

Matlab Implementation Results: Detection and Counting of Young Larvae and Juvenile by Image Enhancement and Region Growing Segmentation Approach

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Abstract— This paper describes techniques to perform efficient and accurate recognition in larvae images captured from the hatcheries for counting the live and dead larvae's. In order to accurately model small, irregularly shaped larvae and juvenile, the larvae images are enhanced by three enhancement methods, and segmentation of larvae and juvenile is performed by orientation associated with each edge pixel of region growing segmentation method. The two vital tasks in image analysis are recognition and extraction of larvae and juvenile from an image. When these tasks are manually performed, it calls for human experts, making them more time consuming, more expensive and highly constrained. These negative factors led to the development of various computer systems performing an automatic recognition and extraction of visual information to bring consistency, efficiency and accuracy in image analysis. This main objective of this paper is to study on the various existing automated approaches for recognition and extraction of objects from an image in various scientific and engineering applications. In this study, a categorization is made based on the four principle factors (Input, Segment the larvae, Recognition, Counting) with which each approach is drive .The achieved result of recognition and classification of larvae is around 85%. All the results achieved through matlab implementation are discussed in this paper are proved to work efficiently in real environment.

Index Terms— Enhancement, Segmentation and Counting

I. INTRODUCTION

The early life history of fish is often considered critical for recruitment to the adult population. Thus, understanding how larval fish population's distribution varies through time and among habitats is important for answering questions related to both applied and theoretical ecology in marine research. The global demand for aquaculture software, supplies and equipment is predicted to exceed \$80 billion by 2016 due to increasing demand for fish in the market. Commercialization of farming across the world and increasing intensities of production will necessitate the use of commercial grade feeds, chemicals and biological enhancements as well as more mechanization on fish farms. Therefore, demand for fish is expected to continually outpace

growth in other global food sources such as livestock and agriculture. The Asia Pacific region is projected to account for over 80 percent of global demand for aquaculture software supplies and equipment by 2016. This is in direct correlation to the region's global dominance in aquaculture production. Several factors contribute to the huge aquaculture production turnover from Asia: a long coastline; tropical and temperate weather suitable for rearing aquatic species; low labor costs in a hitherto labor intensive industry; strong local demand as well as export competitiveness; integrated farming practices enabling multiple crops, better land and resource utilization; and a growing manufacturing base for supplies and inputs. Due to the increasing exploration on the fishery industry, new method had to be explored in order to support it and to keep the sustainable. machine learning approach might give solution for supporting the fishery industry. For instance, it can help to detect, recognize, and analyze the fish by using image processing techniques and it will be faster, easier and convenient than the manual way. But there are several problems in detecting and recognizing the fish in the image such as the target object is obscured due to the presence of the other object which can interfere with recognition process and any other noise. It makes the system difficult to identify the feature of the fish stages.

In fishing hatcheries, when the reproduction system of fish breeding starts from egg to spawning stage. Each fish species has a unique reproductive strategy and favors certain habitats for spawning and for early development of their newly hatched young. Fish life cycles vary among species. In general, however, fish progress through the following life cycle stages: 1) Eggs: Fertilized eggs develop into fish. Most eggs do not survive to maturity even under the best conditions. Threats to eggs include changes in water temperature and oxygen levels, flooding or sedimentation, predators and disease.2) larval: Larval fish live off a yolk sac attached to their bodies. When the yolk sac is fully absorbed, the young fish are called fry.3) Fry: Fry are ready to start eating on their own. Fry undergo several more developmental stages, which vary by species, as they mature into adults. 4) Juvenile: The time fish spend developing from fry into reproductively mature adults varies among species. Most fish do not survive to become adults. Threats to

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survival include fluctuations in water temperature, changes in oxygen levels, competition for habitat and predators.5) Adult: When fish are able to reproduce, they are considered adults.6) Spawning: Female fish release eggs into the water and male fish fertilize eggs by releasing milt. Not all eggs are fertilized. Some fish spawn each year after reaching maturity; others spawn at intervals while others spawn only once and then die.

Our research involves in counting the larvae and juvenile in second and fourth stage of the cycle which is important for aquatic researchers to monitor the growth of fish by categorized into alive, partially alive, and not alive. However, the counting process is time consuming and can be subjected to human error. In this paper, we explore how this counting can be automated using image processing approaches. Early studies have shown that some possible ways of fish counting. However, they are designed for bodies of water with different varieties of fish so they include some form of fish species detection algorithm so as to be able to count the number for each species. In addition, fish tracking algorithms are also used in the counting of fish. Thus, their suggested methods are computationally intensive and will increase costs and slow down the counting speed.

The key idea behind our proposed method is the use of camera to mark the position of the fish breeding in the hatcheries, and then analyzing the area of each image to decide how many larvae's and juvenile are captured in each image. This in turns yields the number of fish in a multiple images. Individual images from various positions are processed separately, and the number of fish computed from each image is then added up and divided by the total number of images from multiple locations to obtain an average count.

The paper is organized as follows: Section 2 explain the research challenges for counting the early stages of larvae in the hatcheries. Section 3 describes the research objective for the research carried out in the paper. Existing works and commercial software products for counting the fish in market is explained in Section 4. Machine learning approaches are explained in detail at Section 5. The initial results of the proposed method are shown in Section 6. Finally conclusion is made in Section 7.

II. RESEARCH CHALLENGES

Detection and recognizing an object is very difficult and takes a long times especially for the live object. In fisheries industries, species of the fish must be recognizing for calculating their population. Currently, manual approach is done by an official of fisheries department one by one for calculating and measuring fish length. One of the fundamental challenging problems in computer vision is detecting object inside an image or video frames. Therefore monitoring larval fish production in freshwater assesses the overall effectiveness of habitat restoration in lakes and rivers across the nation have challenges as follows: 1) Aquaculture research, to calculate the livestock of larvae, manually performed by human. 2) Count accuracy rate was very poorly

determined. 3) High error margin with less performance result.4) Larva growth information's are not properly maintained and integrated.

A basic problem in recognizing a larvae and juvenile shape is caused by the fact that it can be in any kind of position, rotated, mirrored, etc. Such transformations belong to the group of affine transformations, which includes any kind of transformation that preserves distance ratios as well as co-linearity. To a classification these transformations can quickly lead to difficulties in recognizing the object.

- Rotation: Objects appearing under different angles have very different representations when it comes to their pixels. Without taking this into account in some way, a classifier will incorrectly recognize identical patterns as different ones, depending on rotation.
- Mirroring: Similar to the possibility of an object appearing rotated, it can also be flipped, i.e. in a mirrored position. This creates a problem similar to that of rotation.
- Scale invariance: Different scaling of a shape create another problem of the same class. Shapes can appear in different sizes for many reasons. It can, for instance, be due to the perspective or their actual size can differ. Even though humans have little problem dealing with these and the previous transformations they are far from trivial to a computer.
- Translation: The problem of translation is the problem of an object appearing in a different place in the image. Although this is not one of the most difficult problems to overcome, it certainly should not be ignored when creating an object recognition system.

III. RESEARCH OBJECTIVES

In this paper we look at the difficult task of larvae and juvenile recognition from hatcheries. Larvae recognition can be done employing a machine learning approaches that incorporates aspects of human object recognition. The main reason for our interest in larvae recognition stems from the belief that generalization is one of the most challenging, but also most valuable skills a computer can have. Since the area of vision probably depends on generalization more than any other area, this makes it a challenging endeavor.

Below we have listed the objective of the research done for this paper

- The ultimate goal of larvae and juvenile recognition is to be able to recognize an object no matter what the circumstances (background, lighting, occlusion, etc.) As this is not trivial to achieve, certainly not without making any reservations, we will try a step by step approach, moving from simple shape recognition to more complex object recognition.
- Design enhancement algorithms to reduce the noise in the image
- Designing enhanced algorithm for recognition and segmentation of larvae

and juvenile.

- Development of prototype in matlab. The proposed systems are tested as thoroughly as possible. Due to constraints of computational power and time sometimes tests have been less extensive in order to make way for testing more variations. The system will be tested using different kinds of tests. Simple tests are introduced to check parts of the system. In the end a final test with pictures of actual objects will show the workings of the complete system.

The proposed research solution, the fish counter intends to address several existing issues regarding larval and juvenile fish counting.

IV. EXISTING WORKS

There are few existing research works carried out in the past for counting the fishes based on the length and size of measurement in adult stage not in young stage. The research carried out in the past are by using image processing method. In 2006, D.J White [2] developed a machine system for sorting some fish species by employing modern hardware and programming techniques in real time. The system is called as Catch Meter, which includes conveyor, light box and feeder. The mechanical systems were controlled by a PLC interfaced to the main computer and software via an Ethernet link. Fish moved along the conveyor belt at 1.5 m/s and was analyzed by the computer vision system. Fish detection also was done using camera video like Williams' experiment [3]. Researcher constructed a prototype system for detecting and delineating fish shapes in video footage obtained from a local aquaculture facility. Another method is to use edge detection to identify the fish [4]. The canny edge detector is used because it provides the most number of true edges [5]. To eliminate the edges of the container, the image is filled with redundant black data starting from the sides of the image outwards. This set up an additional rectangular edge denoting the original outer border of the image. Morphological closing is done next to join the edges that were not terminated properly and to fill

the areas. Blobs are thus created from the edges. This step is also necessary to connect the round edges of the container to the original outer border of the image so they can all be eliminated by eliminating blobs which has a major axis much longer than the length of five fish. The final results are obtained after eliminating noise and background objects. This results in inaccuracies when we use the area to count the number of fish in a blob. These methods are not promising to produce accuracy and reliability in counting the number of fishes from hatcheries.

There are few commercial products available in the market to count the fish from the different type of environment. Several competing companies have introduced fish counting and monitoring solutions that enable the detection of fishes through specialized equipment. These tools range from light counters which detect fish through underwater lights, to sound waves which count the number of fish. Although capable of accurately counting fish, these options fail to detect fish under certain measurements (e.g.

below 5cm). Furthermore, the cost of acquiring such equipment may be high (e.g. around \$75,000 and above). Vaki, an Icelandic company, allows for fish counting by a light valve. When a fish passes their counter, light is blocked, therefore indicating that a fish is present. Although able to count fish with a high accuracy rate, the Vaki fish counter may encounter difficulties when detecting smaller fish. Furthermore, it may function incorrectly when used in turbid water [6]. The company, Sound Metrics, provides Dual frequency identification sonar (DIDSON) which detects fish through sound waves. Underwater pictures are produced which are later processed with fish recognition software. Although high quality images can be produced, the DIDSON module also faces issues when counting small (below 5 cm) fish. Additionally, the cost for each DIDSON unit is expensive with prices from \$75,000 and above [7]. AKVA Group with their Fishtalk software enables users to store aquaculture data as well as create reports. Moreover, the software is not species dependent meaning that it can be compatible with numerous fishes. Although this is so, the Fishtalk software does not specifically support monitoring larval fish, and therefore may omit collecting certain important information. The current work differs from these existing products in terms of cost as well as hardware and software usage. Though other solutions offer specialized tools, they must be directly purchased and may incur a high price. Additionally, most of these tools are not able to accurately estimate the larval fish population due to their reduced size. In contrast, the proposed prototype can function with any normal camera that provides sufficient picture quality, consequently reducing equipment costs. Furthermore, custom larvae detection software enables the counting of small larval fish which may remain unrecognized by other solutions.

Furthermore, research has been undertaken to improve support towards fisheries which leads to better aquaculture development. The main benefits from the outcome of this research include fish farmers, hatcheries or marine researchers who require low cost solutions in improving their fish production or aquaculture research. Since the outcome of this research is a prototype which only requires a camera and recognition software by using machine learning approaches, it is fit for any research experts or industry wanting to detect and study larval and juvenile fishes.

V. METHODOLOGY: ENHANCEMENT AND SEGMENTATION

Larvae and Juvenile detection and recognition system is an image processing technology used to detect the young larvae and juvenile in an image and recognize the number of larvae and juvenile present in an image. Therefore the main aim of this paper is to segment the images into separate single image and it is counted. Segmentation is used for detecting the edges in an image. The purpose of segmenting an image into a set of disjoint areas/segments is to simplify the image. The image may be further simplified by assembled the small areas into larger objects by building a symbolic scale space over the

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segments. The segmentation in this image is entirely based on the gradient transformation. Segmentation and the choice of segmentation algorithm cannot be proven optimal to the task of recognizing objects in any strict sense. The gradient transform has proven itself useful in many contexts, but the choice is heuristic and can only be justified by experience. In the case of recognition of objects such as young larvae and juvenile in images, the object must in some sense be different from its surroundings. Therefore the methodology is categorized in four stages: Image Acquisition, Image Enhancement, Segmentation and Classification, in final classification are performed with counting the number of young larvae and juvenile fishes in the captured image. Below Figure 1 illustrates the working methodology of machine learning approach.

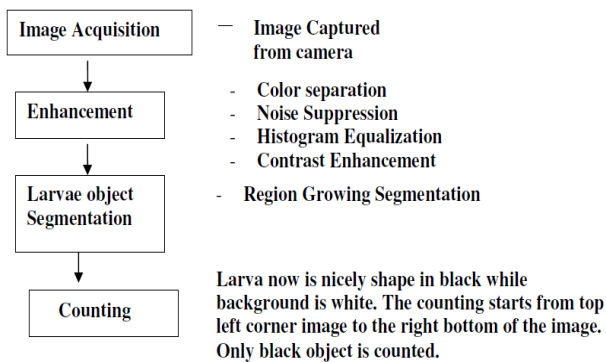


Figure 1 illustrates the methodology of machine learning approach

A. Image Acquisition

Images were captured via camera mounted on the aquatic basin (See Figure 2). Once the camera captures the larvae, it will be transferred to the video software for processing the image. The captured image is converted into grayscale image by color transformation method. Below figure illustrates the larvae image. Figure 1 illustrates the acquiring images by camera from the hatcheries and sent it to the computers for processing the captured images.

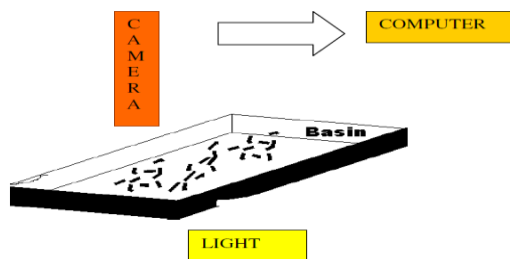


Figure 2 illustrates the Image Acquisition of Capturing the Larvae Image from Hatcheries

B. Image Enhancement

The very basic enhancement approach applied in the larvae image is to improve the contrast. In the larvae images, young ants and larvae have the variation in contrast. As we

have seen in our earlier approaches, there are many research works are done based on enhancement techniques. The reason for performing enhancement is to provide marine specialist a quality image for counting. There are only few enhancement methods are applicable for larvae and juvenile images captured through camera in hatcheries; all the techniques are not suitable for these images. By traditional methods, it's very hard to achieve good result of enhancement. From the studies, there are challenges faced by researchers in local contrast enhancement without loss information's from the image. In the preparation stage, larvae images need to improved by enhancing the contrast and reduce the noise in the image. Our main objective is to improve the image quality and remove the unwanted objects in the background of the image by further enhancement processing and make it ready for segmentation. The approach used in this research is of three stages; first stage is to apply Gaussian smoothening function to suppress the noise in the image. Second stage is to use histogram equalization with few modifications from the traditional methods to enhance the contrast in the image. Third stage is to apply modified contrast enhancement, which can identify the hidden information's from the image. Three stages of enhancement approach used in our research is identify the local information about the image. These proposed approaches can provide more accurate results and will obtain full detailed information about the image for segmentation approach in the mammogram image.

Noise Suppression: In camera captured larvae images have noises in different types. Noise with higher intensity will be having more values for the optical densities which have irregular shapes. Shadows and blur are part of the noise, which can reduce by replacing the black pixels.

Suppression of noise is performed by applying Gaussian smoothing operator. Gaussian operator is 2-D convolution operator which can be used for blur images and more noisy images. Kernel is represented in the form of Gaussian shape or in form of bell-shape. Gaussian is represented in the form of:

$$Gaussian(p, q) = \frac{1}{2\pi\sigma^2} e^{-\frac{p^2+q^2}{2\sigma^2}} \quad (1)$$

Gaussian smoothing is considered as point spread function. Convolution is applied to reach the function in a 2 D distribution. Imaging will be having collection of random pixels, need to make a approximation on the function before the convolution. It is a non zero in all part of the image, it requires a larger kernel of convolution, while in implementation it has higher values in standard deviation from mean, kernel can taken out , when we are in need of suitable kernel, Gaussian smoothening can performed. Kernel used for our research is 7×7 kernel as part of convolution filter. The images of larave have been classified in to three types, complete, partial , incomplete which have dead objects in the larvae image. Each category will have different intensity pixels and variations are observed in every type. Based on the types, standard deviation values are

computed and made as choice to adjust the level of smoothening.

Histogram Equalization: Histogram Equalization (HE) approach is technique applied in the images for improving the contrast, idea is to map the gray level pixels based on probability distribution, it orients the image, flattens and stretch the histogram of the image for improving the contrast.

The image of the histogram is represented with gray level value of $K = 0,1,2, \dots, L-1$; the discrete function is computed by number of pixel identified with gray level values (n_g), it is denoted by $D(G_k) = n_g$. Histogram of the image is normalized by each value computed is divided by total number of pixels presented in the image; therefore histogram normalization is obtained by probability density function:

$$P(G_k) = \frac{N_g}{N} \quad (2)$$

Therefore computation results provide the probability of gray level occurrence in the image. Transformation function is applied and it is represented by $T(G_k)$, which produces the cumulative cost of adding all the pixels from the known histograms and its maps the input to the output.

$$Tran(G_k) = \sum_{i=0}^k p_r(r_i) \quad (3)$$

Transformation function output value is a single value, and intervals are increased continuously, where value of interval ranges between 0 to 1, therefore it provides inverse transformation from the scale of output to be from black to white pixels in the image. If the function does not increase the interval values, it will invert the intensity values and produce gray levels in the image. It can guarantee by mapping the output gray level value pixels to input pixels. Inverse transformation is represented by:

$$Trans' = invtrnsf \left[\frac{(Trans - Trans_{min})(L-1) + 0.5}{1 - Trans_{min}} \right] \quad (4)$$

The values are normalized and expanded to 0 to L-1, whereas $Trans_{min}$ is the smallest value from the cumulative function vector, Trans is the transformation value of gray scale ranges from 0 to 255 in each gray level. This approach is simple and powerful in the range of change in brightness of the image. The output achieved my larve image improves but missing of local information occurred in this approach. In this traditional approach, there are few changes performed and applied to obtain good result. Basically when histogram distribution is uniform by mapping the cumulative distribution, during this stage, there is a simple medication performed in output of the histogram, and make it closer to the uniformly distributed histogram.

The histogram equalization method does support adjustments for enhancement, but can control level of enhancement by adjusting the parameters. In this method, modified histogram H_1 and input histogram H_2 and difference computed is $H_1 - H_2$ and it is modified and closer to Uniform histogram, therefore it increases the

contrast enhancement. Formulation for modified histogram output result is determined by:

$$\min \| H_1 - H_2 \| + \mathcal{G} \| H_1 - u \| \quad (4)$$

Whereas H_1 is the modified histogram; H_2 is the input histogram; U is the Uniform histogram; \mathcal{G} is the parameter value for adjustments. It varies from 0 and α . If the values are 0 means standard HE and α means it is a original image. Modified histogram is average computation weight between input histogram and uniform histogram, finally based on changing the parameter values, contrast can be adjusted in the image. The resultant image will be processed for modified contrast enhancement stage.

Contrast Enhancement: In histogram equalization, local information's are missing, to maintain the local information details in mammogram images; modified contrast enhancement technique is performed. During this computation of global transformation, number of pixels may remove or not identified, then transformation function is applied on gray level distribution in the image. After modified histogram equalization is applied, and then contrast enhancement is performed. The contrast method has obtained statistical values from the output of histogram.

Discrete gray level vales are represented by [0, L-1] and it is denoted by d. Normalized histogram are computed and it is denoted by $P(d_i)$. The moment of D and its mean is calculated for measuring the average gray level occurrence in the image, average contrast is computed by standard deviation or variation.

$$m = \sum_{i=0}^{L-1} d_i P(d_i) \quad (5)$$

Moment is calculated based on first order and second order where as $n = 1, 2$. The mean and variance are used as the parameters for contrast enhancement.

The modified contrast enhancement is computed after achieving the histogram modification.

$$H_1(x, y) = \begin{cases} E.f(x, y), m < K_0, K_1 D, K_2 D \\ F(x, y) \text{ otherwise} \end{cases} \quad (6)$$

$H_1(x, y)$ and $F(x, y)$ are the final outputs of enhancement and modified histogram images, where the values of E, K_0, K_1 are the parameters to be adjusted D is the standard deviation, if the values of $K_0 < K_1 < \dots < K_n$, if the values are greater than 1, it will enhance light areas of the pixels and lesser means for darker area of pixels. The parameters are very powerful in enhancing the images, it provides promising results on images, level of contrast enhancement is adjusted based on input of the original image contrast. When we have the contrast to be lower, images have narrow histogram and then we apply the histogram equalization to reduce the contrast and make it uniformed by further enhanced with modified contrast

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enhancement. In histogram modification, value of \mathcal{G} is 0.9 for the image in larvae image dataset. The values of $E = 2$, $K_0 = 2K_1 = 0.005$. are the taken for enhancement. The E value is very important for balancing the contrast in the image, and computational complexity is also balanced in the image. Therefore these methods are proposed to enhance the quality image for next stage of detecting the edges to remove the partial larvae's and detect shape in the image to find out the region of interest in the image for segmentation.

C. Segmentation by Region Growing Method

Segmentation is a method which partitions the image pixels into smaller units which have the structure that will relates to region of interest (ROI). Based on the characteristics, pixels are segmented and it will similar in the ROI. First step in the segmentation is to identify the region of interest. Each image containing a square field was processed in order to establish a region of interest. The captured image is processed using a simple algorithm that is able to detect the four vertices of the square field. Horizontal coordinates of these vertices are estimated by observing local minima on a profile function which is obtained with the sum of pixel values over each column of the image. Vertical coordinates are obtained similarly but with a profile function considering the sum over each row of the image.

Second step is to pre-segment the edges in the image. The binary gradient mask shows lines of high contrast in the image. These lines do not quite delineate the outline of the object of interest. Compared to the original image, gaps can be viewed in the lines surrounding the object in the gradient mask. These linear gaps will disappear if the Sobel image is dilated using linear structuring elements. Therefore the gaps are filled. Next stage where the binary gradient masks is dilated using the vertical structuring element followed by the horizontal structuring element. The dilated gradient mask shows the outline of the larvae cell and ant quite nicely, but there are still holes in the interior of the cell, therefore the gaps are filled in uniform format.

The larvae and juvenile cell of interest and ant has been successfully segmented, but it is not the only object that has been found. Any objects that are connected to the border of the image need to be removed. The connectivity was set to 4 to remove diagonal connections, so that objects are separated into individuals and it is detected in order to make the segmented object look natural; smooth the object by eroding the image twice with a diamond structuring element, so that each and every larvae cells and ants are detected and it is easy to count the number of larvae's and ant in image. Therefore while overlapping or contradiction appears in an image, it is detected by boundary detection algorithm. Therefore if there are multiple larvae are overlapped, then considered two nodes and by that the two nodes are replaced by one, their mutual edge is ignored, and the neighbors of the new node is the union of the two original nodes individual neighboring sets. Instead of contracting the two nodes imposed by a connected operation, a new node can be introduced, and the two nodes can both be linked to the new node by edges. Then the full set of nodes (both original and new ones) and the set

of edges alone constitute a tree. So that overlapped nodes are separated and it counted easily into one full object in an image.

Procedure for Segmenting the larvae and Juvenile

Step1: Read the image and convert the image into gray scale image

Read the image and convert the image into grayscale image by color transformation methods

Step 2: Detect the entire larvae

Multiple young larvae are present in this image, so that the larvae can be seen in its entirety. We will detect these larvae. Another word for object detection is segmentation. The object to be segmented differs greatly in contrast from the background image. Changes in contrast can be detected by operators that calculate the gradient of an image. One way to calculate the gradient of an image is the Sobel operator, which creates a binary mask using a user-specified threshold value.

Step 3 Filling the Gaps

The binary gradient mask shows lines of high contrast in the image. These lines do not quite delineate the outline of the object of interest. Compared to the original image, you can see gaps in the lines surrounding the object in the gradient mask. These linear gaps will disappear if the Sobel image is dilated using linear structuring elements. Therefore the gaps are filled.

Step 4 Dilate the image

The binary gradient mask is dilated using the vertical structuring element followed by the horizontal structuring element.

Step 5 Fill Interior Gaps

The dilated gradient mask shows the outline of the larvae cell quite nicely, but there are still holes in the interior of the cell, therefore the gaps are filled in uniform format

Step 6 Remove Connected Objects on Border

The larvae cell of interest has been successfully segmented, but it is not the only object that has been found. Any objects that are connected to the border of the image can be removed. The connectivity was set to 4 to remove diagonal connections, so that objects are separated into individuals and it is detected.

Step 7 Smooth the Object

Finally, in order to make the segmented object look natural, we smooth the object by eroding the image twice with a diamond structuring element, so that each and every larvae cells are detected and it is easy to count the number of larvae's in image.

D. Classification and Counting Method

Larvae and Juvenile in the image were classified depending on whether they had contact with each other. It is identify, whether the larvae were entirely inside the region of interest or not from the image. Two processes were undergone in the stage; those larvae that were not connected in any way with the border edges and those that were connected in some way. The process of classification is based on neural network approach. The method is divided into two main components: firstly, the recognizing system that uses neural network, and secondly the scanning method that examines

each location in the image at several scales, looking for locations that might contain a larvae and juvenile fish. The neural network that is used in this system is multilayer perceptron. The architecture used is based on the work that done by previous work [8]. Multilayer perceptron neural network is one of the conventional feed-forward artificial neural networks. The multilayer perceptron used has 400 input units, which receive input from 20×20 grayscale pixel from window scanner. The feature used for this work is the edges of the larvae. This is used for the first experiment purpose for this work. When the larvae and juvenile are detected, usually the object would be detected for several times. This makes the detection result are overlapped each other. The object detected should be in one detection area. Therefore the detected objects should be merged. The object candidates are merge by the considering the number of overlapping detection in the method.

Counting of Larvae- Each object is categorized as a single larva or juvenile or a multiple larvae that are connected with each other in the image. Pixel counting was used to calculate each object's area. System processes an image in rows and columns, a pixel is at the intersection of a line and column and the system stores a value for each pixel. Therefore 0 is for no larvae present (black) and 255 for larvae present (white). While determining the area of a larva, then it is needed to calculate the number of larvae/juvenile contained in all images. It is assumed that the area of different objects contained in images can either be of a single larva or of a multiple number of the area of a single larva. While calculating the larvae, histogram is calculated. The histogram shows a periodic behavior that is caused by the fact that multiples of the area of a single larva will be the main objects present in all images. The period in this histogram is considered as a valid interpretation of the area of one larva. Second stage is to apply sobel operator to enhance the contrast from background to detect the larvae. ROI is calculated and boundary detection algorithm is applied to segment and count the number of larvae's/juvenile through connected regions.

VI. RESULTS AND DISCUSSION

A testing conducted to give a view of its performance in detecting young larvae and juvenile fish [12]. A preliminary experiment was carried out to determine the accuracy rate of the method. Images were captured via camera mounted on an aquatic basin. Once the camera captures the larvae image, it will be transferred to the counter system for image processing. The container acts as the background while the fish are the foreground objects to be extracted. Therefore the container must be bright in color to provide an acceptable contrast to the fish. A video camera records images of the fish for a predefined amount of time. The captured image is then converted into a grayscale image by color transformation methods, enhancement method, segmentation and classification. The data used in this testing divided into two data which are the training data set for training, and the testing data set for the testing. The neural network architecture used in this work is multi-layer perceptron. The

system will be given 400 input unit of 20×20 pixel grayscale image of the sub-image. The output value from the unit will be around -1 and 1. In the training data set, the value 1 is defined as the larvae edges, while -1 is defined as the non larvae. The result shows that the counter gives a number of false positive and false negative. Some area was detected and somewhere not detected, which need to further developed for accuracy. Currently accuracy achieved in detecting larvae is 82% and juvenile is 87%. A simple setup for practical implementation is performed as explained above, Larvae and Juvenile required to be counted flow from a smaller container. These images of larvae and juvenile are processed to produce the count of the fish. The first set of experiment is implemented in MATLAB. The results of the machine learning approach in detecting and counting the larvae and juvenile is shown below from figure 3- figure 10.

A. Original Image and GUI Interface

The interface of the larvae detection system is implemented in matlab, the interface includes loading the image, detection and counting of larvae, detection and counting of juvenile, total number of counts after processing by machine learning approaches.

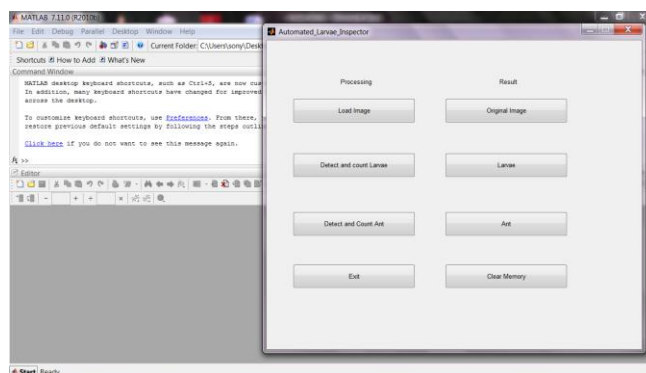


Fig 3 illustrates the GUI of the prototype implemented in MATLAB

The captured image from the camera placed in hatcheries is shown below in Figure 4. The image has more noise and it's in color scale.

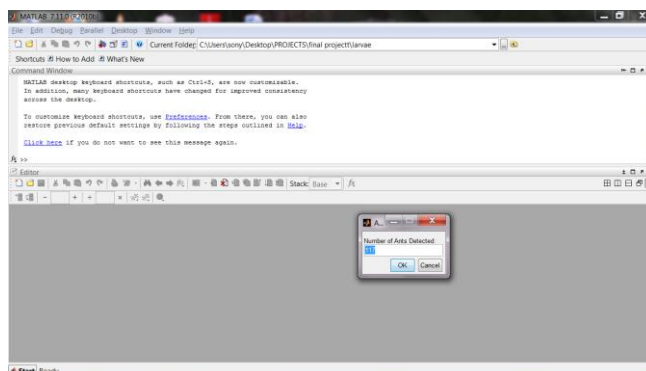


Fig 4 illustrates the original image captured from camera

The GUI is designed to select the image from the file located on directory to choose which image is chosen for machine learning process

Matlab Implementation Results: Detection and Counting of Young Larvae and Juvenile by Image Enhancement and Region Growing Segmentation Approach

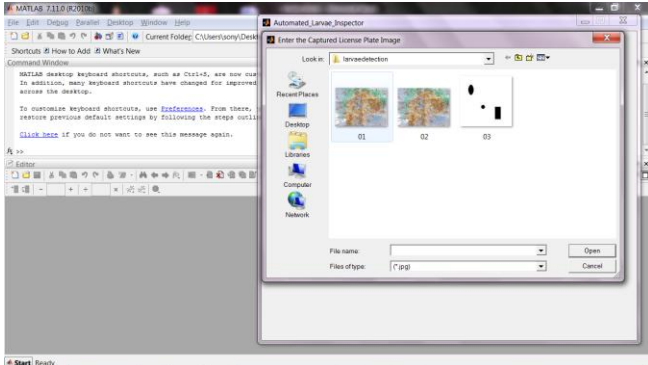


Fig 4 illustrates the original image selected for processing

B. Image Enhancement

The color image is transformed into gray scale for the input of preprocessing methods. The gray-scale image is represented by only the luminance values that can be matched between the two images. Because a single luminance value could represent entirely different parts of an image, the remaining values within the pixel's neighborhood are used to guide the matching process. Once a pixel is matched, the color information is transferred but the original luminance value is retained.

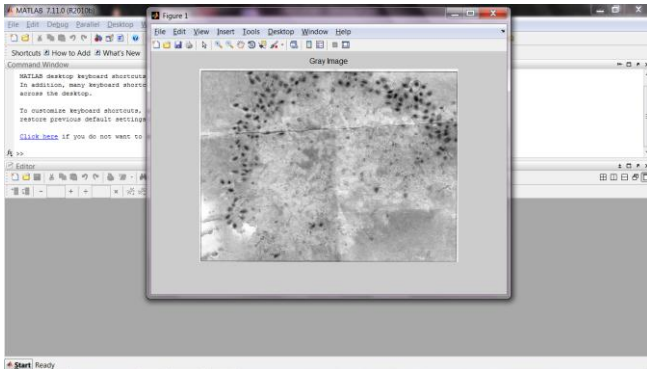


Image noise can compromise the level of detail in the captured camera, and so reducing this noise can greatly enhance the final image. The problem is that most techniques to reduce or remove noise always end up softening the image as well.

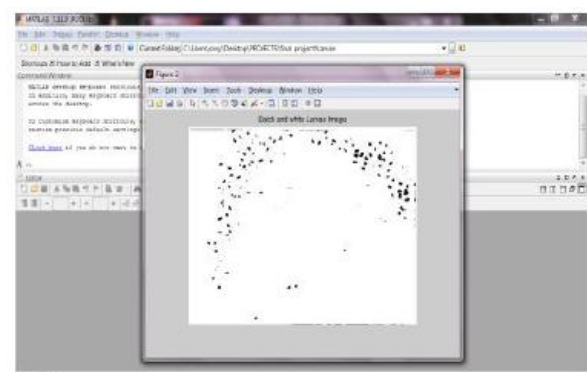


Fig 5 illustrates the noise elimination and contrast enhancement by preprocessing stage.

C. Segmentation

As a third step, a set of rudimentary region-based detection of parts of the object are done. Then, using those regions as initialization, then enhancement is applied, the segmented image which contains the detected and segmented object, possibly cropped and resized) and input image are processed

through the recognition and counting pipeline is obtained.

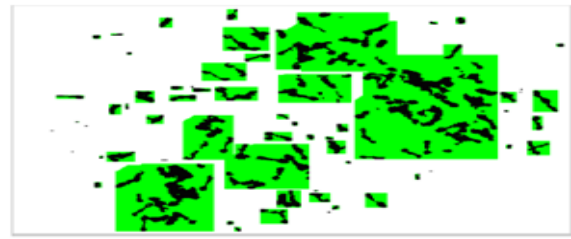


Fig 6 illustrates the Segmentation by edge detection method.

While segmenting the larvae and juvenile, the binary gradient mask shows lines of high contrast in the image. These lines do not quite delineate the outline of the object of interest. Compared to the original image, gaps can be viewed in the lines surrounding the object in the gradient mask. These linear gaps will disappear if the Sobel image is dilated using linear structuring elements and result is obtained.

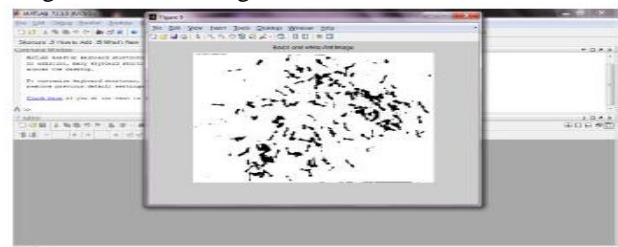


Fig 7 illustrates the Segmentation by Dilation process

D. Classification and Counting

Classification of larvae images in many category datasets has rapidly improved in our testing. However, systems that perform well on particular datasets typically have one or more limitations such as a failure to generalize across visual tasks, insufficient translation invariance, inability to cope with partial views and occlusion, or significant performance degradation as the number of classes is increased. But our classification of larvae and juvenile accuracy is more improved compared to previous works.

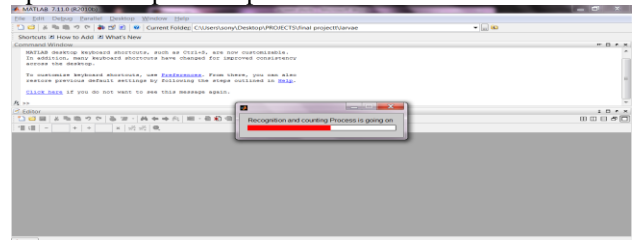


Fig 8 illustrates the Recognition process of total number of larvae ant and juvenile

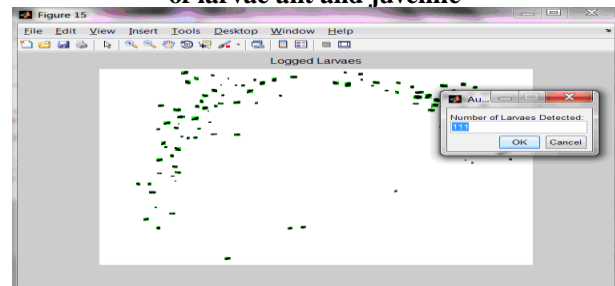


Fig 9 illustrates the Classification of Larvae by Neural Network Approach and Counting Method

Once the classification is done, counting objects of larvae at test time is simple. One simply needs to extract feature vectors at each

pixel and multiply them with the learned linear coefficients to obtain a density value. The density can then be integrated over an arbitrary-shaped region of interest, for e.g. the full image to estimate the number of objects present in it. Below figure illustrates the total count of larvae in the image.

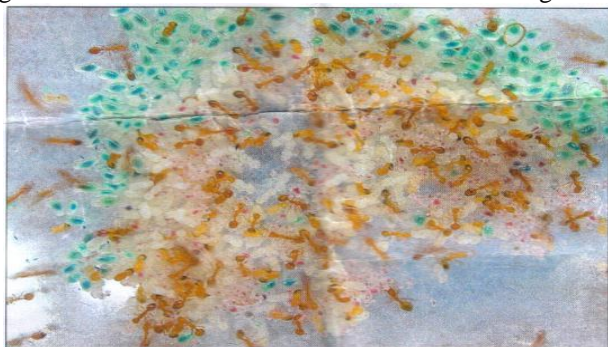


Fig 10 illustrates the Total Number of Larvae Count
E. Performance Evaluation

Larvae Image dataset is a used dataset for fine-grained recognition. The dataset contains 102 images of various positions of larvae and juvenile and each category containing between different positions of ant and larvae. It has well established protocols for training and testing, which we adopt in this paper too. A lot of methods have been tested on this dataset including some segmentation-based. Some of the segmentation methods are designed to be very specific to the appearance of complete larvae and juvenile, while others [3] are more general and can also be applied to other types of datasets. Our approach, too, does not make assumptions about the set of categories for classification or the initial location or size of the objects in the image. The performance of our approach on this dataset is 85% which outperforms all previous known methods in the literature [3, 8, 9,10]. One important thing to note is that the improvement of our algorithm over is about 4%, and the only difference is the addition of the proposed segmentation algorithm and the extracted shapes from the segmented image.

The proposed algorithm improves the performance both with and without using segmentation. Our algorithm achieves 30.17% classification performance compared to 19.2% of other approaches in previous works in the same setting, which is an improvement of 11% over the best known baselines for the larvae images of high noise. Another interesting observation is that our algorithm achieves a performance of 27.60% when applying segmentation alone i.e. without combining it with thresholding algorithm. This is by itself an impressive improvement over the other known algorithms for this dataset even when not taking advantage of our baseline performance. When we consider the benefits of the segmentation and classification, accuracy achieved is around 85% compared to previous works. This achieved result helps the aqua researchers to count the number of larvae and juvenile which has higher noise ratio and make decisions for further monitoring the growth of fish.

VII. CONCLUSION

This research presents one of the object detection techniques for detecting young larvae and juvenile fishes from hatcheries. The result achieved of 85% is promising based on the first set of implementation. The result shows that the system is affected by the training data and the fish

image that obscured and has a lot of noise. In future work, certain measures can be taken to improve the accuracy of classification and counting the missed larvae's and juvenile fish by improving the classification algorithm.

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