Identification of an Efficient Filtering-Segmentation Technique for Automated Counting of Fish Fingerlings

Lilibeth Coronel[1], Wilfredo Badoy[2], and Consorcio Namoco[3]
[1]College of Science and Environment, Mindanao State University at Naawan, Philippines
[2]Department of Information Systems and Computer Science, Ateneo de Davao University, Philippines
[3]College of Industrial and Information Technology Mindanao, University of Science and Technology, Philippines

Abstract: *The counting of fish fingerlings is an important process in determining the accurate consumption of feeds for a certain density of fingerlings in a pond. Image processing is a modern approach to automate the counting process. It involves six basic steps, namely, image acquisition, cropping, scaling, filtering, segmentation, and measurement and analysis. In this study, two (2) filtering and two (2) segmentation algorithms are identified based on the following observations: the non-uniform brightness and contrast of the image; random noise brought about by feeds, waste, and spots in the container; and the likelihood of the image samples or application used by the different authors of the smoothing and clustering algorithms in their respective experiments. Four (4) combinations of filtering-segmentation algorithms are implemented and tested. Results show that combination of local normalization filter and iterative selection threshold yield a very high counting accuracy using the measurement function such as Precision, Recall, and F-measure. A Graphical User Interface (GUI) is also presented to visualize the image processing steps and its counting results.*

Keywords: *Digital image processing, filtering, segmentation, image normalization, threshold.*

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1. Introduction

Fish fingerling has to be handled several times before stocking into ponds or containers. Fingerling stocking marks the beginning of a production cycle. It is among the most delicate and stressful processes the fingerlings go through in the course of production. The process of stocking starts with the counting of fingerlings from the hatchery, transporting them to the farm and, finally, putting them into the pond. Traditional process of counting fish fingerlings such as manual, volumetric, and surface area methods are still adopted nowadays. Problem like handling of fingerlings are very critical since the fingerlings are weighted in volume in a container and again count them manually. But today, through the continuous advancement of information technology, innovations and integration between computer science and aquaculture facet is very promising and remarkable. Image processing is a rapidly growing area of computer science. It involves six basic steps, namely, image acquisition, cropping, scaling, filtering, segmentation, and measurement and analysis.

Several studies have been conducted to automate the counting of fish using image processing [2, 5, 6, 10]. Different filtering and segmentation algorithms have been used for different purposes of the studies, namely, counting accuracy, classification, behavioural aspects of the fish, and the overall installation and setup of image/video acquisition. Problems like error of counting escalate as the number of fish increases; fish sizes are unknown; and fish orientation differ. Sometimes fish may not be segmented reliably, lighting variations in acquiring image and changes in water quality, thus causes an error in counting. In addition, installations and the use of fragile equipment can be problematic when used in remote locations.

In this study, we identify two filtering and two segmentation algorithms based on the following observations: the non-uniform brightness and contrast of the image; random noise brought about by feeds, waste, and spots in the container; and the likelihood of the image samples or application used by the different authors of the smoothing and clustering algorithms in their respective experiments. Such filtering and segmentation algorithms considered in this study include Local Normalization filter [9], Median filter [7], Iterative Selection threshold [8] and Minimum-Error threshold [4].

The study also designed and developed a prototype to automate the counting of fish fingerlings employing the image processing steps with the identified combinations of filtering and segmentation techniques using java-programming language and an open source image processing and analysis program.

2. The Research Method

Figure 1 shows the overall image processing system model used in this study. Combinations of filtering and segmentation algorithms are applied to identify the efficient technique for counting the fish fingerlings.

2.1. Image Acquisition

In this step, images of tilapia fish fingerlings are acquired using a Canon PowerShot A3200 IS digital camera with 14.1 megapixels. The samples are placed in a white plastic dishpan of size 48x12 cm with water level of 4.45 cm in height. The size and age of the samples are approximately 14-16 mm and 21-28 days old.

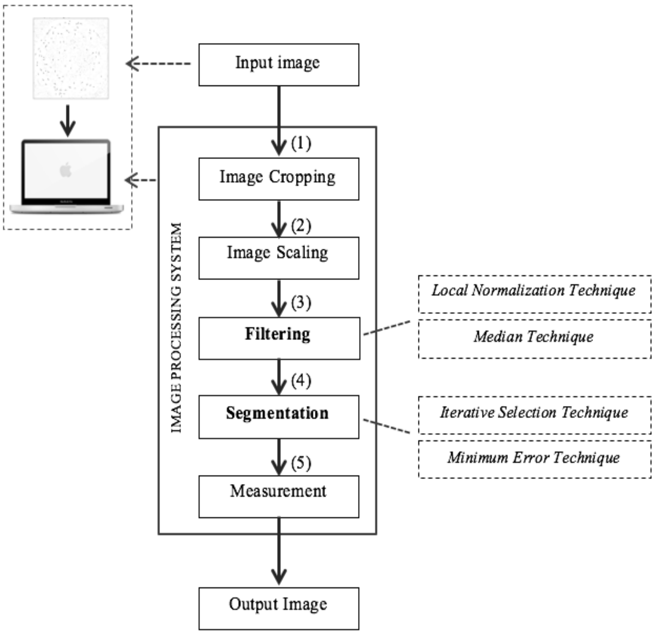


Figure 1. Image processing system model used.

The position of the camera must be stable and the distance from the dish is 60 cm in height with respect to the dimension and areas inside the dishpan. The images are taken between 1:00 to 3:00 in the afternoon notwithstanding the lighting installation and setup. Figure 2 shows the image acquisition setup used in the implementation. The camera settings applied include: ISO speed at ISO-80, F-stop of f/8, focal length of 5 mm with aperture of 2.968, and flash mode is set to Off. The dimension of the image is 4320 x 3240 pixels. The image file is in Joint Photographic Experts Group (JPEG) format.

Figure 2. Image acquisition setup.

2.1.1. Input Image Representation

The image is denoted as two-dimensional function of the form $f(x, y)$. The amplitude of the image f at spatial (plane) coordinates (x, y) is a positive scalar quantity whose physical meaning is determined by the source of the image. The image result has W rows and H columns. The complete W x H digital image in a compact matrix form is:

$$f(x,y)=\begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,H-1) \\ f(1,0) & f(1,1) & \cdots & f(1,H-1) \\ \vdots & \vdots & & \vdots \\ f(W-1,0) & f(W-1,1) & \cdots & f(W-1,H-1) \end{bmatrix} \quad (1)$$

The right side of this equation is by definition a digital image. Each element of this matrix array is called pixel.

2.2. Image Cropping

In this process, the image is cropped using ImageJ built-in cropping function as seen in Figure 3.

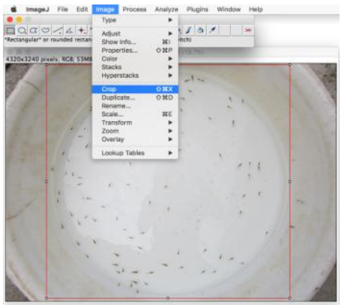


Figure 3. Image cropping.

2.3. Image Scaling

After cropping, the image passes through the image scaling using again the ImageJ built-in scaling function as seen in Figure 4.

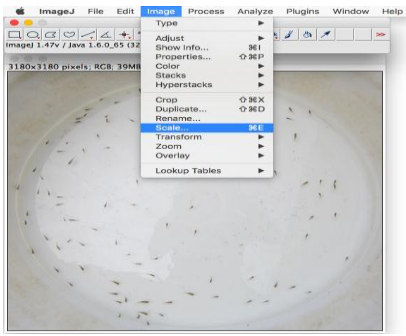


Figure 4. Image scaling.

2.4. Filtering

In the filtering step, two techniques are used separately as filtering step in the image processing system.

2.4.1. Local Normalization

The local normalization [9] is a modern and efficient filtering technique used for correcting non-uniform illumination or brightness and eliminates the effects of uneven noise in an image. The local normalization of $f(x,y)$ is computed as:

$$g(x,y)=\frac{f(x,y)-m_f(x,y)}{\sigma_f(x,y)} \quad (2)$$

Where $f(x,y)$ is the input image, $m_f(x,y)$ and $\sigma_f(x,y)$ represents the estimation of the local mean and variance of $f(x,y)$ and $g(x,y)$ is the output filtered image. The local mean and variance of the image are estimated by a recursive Gaussian filter. The parameters of the algorithm are the sizes of the smoothing window σ_1 and σ_2 which value is larger than σ_1 that controls the estimation of the local mean and variance.

2.4.2. Median Filter

The median algorithm [7] is the simplest and widely used median filtering that normally reduces random noise in an image. The values of the pixel in the window are stored and the median – the middle value in the sorted list (or average of the middle two if the list has an even number of elements)-is the one plotted into the output image. The median filtered image $g(x,y)$ can be obtained from the median pixel values in a neighborhood of (x,y) in the input image $f(x,y)$, as defined by the following formula:

$$g(x,y)=median\left[\sum_{i=-1}^{1}\sum_{j=-1}^{1}f(x-i,y-j)\right] \quad (3)$$

2.5. Segmentation

Similarly, two techniques are used separately as segmentation step in the image processing system.

2.5.1. Iterative Selection Threshold

The simplest of all the thresholding techniques is the iterative selection method [8]. The method models the gray level distribution in an image as mixture of two Gaussian distributions representing, the background and foreground region. The threshold is computed as:

$$T_n=\frac{m_{f,0}+m_{b,0}}{2} \quad (4)$$

Where at iteration n, a new threshold T_n is computed using the average of the foreground $m_{f,0}$ and background $m_{b,0}$class means. On each iteration, the mean gray level for all pixels greater than T is determined, and is denoted asG_1. The mean gray level for all pixels lesser than or equal to T is also determined, and is denoted asG_2. Iteration terminates when the changes $|T_n$–T_{n+1} becomes sufficiently small.

2.5.2. Minimum Error Threshold

The minimum error threshold algorithm [4] is based on the assumption of object and background pixels gray level values in the image being normally distributed. Normal distributions are defined by their means μ_i, standard deviations σ_i, and a priori probabilities P_i. The background and foreground represents two different classes (i=1, 2) and a given threshold T. The minimum error threshold can be computed by minimizing the criterion function $J(T)$ calculated as:

$$\begin{aligned}J(T)&=1+2\left[P_1(T)\log\sigma_1(T)+P_2(T)\log\sigma_2(T)\right]\\&-2\left[P_1(T)\log\sigma_1P_1(T)+P_2(T)\log\sigma_2P_2(T)\right]\end{aligned} \quad (5)$$

This is applied since some of the images have non-uniform brightness or poor intensity condition with fishes as object of interest.

2.6. Measurement

Measurement of the object of interest or the fingerlings thru defining the *size*, *circularity* ranges of the fingerlings as pixels and its *height-to-width-ratio* is implemented. The output of this measurement method is the summary of the total number of fish fingerlings identified. The parameters of this method are the *sizes* and *circularity* that specifies the range pixel values inside the object and its shape. The parameters may vary depending on the age of the fingerlings.

The number of pixels it contains defines the *size* of an object. A patch P consisting represents each object of a list of lines l, the number of pixels n is given by:

$$n=\sum\nolimits_{l\in L(P)}\left(x_e(l)-x_s(l)\right) \quad (6)$$

The *circularity* C_r specifies the object-based shape measurement calculated by the formula:

$$C_r=\frac{4\pi\times A}{\rho^2} \quad (7)$$

Where A is the area and ρ is the perimeter.

In determining the object of interest, the *Height-To-Width Ration (HTWR)* is applied represented by a patch P is given by:

$$HTWR=\frac{y(i_{\max}(P))-y(i_{\min}(P))}{x(i_{\max}(P))-x(i_{\min}(P))} \quad (8)$$

Which helps identify objects that are either too long compared to their height or too tall compare to their breadths. Thus, if either of the following conditions for patch P is satisfied,

$$\begin{aligned}&HTWR(P)<HTWR_{\min}\\&HTWR(P)>HTWR_{\max}\end{aligned} \quad (9)$$

P is classified as noise and taken off from the *PatchList*.

2.6.1. Identifying Combinations of Filtering and Segmentation Techniques

In identifying Combinations C for the experiments,

where F stands for filtering (Local Normalization, Median filter) and S stand for segmentation (Iterative

Selection threshold, Minimum Error threshold), the product F x S is the set of all pairs (f,s) where f denotes filtering techniques such as Local Normalization and Median, $f \in F$ and s denotes segmentation techniques such as Iterative Selection and Minimum Error, $s \in S$. The groupings must satisfy the following rules for each of the image processing model:

1. A group must have only one filtering and one segmentation technique.
2. The filtering technique must come first before segmentation technique.

These combinations are evaluated based on the accuracy of counting the fish fingerlings, namely, Combination A *(Local Normalization and Iterative Selection),* B *(Local Normalization and Minimum Error),* C *(Median and Iterative Selection)* and D *(Median and Minimum Error),* respectively.

2.6.2. Counting Evaluation

Four combinations of filtering and segmentation algorithms are compared and evaluated thru calculating the following information retrieval measures, namely, *Precision*, *Recall*, and *F measure*. The evaluation is widely used in other studies in terms of image analysis [1, 2, 3]. The *Precision (P), Recall (R),* and *F-measure* are calculated by:

$$P = \frac{tp}{tp + fp} \tag{10}$$

$$R = \frac{tp}{tp + fn} \tag{11}$$

$$F\,measure = \frac{2 * P * R}{P + R} \tag{12}$$

where True Positives (TP) represent the number of fish fingerlings correctly identified as fish fingerlings, False Positive (FP) represents incorrectly identified by the method as a fish fingerlings such as noise in the image and False Negative (FN) represents fish fingerlings that are not identified as fish fingerlings but are existed.

Furthermore, the best *F measure* among the four combinations is compared with the actual number of fish fingerlings. That is, the level of closeness of measurements of the total number of fish fingerlings to that of the actual (true) number of fish fingerlings. The computed *F measure* are between 0 and 1. A higher value of *F measure* indicates a higher classification or clustering quality and lower error rates or misclassification of fish fingerlings.

3. Experimental Results

The image processing system is implemented as a plugin to an image processing software and analysis tool (ImageJ, [7]) employing the four identified combinations of filtering and segmentation techniques to automate the counting of fish fingerlings.

Figures 5, 6, and 7 show the visualization results of the image processing system employing the Combination A technique. Figure 5 shows the sample acquired JPEG format image of Tilapia fish fingerlings with the dimension of 4320x3240 pixels used as input image. The input image is cropped to approximate the region of interest. The dimension of the image is reduced to 3180 x 3180 pixels as shown in Figure 6.

The cropped image is rescaled to half of its dimension to downsize and classify the pixel values that surrounds the image as shown in Figure 7. The dimension of the image is reduced to 1590x1590 pixels. The scaled image is filtered according to the parameters set. The filtered image is segmented to cluster the object of interest from its background region. The segmented image is then processed to measure the object of interest being identified.

Figure 8 shows the visualization results of the image processing systems employing Combination A. The image results show significantly very high in noise reduction and feature identification thus generating remarkable counting results. Combination B shows significantly very high in noise reduction but very poor in feature identification thus generating very poor counting results. This is shown in Figure 9. Figures 10 and 11 shows significantly poor in noise reduction and relatively poor in feature identification thus also generating poor counting results for both Combinations C and D. Figure 12 shows the ImageJ Graphical User Interface (GUI) of the automated system using Combination A.

The parameters defined are based on the actual size of the fish fingerling samples, the non-uniform brightness and contrast of the image; random noise brought about by feeds, waste, and spots in the container. Combinations A and C requires two input parameters since these combinations used Local Normalization as the filtering method. Such parameters includeσ_1=2, σ_2=50, *size*=80-300*pixels*, and *circularity*=0.09-1.0. While Combinations B and D only requires *radius*=2 as input parameter with the same *size* and *circularity* values.

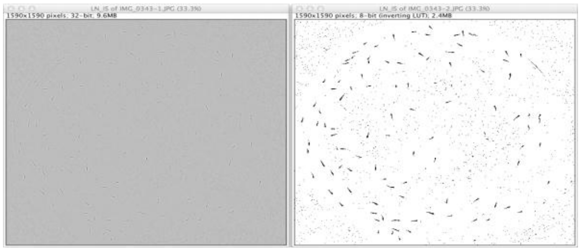
Table 1 shows the average measurement result of the image processing system employing the four different combinations of the filtering and segmentation techniques. The experiment considered 2 groups of images, each group having 5 images. Group A contains 50 Tilapia fish fingerlings in each image and Group B has 100 fish fingerlings in each image.

The result shows that Combination A has the highest *Precision*, *Recall*, and *F measure* values as compared to other combinations of the filtering and segmentation techniques.

Figure 5. Sample tilapia fish fingerling.

Figure 6. Cropped image.

Figure 7. Scaled image.



a) Local Normalization filter. b) Iterative Selection threshold.

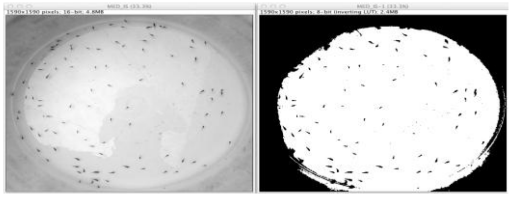
Figure 8. Image result using combination A.

Table 1. Average measurement results of the four combinations of Filtering and Segmentation techniques.

Images	Techniques	Measures (%)		
		Precision	**Recall**	**F measure**
Group A	*Combination A*	99.59	98.41	98.99
	Combination B	NaN	23.60	NaN
	Combination C	89.20	49.20	63.15
	Combination D	85.92	33.65	48.06
Group B	*Combination A*	100	97.40	98.68
	Combination B	NaN	11.60	NaN
	Combination C	91.26	48.40	62.90
	Combination D	84.46	34.60	48.83

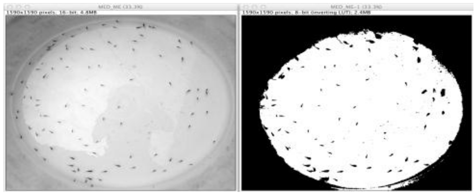
a) Local Normalization filter. b) Minimum Error threshold.

Figure 9. Image result using combination B.



a) Median filter b) Iterative Selection threshold.

Figure 10. Image result using 1Combination C.



a) Median filter. b) Minimum Error threshold.

Figure 11. Image result using combination D.

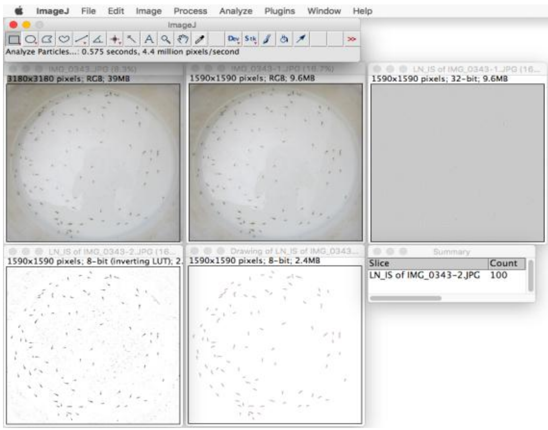


Figure 12. ImageJ GUI of the automated system.

Table 2. Detailed experimental results comparing the combination A and the manual counting process.

Image no.		Automated Counting System using Combination A technique						Manual Counting process					
		No. of Tilapia Fingerlings			Measures			No. of Tilapia Fingerlings			Measures		
		TP	FP	FN	*P*	*R*	*F measure*	TP	FP	FN	*P*	*R*	*F measure*
Group A (with 50 Fingerlings)	1	50	0	0	1	1	1	50	0	0	1	1	1
	2	49	0	1	1	0.98	0.98989899	50	0	0	1	1	1
	3	49	0	1	1	0.98	0.98989899	50	0	0	1	1	1
	4	50	0	0	1	1	1	50	0	0	1	1	1
	5	48	1	2	0.979591837	0.96	0.96969697	50	0	0	1	1	1
		Average			0.995918367	0.984	0.98989899	*Average*			1	1	1
Group B (with 100 Fingerlings)	6	97	0	3	1	0.97	0.984771574	100	0	0	1	1	1
	7	95	0	5	1	0.95	0.974358974	100	0	0	1	1	1
	8	97	0	3	1	0.97	0.984771574	100	0	0	1	1	1
	9	100	0	0	1	1	1	100	0	0	1	1	1
	10	98	0	2	1	0.98	0.98989899	100	0	0	1	1	1
		Average			1	0.974	0.986760222	*Average*			1	1	1

This means that Combination A has the highest percentage of correctly identified fish fingerlings, the lowest percentage of incorrectly identified fish fingerlings and the lowest percentage of noise identified. It is observed that the Combination B yields insignificant results in which *Precision and F measure* result are Not-a-Number (NaN). It can be seen from Table 1 that Combinations C and D cannot outperform the accuracy of Combination A.

On the other hand, the efficiency of the local normalization technique to correct non-uniform lighting and the reduction of noise in an image are very significant. The Iterative Selection technique also achieves significant results in feature identification.

It can also be observed from Table 2 that the variance of counting results between Combination A and the manual counting are 0.20%, 2.10% and 1.17% in average *Precision*, *Recall* and *F measure* values, which are very minimal. These measurements indicate that result of the automated system is very close to the manual counting results.

The automated counting system results show that the total number of correctly identified fish fingerlings (*tp*) are very high in the two groups of images but it is observed that as the number of fish fingerlings increases, the number of fish fingerlings that are present but are not actually counted (as if they did not existed) (*fn*) also increases. Moreover, the automated counting system using Combination A obtained the value of zero (0) in terms of the number of incorrectly identified as fish fingerlings (*fp*) such as noise, hence it is very close to that of the manual counting.

Furthermore, the rate of time in counting the fish between automated and manual system is also compared as seen in Table 3. The automated system is tested on an Intel Core i5 processor with 4Gb of memory. The time measurement indicates that automated system significantly performs best compared to manual counting process.

4. Conclusions

Combination A (Local Normalization and Iterative Selection) provides significantly very high in correcting non-uniform lighting in an image, noise reduction and feature identification compare with other combinations of filtering and segmentation techniques. In terms of counting accuracy, Combination A obtained an average *Precision*, *Recall* and *F measure* of as high as 99.80%, 97.90% and 98.83% which outperformed other combinations, respectively. Moreover, with the automated system, manual-counting delays can be resolved. Mortality rate of the fish fingerlings also decreases, thus, providing an increase in production of fish fingerlings among the growers and aquatic biological experts.

Table 3. Time measurement results between automated counting system using combination A and manual counting process.

Image no.		Automated Counting System using Combination A technique		Manual Counting process	
		Count	Time (sec)	Count	Time (sec)
Group A (with 50 Fingerlings)	1	50	0.526	50	28
	2	49	0.503	50	26
	3	49	0.488	50	25
	4	50	0.478	50	24
	5	49	0.494	50	23
Group B (with 100 Fingerlings)	6	97	0.501	100	55
	7	95	0.446	100	53
	8	97	0.513	100	51
	9	100	0.575	100	50
	10	98	0.512	100	49

5. Recommendation

For future work, it is suggested to further enhance the identified technique to improve the counting efficiency of the automated system with higher number of samples that would not just provide counting statistics but as well as identify the type of fingerlings. Implementation of connected and independent components algorithm is also recommended for accidentally connected or overlapping fingerlings. The algorithms used in the study may also be enhanced for possible applications in other non-aquatic and non-biological samples.

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Lilibeth Coronel completed her Master's Degree in Information Technology at Mindanao University of Science and Technology, Philippines last 2014 and Bachelor's Degree in Computer Science at AMA Computer College, Philippines last 2001. Presently, she is an assistant professor in the Department of Information Technology at Mindanao State University-Naawan Campus, Philippines and at the same time ICT Unit Head of the Campus.

Wilfredo Badoy received an Electronics Engineering degree at Mindanao Polytechnic State College in 1995, his MS Information Technology at Ateneo de Davao University in 2009. He is currently finishing his Ph.D. in Computer Science at Ateneo De Manila University. He has worked with various schools in Northern and Southern Mindanao for more than 15 years. His interests are in Artificial Intelligence, Affective Computing, and Computer Simulation. He has published researches in journals and conference proceedings.

Consorcio Namoco completed his Doctor of Engineering from Kyoto Institute of Technology, Kyoto City, Japan last 2012. His research interests are in the fields of metal forming, computer simulation, materials processing, industrial technology and information technology education. Presently, he is a full professor and the vice chancellor for academic and student affairs, University of Science and Technology in Southern Philippines, Cagayan de Oro City, Philippines. He also serves as editorial board member and peer reviewer to various local and international research journals.