Fish Larvae Counting System Using Image Processing Techniques

E A Awalludin¹, W N A Wan Muhammad¹, T N T Arsad¹ and W N J Hj Wan Yussof²

¹Faculty of Fisheries and Food Science, Universiti Malaysia Terengganu (UMT), 21030 Kuala Nerus, Terengganu, Malaysia.
²Faculty of Ocean Engineering Technology and Informatics, Universiti Malaysia Terengganu (UMT), 21030, Kuala Nerus, Terengganu, Malaysia.
e.afreen@umt.edu.my

Abstract. This paper presents the use of computer technology based on image processing techniques to count the number of fish larvae with less time processing. Computer technology used is as an alternative solution to the manual counting approach method in term of determination fish larvae survival rate, stock assessment and monitoring fish growth population. Generally, the fish larvae counting is performed with sequential process with labor-intensive task which difficult to be used for counting large sample dataset. Traditional counting method has been used for many years, however many researchers highlighted several drawbacks of the manual counting process such as time consuming, laborious, required human skills-eyes, less-accurate, less consistent, difficult to estimate with many large sample and too many involve with human intervention. Since the problems is addressed, many researchers are interested to develop many techniques to facilitate the process of fish counting with fast assessment. In this study, we present combination of image processing techniques that consists of image enhancement, edge detection, and thresholding process. Meanwhile, the blob analysis is used as the statistical information to measure the objects properties in the image automatically. Total number of 150 samples dataset of Nile Tilapia (Oreochromis niloticus) were used in the experiment. All the samples are divided into three part which are small dataset (50 samples), medium dataset (50 samples) and large dataset (50 samples). The performance of the proposed method and the manual approach method are compared based on the number of fish that was successfully estimated and processing time taken through the experiment. All 150 samples of fish larvae were collected from the Freshwater Hatchery of University Malaysia Terengganu. The experimental results shows that the proposed method based on computer technology is outperformed compared to the manual counting approach in the experiment. This is because, the number of fish larvae measurement by using the proposed method is almost similar and some of samples present accurate result compared to the traditional approach. Moreover, the proposed method is promising on the processing time for measuring all samples with less time processing and more reliable.

Keywords: image enhancement, edge detection, and thresholding process, blob analysis, image processing techniques, Nile Tilapia (Oreochromis niloticus).
1. Introduction
The larvae counting system is significant in fisheries study especially to understand the pattern and structure of larvae growth as well as a platform to monitor fish larvae stock. In traditional approach, the process of fish larvae was measured under microscope using human hand-held and required eyes-skills which labour intensive task and time consuming [1]. Moreover, the manual approach can be used to count small sample dataset rapidly but for a large sample dataset the process of larvae counting become more difficult to be handled. Cadena-Herrera et.al [2] mentioned in their study that the use of the manual counting is very time consuming especially to measure a large sample dataset and more expertise knowledge are required. Raman et.al [3] addressed some problems of the manual counting such as laborious, less accurate, sequential process, prone to error and information data of larvae growth not integrated properly. All these deficiency will affect the process of counting larvae which these problems also addressed in the previous study by [4]. Since the existence method presents with many constraints, improvement of the traditional method counting using computer based technology is required. In this study, the proposed system has been developed using combination of image processing techniques and blob analysis. In general, there are a few research publications focus on the process of fish larvae counting specifically using image processing techniques. One of the study that related is [3] proposed a process of larvae counting based on machine learning techniques to measure number of shrimp larvae and juvenile on growth population. Based on their study, several image processing techniques were used such as thresholding process, edge detection and morphological operator. Loh et.al [5] developed the aquatic tool kit to calculate distribution number of fish larval and juvenile based on combination image processing techniques. Pandit et.al [6] used image processing techniques to count the number of silkworm eggs in the image with less time processing and labor intensive. In previous study, show that image processing techniques are also beneficial in identification fish shape and pattern from anatomy characterises. In live feed study, Kim and Cho [7] proposed an automatic system based on image processing techniques to estimate distribution of artemia hatching rate, Image processing techniques also widely used on classification of fish and shrimp larvae [8], fish Species classification [9], fish population estimation and species classification [10], Fully-automated identification of fish species based on otolith contour [11], statistical analysis on cells and colony [12], automated counting tools for Aedes eggs tools using wavelet techniques [13] and feature-based video Stabilization using Gabor Wavelets [14]. Since the image processing techniques are widely used in many application, development of fish larvae counting system has high potential to be used in fisheries area. The use of image processing techniques is promising to produce more reliable result, rapid assessment and available to achieve the statistical information with less time consuming. This paper is organized as follows. Section II describes the methodology of the study. Section III presents the experimental results. Section IV shows the discussion of finding. Finally, section V concludes this paper.

2. Methodology
In this paper, the use of image processing techniques and blob analysis for fish larvae counting are discussed throughout the following sections.

2.1. Data collection
Nile Tilapia (*Oreochromis niloticus*) was used as sample in the study. This sample was obtained from the Freshwater Hatchery Universiti Malaysia Terengganu (UMT) due to its high protein content and abundance in freshwater area. In the first process of data collection, all the fish larvae samples were collected from several tanks by using the beaker. Then fish larvae from the beaker are placed into petri dish and divided into three sample dataset which small dataset (50 samples), medium dataset (50 samples) and large dataset (50 samples) respectively. Each petri dish that contains fish larvae were captured using a high resolution camera with dimensions size of 4608 x 3456. Therefore, number of 150 images of fish larvae were obtained from the process of image acquisition. Figure 1 shows three different types of fish larvae samples dataset that used in the experiment.
2.2 Image Enhancement

Image enhancement is commonly used to make process on an image more appropriate than original image as for improving the quality of images. If the image has sufficient contrast that means the fish larvae in the image can be easily divided from the background otherwise improvement of contrast is required. In this paper, we used Sobel edge detection to enhance the contrast of fish larvae by creating a binary mask based on a user-specified threshold value [15]. Therefore, the aims of the image enhancement is to minimise noise and preserving the important edges from the image background.

2.3 Thresholding Process

The threshold-based segmentation is simplest method in image segmentation because this technique can apply directly to the image [16]. In the study, the thresholding process based on Otsu method is used especially to supress unwanted objects background in the image [17]. In addition, Otsu method is one of global thresholding method that depends only on gray level value of the image [18]. The process of thresholding can be defined as:

\[ g(x,y) = \begin{cases} 
1, & \text{if } f(x,y) > T \\
0, & \text{if } f(x,y) \leq T 
\end{cases} \]

where, \( f(x,y) \) presents the gray level values at the point \((x,y)\), \( g(x,y) \) denotes the segmented function and \( T \) is the threshold values.

2.4 Edge Detection

Edge detection is commonly used in image segmentation by dividing the image into several areas that corresponding to different types of objects [16]. In the study, Sobel edge detection is used to reduce the amount of data efficiently while preserving the image information significantly. Edge detection technique gives the different edges to form the outline of the object and it useful to recognise an object [19]. The important of edge detection in image analysis is can be extracted the important features from the edges such as corners, lines and shapes [20]. Sobel edge detection can be calculated as follows:-

\[
G_x = \begin{bmatrix} 
-1 & 0 & +1 \\
-2 & 0 & +2 \\
-1 & 0 & +1 
\end{bmatrix} \ast A \\
G_y = \begin{bmatrix} 
+1 & +2 & +1 \\
0 & 0 & 0 \\
-1 & -2 & -1 
\end{bmatrix} \ast A
\]
where, $A$ is defined as the source image, $G_x$ and $G_y$ represents each point that contain vertical and horizontal values in the images. Sign of $*$ denotes the 2-dimensional convolution operation. The result of gradient approximation can be combined together to obtain the gradient magnitude using Equation (3).

$$G = \sqrt{G_x^2 + G_y^2}$$

2.5 Blob analysis

Blob analysis is commonly used to determine the properties of object in the image especially for object detection and recognition. Among the blob properties for the object such as areas, diameter, major and minor axis length, shape, location and perimeter. In the study, three types of properties were used such as area, centroid and boundary. For the blob area properties, the size of the fish larvae can be determined in pixel values. Meanwhile the blob centroid properties is used to determine the centre of the fish larvae and counting the number of fish larvae in the image. The blob boundary properties can help on highlighted the fish larvae edges boundary from the image. For the area properties, the size of the object in the picture whether small or large can be measured by calculating the number of pixels in the area of the object using Equation (4).

$$A = \sum_{(r,c) \in D} 1$$

Meanwhile, the centroid properties is used by labelling one object with one centroid point in the image. Then, information of the centroid property is used to measure the number of fish larvae in the image. For the centroid property, the midpoint is measured based on the pixels average location coordinates of rows and columns in the image. The rows and columns of each object in the image can be estimated using Equation (5) and Equation (6), respectively.

$$\bar{r} = \frac{1}{A} \sum_{(r,c) \in D} r$$

and

$$\bar{c} = \frac{1}{A} \sum_{(r,c) \in D} c$$

where, the centroid $(\bar{r}, \bar{c})$ represents the average location of pixels at the set of $D$. Meanwhile, $r$ and $c$ denote row and column of pixels values in the image, respectively. $A$ shows the area of object in the image.

2.6 The Proposed Method Approach

Figure 2 shows the flowchart of fish larvae counting system using Sobel edge detection and Blob analyze techniques. In the first process, the fish larvae images are transforming from RGB color space to gray color space in order to separate image intensity components from color information. In the paper, Sobel edge detection is used to minimize the noise background and preserving significant edges of fish larvae in the images. Then, the information edges of fish larvae are measured using the blob processing techniques that consists of three properties such as centroid, area and boundary. For the centroid properties, one of the fish larvae is represented with one centroid point in the images. From the centroid point also the number of fish larvae can be easily calculated from the image.
2.7. Experimental design

2.7.1 The Manual Counting
For the manual counting, six number of students (C1 to C6) were selected as observers to conduct the counting process for 150 samples. Each sample is divided into three categories which consist of small dataset (50 samples), medium dataset (50 samples) and large dataset (50 samples). In the experiment, the number of larvae and the processing time are recorded by all observers (C1 to C6) sequentially. All important information are recorded and stored into excel program manually before further analysis can be done.

2.7.2 The Proposed Method Counting
For the proposed method counting, the Graphical User Interface (GUI) was developed using the Matlab software to facilitate user for counting the fish larvae automatically without labor-intensive task as shown in Figure 3. In the Graphical User Interface (GUI), user is required to input image from computer folder before starting further process. Then, the input image is adjusted by clicking the first slider value due to image input normally contains different intensity. Finally, user needs to click second slider to perform larvae counting system analysis which consists of several image processing techniques such as thresholding process, edge detection process and blob processing. The number of larvae counting and processing time are recorded automatically to excel program as well as can be displayed on Graphical User Interface (GUI).

**Figure 2.** The Flowchart of fish larvae counting system using the Sobel edge detection and blob processing technique.
2.7.3 Ground Truth
In the study, the ground truth work was determined by an expert with good knowledge in fish larvae counting. The ground truth is then used to validate performance both of the manual approach results (C1 to C6) and the proposed method through 150 samples of fish larvae in the experiment.

3. Experimental Result

3.1 Small Sample Dataset
Figure 4 shows the result of fish larva counting for small sample dataset. The comparison counting were made between the proposed method approach and the manual approach through number of 50 samples of fish larvae. For the manual approach, six number of students (C1 to C6) were selected to conduct counting process for 50 samples in the experiment. The proposed method was developed using the Matlab software with Graphical User Interface (GUI) to facilitate user for counting the fish larvae as shown in Figure 3. The performance of all observers include the proposed method were recorded by estimating the value of percentage error between the small sample datasets as shown in Table 1 at column 3. Based on the experimental results, the proposed method achieves the lowest percentage error value compared to the manual observer with 0.31% error. Meanwhile, the highest percentage error value is 1.33% error which obtains by the manual observer number C5. Rest of the manual observers presents moderate percentage error values which C1 =0.54%, C2=0.47%, C3=0.62%, C4=0.47% and C6=0.86%, respectively. Meanwhile, Figure 5 shows the result of time processing for small sample dataset. The proposed method presents the fastest processing time which is performed only at 0.05 sec compared to other the manual observers through the experiment for small sample dataset. However, an observer number C6 achieves the slowest processing time with 13.44 sec in the experiment. Rest of the observers presents moderate time processing for all samples C1=12.46 sec, C2=12.17 sec, C3=12.62 sec, C4=12.20 sec and C5=12.88 sec as shown in Table 1 at column 4.

Figure 3. The proposed method counting.
Table 1. The percentage error value for small sample dataset

| Number | Observers | Small Dataset, (50 samples) | Percentage Error, (%) | Average processing time, (second) |
|--------|-----------|-----------------------------|------------------------|----------------------------------|
| 1      | C1        |                            | 0.54                   | 12.46                            |
| 2      | C2        |                            | 0.47                   | 12.17                            |
| 3      | C3        |                            | 0.62                   | 12.62                            |
| 4      | C4        |                            | 0.47                   | 12.20                            |
| 5      | C5        |                            | 1.33                   | 12.88                            |
| 6      | C6        |                            | 0.86                   | 13.44                            |
| 7      | Proposed Method |                        | 0.31                   | 0.05                             |

Figure 4. Number of Fish Larvae Counting for small dataset

Figure 5. Time processing for small sample between the proposed method and the manual approach

3.2 Medium Sample Dataset

Figure 6 shows the result of fish larve counting for medium sample dataset. The comparison counting were made between the proposed method approach and the manual approach through number of 50 samples of fish larvae. The proposed method achieves the lowest percentage error value compared to other the manual observers which is 1.99% error as shown in Table 2 at column 3. Meanwhile, the highest percentage error value is 3.16% error which obtains by the manual observer number C5. Rest
of the manual observer presents moderate percentage error values which C1 =2.22%, C2=2.15%, C3=2.42%, C4=2.96% and C6=2.5%, respectively as presented in Table 3 at column 3. Meanwhile, Figure 7 presents the experimental results of time processing for medium sample dataset. The proposed method presents the fastest processing time which is 0.37 sec compared to other manual observers in the experiment. Meanwhile, the slowest processing time presents by the manual observers of number C6 with 44.98 sec. Rest of the manual observers shows moderate processing time that consist of C2=31.20 sec, C3=32.06 sec, C4=31.92 sec and C5=43.77 sec through 50 samples in the experiment as shown in Table 2 at column 4.

Table 2. The percentage error value for medium sample dataset

| Number | Observers | Percentage Error, (%) | Average processing time, (second) |
|--------|-----------|------------------------|----------------------------------|
| 1      | C1        | 2.22                   | 44.29                            |
| 2      | C2        | 2.15                   | 31.20                            |
| 3      | C3        | 2.42                   | 32.06                            |
| 4      | C4        | 2.96                   | 31.92                            |
| 5      | C5        | 3.16                   | 43.77                            |
| 6      | C6        | 2.05                   | 44.98                            |
| 7      | Proposed Method | 1.99         | 0.37                             |

Figure 6. Number of Fish Larvae Counting for medium dataset

Figure 7. Time Processing For Medium Sample
Figure 7. Time processing for medium sample between the proposed method and the manual approach.

3.3 Large Sample Dataset
Figure 8 shows the output results of fish larve counting for number of 50 large sample dataset. From the experiment results observation, the proposed method is outperformed which obtaining the lowest percentage error value compared to manual observers which is 1.36% error as shown in Table 3 at column 3. Meanwhile, the highest percentage error value is 4.02% error which obtains by the manual observer of number C3. Rest of the observer shows moderate percentage error values which C1=1.87%, C2=2.92%, C4=2.43%, C5=2.85% and C6=1.65%, respectively. Figure 9 presents processing time results for large sample dataset. The proposed method presents the fastest processing time which is 1.04 sec compared to the other manual observers in the experiment as shown in Table 3 at column 4. The slowest processing time with 136.92 sec was achieved by the manual observers of number C1. Rest of the observers presents moderate processing time for all samples C2=112.83 sec, C3=120.15 sec, C4=88.49 sec, C5=113.04 sec and C6=111.01 sec, respectively.

Table 3. The percentage error value for large sample dataset

| Number | Observers | Percentage Error, (%) | Average processing time, (second) |
|--------|-----------|-----------------------|----------------------------------|
| 1      | C1        | 1.87                  | 136.92                           |
| 2      | C2        | 2.92                  | 112.83                           |
| 3      | C3        | 4.02                  | 120.15                           |
| 4      | C4        | 2.43                  | 88.49                            |
| 5      | C5        | 2.85                  | 113.04                           |
| 6      | C6        | 1.65                  | 111.01                           |
| 7      | Proposed Method | 1.36             | 1.04                              |

Figure 8. Number of Fish Larvae Counting for large dataset
4. Discussion
There are a few publications on fish larvae counting using image processing techniques. One of the studies is proposed by Raman et al. [3] which developed the counting system using image processing techniques to classify larvae and juvenile fish. In their study, the proposed system achieves 82% accuracy for larvae and 87% accuracy for juvenile, respectively. To improve the study by [3], we used Sobel edge detection and blob analysis to count the fish larvae number and to record processing time through 150 samples in the experiment. Based on the experimental results, the proposed method achieved the lowest percentage error value for all three samples that consists of small sample (0.31% error), medium sample (1.99% error) and large sample (1.36% error), respectively. Meanwhile, for processing time, the proposed method achieved the lowest processing time compared to the manual approach counting for all samples with small sample (0.05 sec), medium sample (0.37 sec) and large sample (1.04 sec), respectively. The performance of our proposed method provides less percentage error and presents fast processing time for all three different samples used which outperforms in the previous research study of [21], [22] and [23]. Therefore, the proposed method approach is promising as an alternative solution to the manual counting approach specifically for fish larvae counting.

5. Conclusions
This paper describes the finding and distribution of fish larvae based on the three different samples dataset that consists of small, medium and large. This paper adopt the use of Sobel edge detection by minimising the noise from the image and preserving the fish larvae edges efficiently. Meanwhile, the blob analysis is used as connected components to perform statistical analysis for fish larvae that composed of area, centroid and boundary properties. The use of image processing methods were facilitate the counting process in term of reducing time processing and to make counting process of fish larvae more effectively. Moreover, development of the proposed method to facilitate researcher for rapid assessment and providing informative statistical data without human intervention. In the future work, the proposed method algorithm needs to be improved specifically for the thresholding process and image segmentation task. This is because underwater images are commonly suffered with several problems such as low intensity, light attenuation and small particle in the image. These problems are the urgent concern to be addressed that will cause the result less accurate. Moreover, sampling techniques of data collection needs to be highlighted in order to obtain a high quality image as well as to reduce half segmentation process task.

Acknowledgments
The author is greatly grateful thank you to Ministry of Education (MOE) for the financial support through FRGS VOT No: 59544

Figure 9. Time processing for large sample between proposed method and the manual approach
References

[1] Forero M G, Alicia H, Gargiulo G D and Mcewen A 2011 Image processing methods for automatic cell counting in vivo or in situ using 3D confocal Microscopy In Advanced biomedical engineering pp 978-953

[2] Cadena-Herrera D, Lara J E, Ramírez-Ibañez N D, López-Morales C A, Pérez, N O, Flores-Ortiz L F and Medina-Rivero E 2015 Validation of three viable-cell counting methods: Manual, semi-automated, and automated. Biotechnology Reports vol 7 pp 09-16

[3] Raman V, Perumal S, Navaratnam S, and Fazilah S 2016 Computer assisted counter system for larvae and juvenile fish in malaysian fishing hatcheries by machine learning approach. Journal of Computers 11(5) pp 423-431

[4] Aliyu I, Gana K J, Musa A A, Agajo J, Orire A M, Abiodun F T and Adegboye M A 2017 A proposed fish counting algorithm using digital image processing technique. ATBU, Journal of Science, Technology and Education (JOSTE) 5(1) pp 01-11

[5] Loh B, Raman V and Patrick T 2011. First Prototype of Aquatic Tool Kit: Towards Low-Cost Intelligent Larval Fish Counting in Hatcheries. IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing DASC pp 192-195

[6] Pandit A and Rangole J 2014 Literature review on object counting using image processing techniques International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering vol 3(4) pp 8509-8512

[7] Kim S and Cho H Y 2013 Automatic estimation of Artemia hatching rate using an object discrimination method Ocean and Polar research vol 35(3) pp 239-247

[8] Iscimen B, Kutlu Y and Turan C 2017 Classification of serraniid species using color based statistical features Natural and Engineering Sciences vol 2(1) pp 25-34

[9] Hasija S, Buragohain M J and Indu S 2017 Fish species classification using graph embedding discriminant analysis International Conference on Machine Vision and Information Technology (CMVIT) pp 81-86

[10] Fabic J N, Turla I E, Capacillo J A, David L T and Naval P C 2013 Fish population estimation and species classification from underwater video sequences using blob counting and shape analysis International Underwater Technology Symposium (UT) pp 1-6

[11] Salimi N, Loh K H, Dhillon S K and Chong V C 2016 Fully-automated identification of fish species based on otolith contour: using short-time Fourier transform and discriminant analysis (STFT-DA) PeerJ 4 p e1664

[12] Konam S and Narni N R 2014 Statistical analysis of image processing techniques for object counting. International Conference on Advances in Computing, Communications and Informatics pp 2464-2468

[13] HJ Wan Yussof W N J, Man M, Hitam M S, Abdul Hamid A A K, Awalludin E A and Wan Abu Bakar W A 2018 Wavelet-based Auto-Counting Tool of Aedes Eggs In Proceedings of the 2018 International Conference on Sensors, Signal and Image Processing (ACM New York) pp 56-59

[14] Yussof W N J H W, Hitam M S, Hamid A A K A and Awalludin E A 2017 Feature-based Video Stabilization using Gabor Wavelets Journal of Telecommunication, Electronic and Computer Engineering (JTEC) 9(3-4) pp 75-79

[15] Li L and Hong J 2014 Identification of fish species based on image processing and statistical analysis research. International Conference on Mechatronics and Automation pp 1155-1160

[16] Manjula 2015 Role of Image Segmentation in Digital Image Processing for Information Processing International Journal of Computer Science Trends and Technology (IJCST) vol 3(3) pp 11-18
[17] Bhargavi K and Jyothi S 2014 A survey on threshold based segmentation technique in image processing *International Journal of Innovation Research and Development* vol 3(12) pp 234-239

[18] Vala H J and Baxi A 2013 A review on Otsu image segmentation algorithm *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)* 2(2) pp 387-389

[19] Kabade A L and Sangam D V 2016 Canny edge detection algorithm *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)* vol 5(5) pp 1292-1295

[20] Kaewchote J, Janyong S and Limprasert W 2018 Image recognition method using Local Binary Pattern and the Random forest classifier to count post larvae shrimp *Agriculture and Natural Resources* 52(4) pp 371-376

[21] Toh Y H, Ng T M and Liew B K 2009 Automated Fish Counting Using Image Processing *International Conference on Computational Intelligence and Software Engineering* pp 1-5.

[22] Sharma S and Shakya A 2014 Fish population estimation from underwater video sequences using blob counting and shape analysis *Institute of Engineering, Central Campus, Pulchowk, IOE, TU, Nepal* pp 461-467