A PROPOSED FISH COUNTING ALGORITHM USING DIGITAL IMAGE PROCESSING TECHNIQUE

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ABSTRACT

Fish product contributes a significant amount of protein demand of human nutrition and made up of about 16% of human diet all around the world. However, Fish production is one of the factors that have been a bottleneck for development of fish farming for most developing countries such as Nigeria. One of the major and time consuming task in production is providing an accurate estimate of the fingerlings to farmers. The methods of counting fingerlings in most developing countries is done manually. These manual methods are inevitably influence by inaccuracies and exposer of the fingerlings to unnecessary stress that could lead to death. This paper proposed a fingerling counting algorithm using digital image technique. To achieved this aim, a robust segmentation algorithm, feature extraction algorithm and machine learning algorithm for fingerlings classification and counting are hereby formulated. At the end of this research, the proposed algorithm is expected to count different sizes of fingerlings with high accuracy.

Keywords: Algorithm, Aquaculture, Counting, Digital Image Processing, Fingerlings, Fish

INTRODUCTION

Fish product contributes a significant amount of protein demand of human nutrition and its consumption have dramatically increased- about 27 million tons of fish were consume during 1948 and this has increase to about 145 million tons during 2007. Fish product is about 16% of human diet all around the world (Dowlati, de la Guardia, & Mohtasebi, 2012).

In some of the developing countries such as Nigeria, Fingerlings production has increased from 3 million per year in 2001 to more than 30 million per annum in 2006; Several large producers are delivering more than 300,000 fingerlings monthly (Potongkam & Miller, 2006). Despite this increase in fingerlings production, the industries still suffer shortages of high-quality Fingerling; This has driven fish farms/companies to establish hatcheries to fast-track their production (Daniel, 2015). For the past 40 years, fingerlings production has been a bottleneck for the development of fish farming in Nigeria and counting is one of the problems faced by hatcheries (Potongkam & Miller, 2006).

One of the essential most important operations in aquaculture is counting (Zion, 2012). This is very important because it help growers to accurately stock containers; pond or cages; manage precise feeding strategies and design a marketing schedule. Hatchery supply fingerlings to customers and one of the major and time consuming tasks is providing an accurate estimate of the fingerlings (Khantuwan & Khiripet, 2012).

Fingerlings are counted and sorted using a sorting table- into homogeneous groups of different sizes before supplying the fingerlings to the fish farmers based on their sizes. The different size can be temporarily stocked in hapas place (FAO, 2016).

The method of counting fingerlings in rural areas in most developing countries is mostly manual counting with hands which lead to stress and sometimes leads to death of the fingerlings. Manual counting processing is prone to mistakes, occasional omission as well as fatigue. Another method employ is the use of container to estimate the number of the fingerlings which could be inaccurate. Inaccurate estimation affects both hatchery and the customer- it could lead to over or under feeding and payment. On the other hand, digital image technique enable fast and robust counting with less error-prone and high scalability (Huang, Hwang, & Rose, 2016).

Several automatic counting systems have been devised over the years. Most of the available commercial counting product are optical techniques. Also, other techniques such as machine vision have been proposed. Majority of the work review in this work shows that many of such systems are suitable for mainly fishing or underwater counting while efforts has been made towards developing system for aquaculture farm, counting in aquaculture farms still present a major challenge.

In view of the aforementioned facts, counting using image processing technique would reduce the time consumption, minimize the exposure of the fish to unhealthy situation and ensure accurate estimation of fingerlings in the farm. Accurate and fast estimation will enhance fast delivery of fingerlings to farms, adequate feeding and proper financial plan for the growing of the fingerlings.

The rest of the paper is organized as follows: In section 2.0, the overview of related works is given. Section 3.0 discusses the proposed counting methodology while section 4.0 concludes the paper

Related works

The review is classified into four (4) categories as shown in Figure 1.: The classifications are fish counting by size, underwater counting system, commercial counting systems and fish farm counting system.

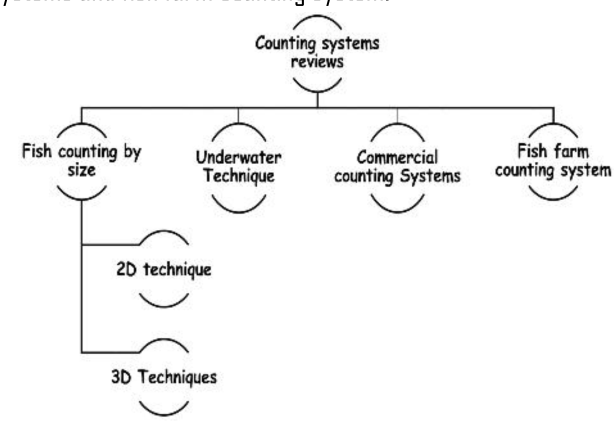

Figure 1. Review of related works

Over the years, a lot of research has been done in the above classification. Summary of fish counting works is shown in Table 1.

In summary, the reviewed works are basically based on other kind of fishes other than catfish; there is was no algorithm for fingerlings segmentation, features extraction, classification and counting. Commercial counting system could also be expensive and limited access among farmer in Nigeria. This warrant a closer look at fish farms issue especially in Nigeria where fish farming processes are mostly done manual. This work is proposed to address counting difficulties in Nigeria fish industries as well as improve accuracy of existing methods and technique by addressing water contamination.

Table 1: Review of Related works

N/O	TYPE OF COUNTING	AUTHORS
1	Fish counting by size	Arnarson (1991); Strachan (1993); Martınez-Palacios, Tovar, Taylor, Durán and Ross (2002); Ruff, Marchant and Frost (1995); Harvey *et al.* (2003); Mathiassen *et al.* (2006); Costa, Loy, Cataudella, Davis and Scardi (2006); Mathiassen, Misimi, Toldnes, Bondø and Østvik (2011); Huang, *et al.* (2016)
2	Underwater counting technique	Cadieux, Michaud, and Lalonde (2000); Morais, Campos, Padua, and Carceroni (2005); Costa, Scardi, Vitalini and Cataudella (2009); Han, Asada, Takahashi and Sawada (2010); Kang (2011); Costa *et al.*, (2013) Fabic, Turla, Capacillo, David and Naval (2013); Westling, Sun, and Wang (2014)
3	Commercial counting systems	VAKI (2016); SMITH-ROOT (2016); Rosenberry (2012); AquaScan (2016); IMPEX (2016)
4	Fish farm counting systems	Newbury, Culverhouse and Pilgrim (1995); Yada and Chen (1997); Friedland *et al.* (2005); Alver, Tennøy, Alfredsen and Øie (2007); Han, Honda, Asada and Shibata (2009); Toh, Ng, and Liew (2009) Zheng and Zhang (2010); Loh, Raman and Then (2011); Labuguen et al. (2012); Luo, Li, Wang, Li and Sun (2015); Duan *et al.* (2015)

PROPOSED FINGERLINGS COUNTING ALGORITHM

The proposed methodology consists of five steps: image acquisition, image preprocessing, image segmentation, features extraction, classification and counting, as well as algorithm evaluation using accuracy and mean square error. Figure 1., shows the block diagram of the proposed algorithm. Details of each unit in the block diagram is given in subsequent subsection.

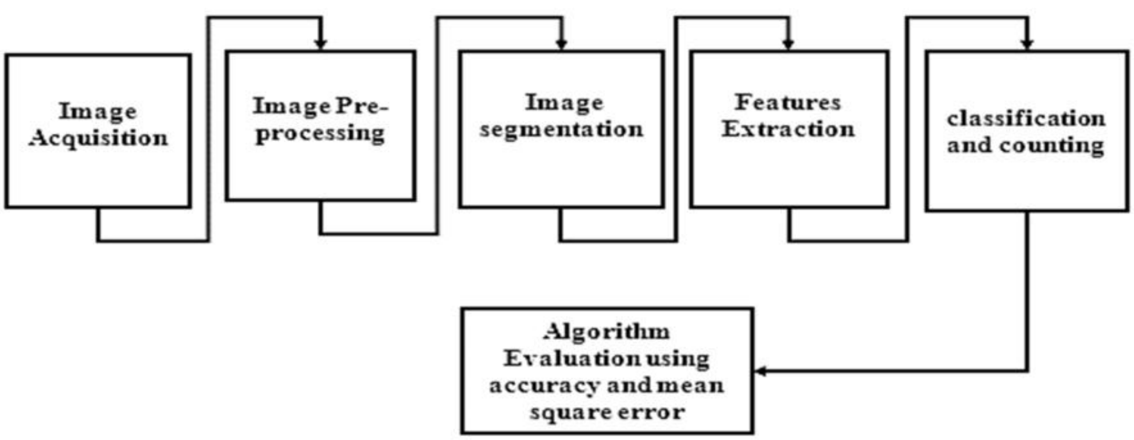

Figure 2: Proposed methodology

Image Acquisition

Image acquisition unit will consist of camera that will capture multiple images of a group of fingerlings. The multiple capture will improve accuracy and reduce the issue of overlapping since the fingerlings are dynamically moving around in the water. Number of fingerlings in each frame would be counted and the average total number of the fingerlings in all the frames will be reported as the estimated numbers of fingerlings using (2). At end of the research, the sizes of the container and depth of water would be reported as well as how these factors affect accuracy.

$$N_f = \frac{1}{N}\sum_{i=1}^{N}(f_i) \qquad (1)$$

Where N_f is the average number of fingerlings, f_i is total number of fingerlings in all the captured frames and N is the number of frames captured

Fish Image Pre-Processing

Water contamination due to feed and other factors is a common problem in fish pond. In order to be able to count successfully with higher accuracy in such water background, a preprocessing algorithm is proposed as shown Figure 2.

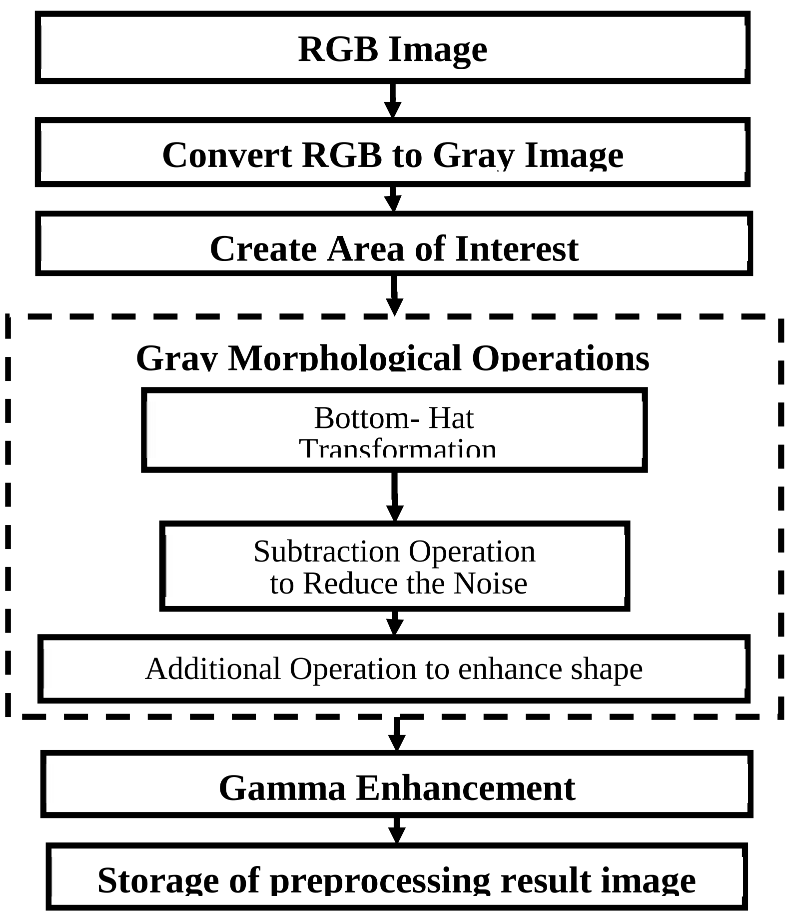

Figure 3: Image preprocessing algorithm

After image capture, the next step is to preprocess the image in order to filter the fingerlings and remove noise from the image. The image will first be converted from RGB to Grayscale image using the (2). Since unwanted portion of image significantly affect result (Duan et al., 2015), region of interest (ROI) image will then be created using the MATLAB function in (3) which generates a polygonal ROI. After this, Gray morphological operations and enhance processing will then be performed on the ROI image. For grey morphological operations, the image will first be bottom-hat transformed to produce a frame representing the change in illumination in the image using (4). Subtraction and Addition operations will be then executed on the image using (5) and (6) respectively. The subtraction operation will be used to subtract background variations in illumination from the image so that foreground fingerlings can be analyze easily (Fisher, Perkins, Walker, & Wolfart, 2003b). The addition operation will be used to make the fingerlings stand uniformly from the background (Fisher, Perkins, Walker, & Wolfart, 2003a). Finally, to make the fish stand out more uniformly from the background as well suppress noise, gamma correction will be used in (7).

$$I\ (x, y) = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \qquad (2)$$

Where R, G and B are Red, Green, Blue respectively of the RGB colour space.

$$I1 = roipoly\ (x, y, I, xi, yi) \qquad (3)$$

where I is the image of interest, vectors x and y are vectors that establish a nondefault spatial coordinate system? xi and yi are equal-length vectors that specify polygon vertices as locations in this coordinate system.

$$I2 = imbothat\ (I1, SE) \qquad (4)$$

where $I1$ is the input image and SE is the structuring element.

$$I3 = |\ I2(x, y) - C1\ | \qquad (5)$$

$$I4 = |\ I3(x, y) + C2\ | \qquad (6)$$

where $C1, C2$ are pixels constants that will be determine by trial and error.

$$I5 = A(I4)^{\gamma} \qquad (7)$$

where A is a constant equal to 1, and γ is the encoding gamma equal to 0.5.

Image Segmentation Algorithm

In the segmentation algorithm, the image would be subjected to a comprehensive three methods: thresholding, morphological operation and watershed segmentation. The process is described in Figure 3. The key operations in the algorithm is described below

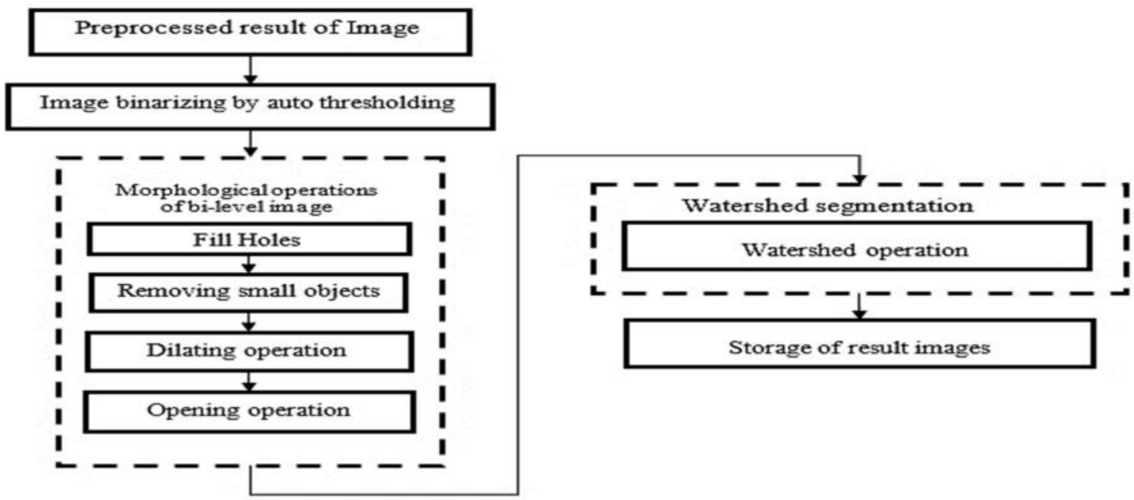

Figure 3: Image Segmentation Algorithm

Auto thresholding: Image binarizing will be done using an adaptive thresholding to correct some variation in mean grey level that could arise due to some factors such as unequal light exposure. The adaptive thresholding will binarized the image into pixel representing the fingerlings and pixels representing background using (8):

$$g = \begin{cases} 1, & \geq T = graytresh(I5) \\ 0, & otherwise \end{cases} \qquad (8)$$

Where g is the resulting binary image, T is the threshold generated by the graythresh MATLAB-function and $I5$ is the output image from the image preprocessing operations.

Morphological operation: After initial binarization by thresholding some fingerlings objects may have holes, some small noise may still exist and part of the fingerlings may be cut out. In order to correct these, a fill holes' operation will be executed using (9).

$$f\ (x,y) = \begin{cases} 1 - g(x.y), if (x,y) \text{ is on the border of } g \\ \quad 0, \quad otherwise \end{cases} \qquad (9)$$

where f is the marker image which is 0 except on the image border, where it is set to $1 - g$

Followed by an area opening operation to remove small objects from the binary image:

$$g\ o\ B = (\ g \ominus B) \oplus B \qquad (10)$$

The opening operation in (9) is obtained by the erosion ($\ominus$) of the image g by structuring element *B*, followed by dilation ($\oplus$)of the resulting image by *B*.

The size filter would be determined by experiment. All objects less than this size will be considered as noise and removed from the background.

Dilatation will then be executed to 'grow' and 'thicken' objects so that divided parts of fingerlings will be connected. Subsequently fill holes and small objects removal procedures will be performed again. Lastly, an opening operation will be used to remove, break and diminish false connections between fingerlings objects.

Watershed segmentation: After morphological operations, there could be still fingerlings that are connected. Watershed segmentation will further be employ to segment the fingerlings.

Features extraction algorithm

The feature extraction algorithm will extract size and shape features, suitable for estimating the average size of fingerlings in a given collection. This information will be use to classify and count the number of fingerlings in the next step. Chain-Code and Corner will be used for feature representation and description respectively. The chain-code boundary representation will be based on 8 connectivity segment in other to clearly represent the fingerlings. Haris Stephen is most suitable in this work for corner description because it allows for identification. Figure 4. shows the features extraction algorithm

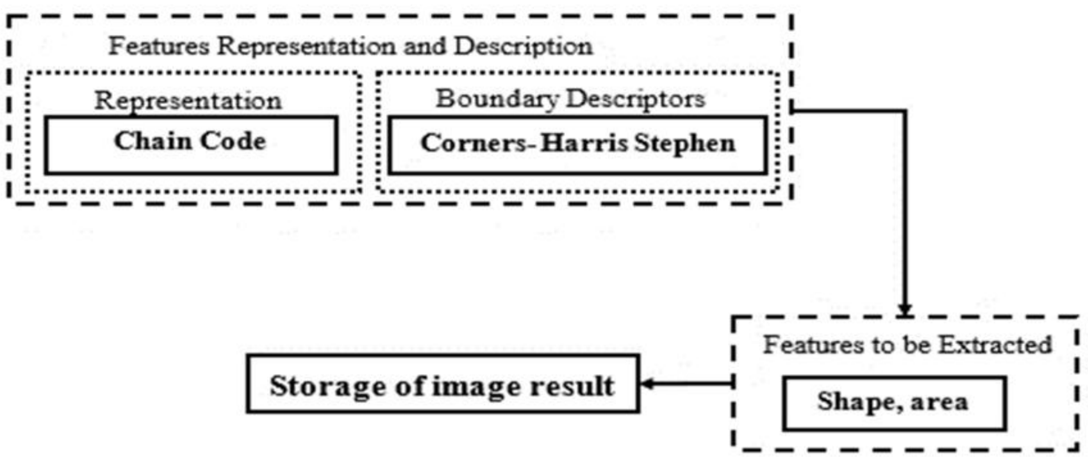

Figure 4. Features Extraction Algorithm

Classification and counting Algorithm

After the features extraction, the image will then be classified into two classes; Class 1 consist of fingerlings not connect in any way and class 2 consist of fingerlings connected in some ways. The features extracted will be use to estimate the area of the two class. From the area of the class 1, the mean and standard deviation of the area of a fingerling will be obtained. Since the fingerlings are of homogenous sizes, the mean and standard deviation of a single fingerling in class 1 represents the average sizes of the entire fingerlings. The means and standard deviation of the area will be used to train the Artificial Neural Network. The training will be done in order for the algorithm to be able to count fingerlings of various sizes and estimate mean and standard deviation for any given size. The mean and standard deviation for class 1 will be used to calculate the number of fish in the cluster of the connected or overlapped fish in class 2. The class 1 and class 2 count will then be sum up and this gives the count of the fingerlings. Figure 5. Shows the classification and counting algorithm.

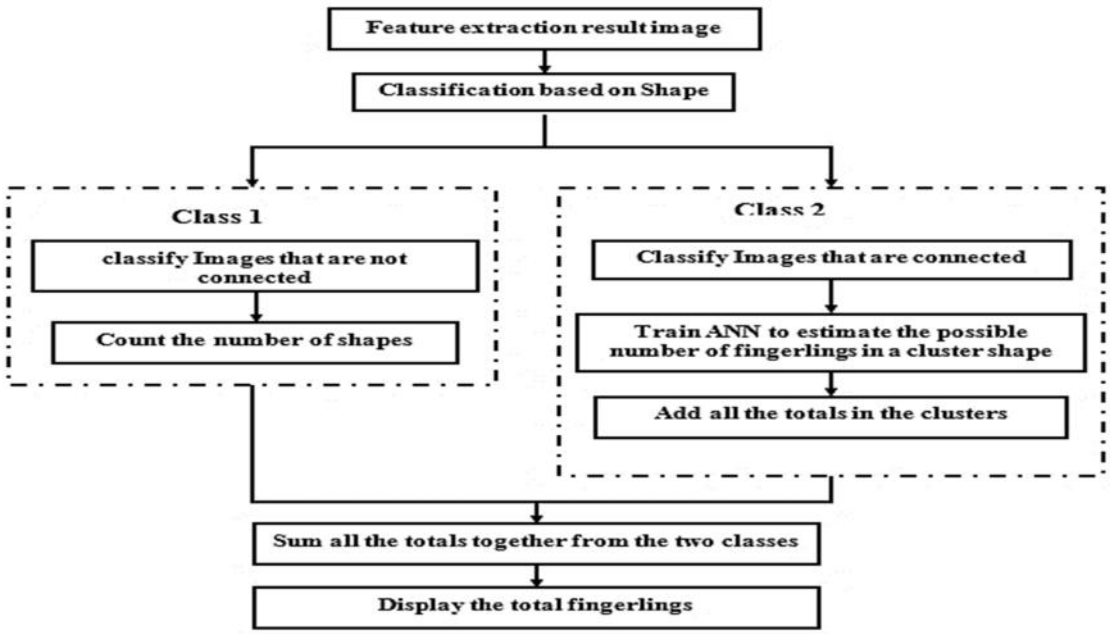

Figure 5. classification and counting algorithm

CONCLUSION

In this paper, a proposed algorithm for fish counting using digital image technique was presented. The review presented here revealed some general challenges faced by the aquaculture farms in counting fishes especially fingerlings in Nigeria. To the best of our knowledge, this review shows more extensive works have been concentrated towards underwater counting which might not be suitable for farms/hatchery. This call for a closer look at fish farms issue especially in Nigeria where fish farming processes are mostly done manually. The accuracy of the technique in the reviews need to be enhanced as well as in order to obtain optimal accuracy. This work is proposed to address counting difficulties especially in Nigerian fish industry as well as improve accuracy of existing methods and technique. To achieve counting with high accuracy, a robust segmentation algorithm for fingerlings segmentation, a feature extraction algorithm for the fingerlings segmentation, machine learning algorithm for fingerlings classification and counting was formulated. At the end of this research the proposed algorithm is expected to count different sizes of fingerlings with high accuracy as compare to existing works.

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