDENAS-VALDEZ, J., TLELO-CUAUTLE, E. (2018). Development and implementation of a fish counter by susing an embedded system. Computer and Electronics in Agriculture 145: 53-62.

MIRANDA, JM, ROMERO M. (2017). A prototype to measure rainbow trout's length using image processing. Aquacultural Engineering 76: 41-49.

MORAIS, EF, CAMPOS, MFM, PADUA, FLC, CARCERONI, RL. (2005). Particle filter-based predictive tracking for robust fish counting. Proceedings of the XVIII Brazilian Symposium on Computer Graphics and Image Processing. 8 pp.

MORETTI, A, FERNANDEZ-CRIADO, MP, CITTOLIN, G, GUIDASTRI, R. (1999). Manual on Hatchery Production of Seabass and Gilthead Seabream, Vol. 1. Food and Agriculture Organization of the United Nations. Rome, Italy. pp 131-133.

NATIONAL INSTRUMENTS. (2003). IMAQ™: IMAQ Vision Concepts Manual. Texas, USA. pp 9-24 to 09-25.

NATIONAL INSTRUMENTS CORPORATION (2010). NI Vision for LabVIEW Help.

NEWBURY, PF, CULVERHOUSE, PF, PILGRIM, DA. (1995). Automatic fish population counting by artificial neural network. Aquaculture 133: 45-55.

PHILIPPINE STATISTICS AUTHORITY (PSA). (2018). Fisheries Statistics of the Philippines Volume 26 2015 to 2017. p 104.

THARWAT, A., HEMEDAN, A., HASSANIEN, A., GABEL, T. (2018). A biometric-based model for fish species classification. Fisheries Research 204: 324-336.

VIAZZI, S., VAN HOESTENBERGHE, S., GODDEERIS, B., BERCKMANS, D. (2015). Automatic mass estimation of Jade perch *Scortum barcoo* by computer vision. Aquacultural Engineering 64: 42-48. ■