

ZOEAL CRAB LARVA COUNTER (CLARCO) BASED ON IMAGE PROCESSING WITH ADAPTIVE GAUSSIAN FILTER ALGORITHM and BLOB DETECTION TECHNIQUE

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ABSTRACT

The size of crab larvae is very small, as best as our knowledge there is no accurate and easy-to-use crab larvae counting tool at an affordable price. The low larval survival rate is due to the unknown larval stocking density, which causes cannibalism, a feed-to-larvae ratio that is out of proportion to the number of larvae needed to maintain water quality, a water supply that is out of proportion to stocking density, and is economically unfavorable in terms of cultivation, feed management, maintaining water quality, and the buying and selling process. Accurately estimating the amount of crab larvae is anticipated to boost their survival rate and make them more economically successful. This research is a continuation of previous research with the addition of different methods using adaptive gaussian filter algorithms and blob detection techniques to count crab larvae in the zoea-2, zoea-3, and zoea-4 phases where an increase in accuracy was obtained with an average of 97.67%.

Keywords: Adaptive gaussian filter, Blob detection technique, Crab larvae, Counter, Image processing

1. INTRODUCTION

Rapid population growth both in Indonesia and the world as a whole is directly proportional to the increasing need for food and food with better nutrition. Since the consumption of safe and healthy food is now prioritized in terms of providing people's nutritional needs, there is a significant demand for alternative proteins. In other words, dietary preferences have shifted from products based on red meat to foods based on white meat, which is food from ocean. Crab meat is one of the most popular products.

The market demand for high-protein crab intake rises as a result of this paradigm shift, and Indonesia, a marine nation, is one of the nations that produces crab for both domestic and international markets. The life cycle of crabs to become adults is divided into five phases, namely eggs, zoea, megalopa, juvenile crab or crablet, and adult crabs. However, only a very small percentage of crab larvae survive to become adult crabs; the maximum survival rate is about 14.12 031% (R & MK, 2012) for the zoea to megalopa phase, only 40.14 ± 0.424%

(Zakaria et al., 2013) from the megalopa to crablet phase and in general the highest survival rate of crab larvae is only between 20 - 50% (Nicholas & Chaoshu, 2008).

The phase with the lowest survival rate is the larval phase (zoea-megalopa) with a survival rate of $14.12 \pm 0.31\%$. Currently, the availability of adult crabs for consumption needs in both domestic and export markets is the result of direct capture in nature, which if it continues will threaten extinction due to greater demand but very low crab survival rates, especially crab habitats that are increasingly eroded by development and world climate change. The process of crab cultivation is still very difficult to do due to high mortality and lack of technologies that can help the cultivation process. It is not surprising that until now there are still very few crab farms in Indonesia. This is a serious issue that needs to be addressed right away in terms of crab production, especially crab farming, by developing technological solutions.

The very small size of crab larvae, about 0.5 mm to 2 mm, and the absence of tools to count crab larvae accurately and easily at a low cost, force farmers to use traditional sampling and evaluation methods, namely by estimation where the impact is that the larval stocking density is not accurately known, this poses a significant danger of escalating larval mortality during cultivation. If the feed ratio exceeds the larvae's needs, the larvae will become polluted, affecting the quality of the water environment, while if the feed ratio is insufficient, the larvae will lack nutrients, leading to mortality or a high level of cannibalism, which also increases the mortality rate. In addition, an inaccurate larval count means that the aquatic environment as a habitat for larvae cannot be controlled according to stocking density.

Due to the uncertainty surrounding the amount of larvae purchased, erroneous larval counts can have a negative economic impact on aquaculturists with high death rates as well as consumers looking to purchase during the larval stage. In the larger business process, it will reduce market confidence and ultimately the crab farming business will not have good business value. Aquaculturists currently employ the population sampling approach and use the average of repeated samplings to count larvae. In truth, when estimating the quantity of crab larvae, the majority of traditional aquaculturists typically rely entirely on estimates.

In the author's previous research, the author has counted crab larvae with image processing only in the zoea 1 larval phase with 89.88% accuracy (Zakiyabarsi et al., 2019). Based on these things, the author raises the research title Image Processing-Based Crab Larvae Counter zoea 2 - zoea 4 with Adaptive Gaussian Filter Algorithm and Blob Detection Technique with a slightly different method to offer information on the quantity of crab larvae that is anticipated to have higher accuracy than prior studies and can be used by the general public for cultivation and economic purposes in a simple and cost-effective manner.

2. THEORY

A. Image Processing

Image processing is a system where the process is carried out with an image as the input and the image as the output. Initially, image processing was carried out to enhance image quality, but as the computing industry developed—characterized by an increase in the capacity and speed of computer processes and as computer sciences emerged, it became possible for

people to extract information from an image. The field of computer vision and image processing are interrelated (Mulyawan et al., 2011).

B. OpenCV

OpenCV, also known as "Open Computer Vision," is a free library created by Intel Corporation especially for image processing. The objective is for computers to be able to process visual information similarly to humans. Both a high-level and low-level OpenCV API is available, and there are pre-built functions for loading, storing, and acquiring images and videos (Mulyawan et al., 2011).

C. Adaptive Gaussian Filter

Thresholding is a method for segmenting color or grayscale images based on color or grayscale values that turns an image into a binary picture by changing each pixel based on whether it is inside or outside of a predetermined range. To process the histogram, the user chooses the lower and upper threshold values. A pixel receives the value "inside" if it is located within this range. Otherwise, the value "outside" is given to it. Thus, testing against a function T can be seen as a component of the thresholding operation,

$$T = T[x, y, p(x, y), f(x, y)],$$

where $f(x, y)$ is the gray level of the point (x, y) and $p(x, y)$ denotes some local property of this point, for instance, the average gray level of a neighborhood. Setting a background value for pixels below the threshold value T and another set of values for the foreground is the actual process of thresholding. The threshold image, $g(x, y)$ is then defined as (Huang & Chau, 2008)

$$g(x, y) = \begin{cases} 0, & f(x, y) < T, \\ 1, & f(x, y) \geq T, \end{cases}$$

According to Figure 2, the normal distribution law serves as the foundation for the Gaussian filter. It varies based on the Gaussian weight parameter from the normal distribution law to average filtering. The Gaussian filter's threshold modulation technique enables us to do adaptive noise reduction and filtering based on the region content (texture or flat). To distinguish between flat and textured surfaces, use the standard deviation. Flat areas have low standard deviation values, which enables the Gaussian filter to operate as an average filter in order to adapt to the low standard deviation and filter flat areas more evenly. To maintain the texture reduction, the filter is biased to act as a normal law filter in texture fields where the standard deviation value is higher.

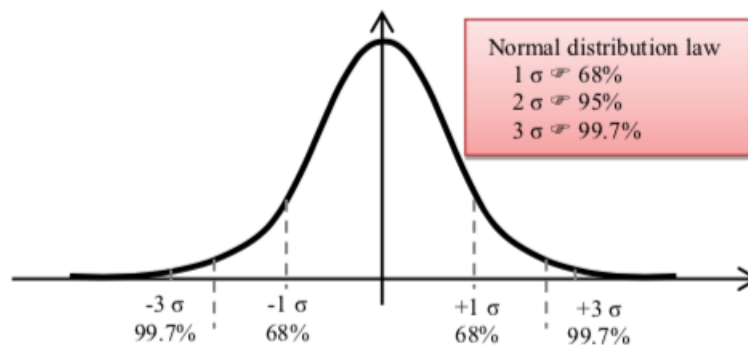


Figure 1. Normal Distribution Law

It is shown very well to use the threshold modulation method of the Gaussian noise removal filter for adaptive noise filtering of flat and texture plane images. A select group of sensor applications, including those in the gaming, security, medical, automotive, and high-end camera industries, are very interested in this method. To evaluate the efficiency of the Gaussian filter noise threshold removal filter modulation technique, some tests were carried out. This approach demonstrated good noise reduction in both textural and flat fields. After using the Gaussian filter with threshold modulation approach, texture information is kept in the final image (Gupta, 2015).

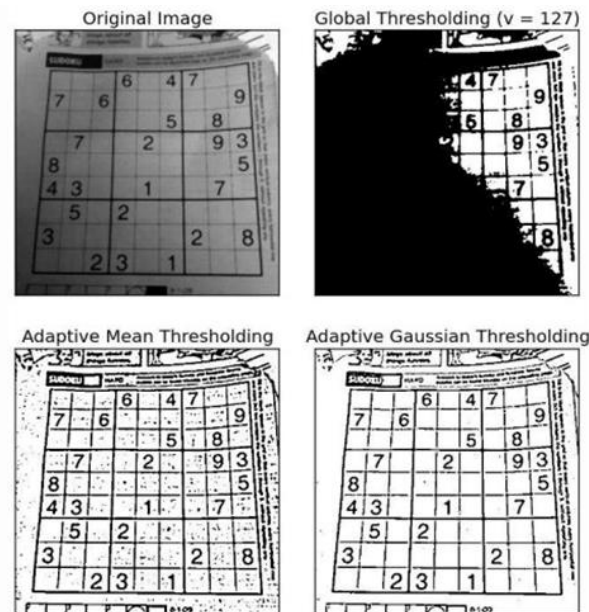


Figure 2. Example of Comparison of Adaptive Gaussian Threshold Results

D. Blob Detection Technique

Blob analysis techniques are used to locate, count, and measure items depending on their characteristics (Damerval et al., 2007). Blob analysis checks the accuracy, logic, and correctness of the operations used to produce the results. Pixel values are the input to the sophisticated algorithms used by image processing software. The image analysis software of today combines both modern and antiquated methods. A blob is referred to in image processing as a collection of linked pixels. Blob analysis is the recognition and examination of areas in photographs (Forss, 2003)(Gerig et al., 1995). This algorithm separates pixels based on their values and assigns them to one of two groups. Specifically, foreground (often a non-zero value pixel) or background (normally a zero value pixel).

Touching foreground pixels are frequently included in the same blob by the analysis tool since a blob is a region of pixels that are close to one another. As a result, the software may perceive what the human eye easily distinguishes as a collection of separate but touching blobs as a single blob. Additionally, during analysis, any area of the blob that has background pixels owing to lighting or reflection is treated as background (Hinz, 2005).

The effectiveness of the blob analysis process depends on effective picture segmentation, which involves deleting everything in the image that is not necessary for detection and

separating good blobs from the background and from one another. Binarization is a step in the segmentation process (Ming, 2007). If a straightforward segmentation cannot be performed because of insufficient lighting or blobs that are the same gray level as the background, a segmentation algorithm tailored to the specific image must be created. The acquired image can have noise, fake blobs, or holes that could have been brought on by noise or lighting. Such superfluous blobs may impede the accuracy of blob analysis results (Khanina et al., 2014). Before using an image, it should be pre-processed if it has some superfluous blobs. Preprocessing is any operation done to prepare an image for analysis, such as thresholding or filtering (Patil et al., 2015).

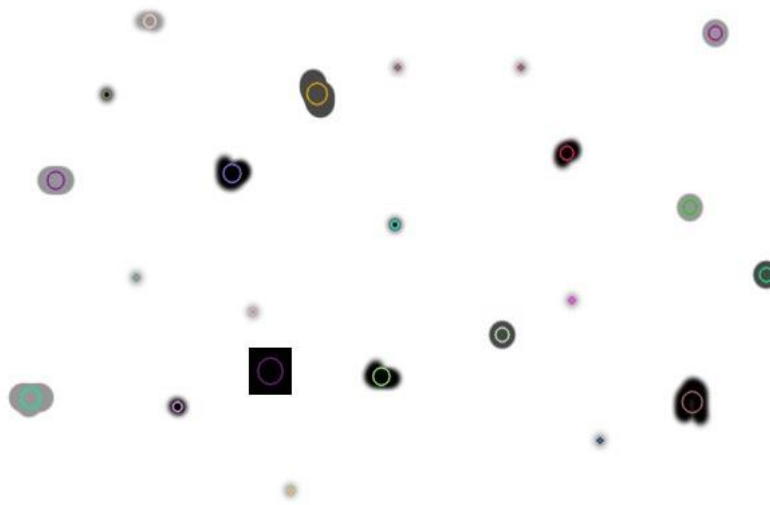


Figure 3. Example of Blob Detection

3. METHOD

A. Image Acquisition

The majority of Indonesians use smartphones with cameras that have specs above 8 Mega Pixels, thus it is anticipated that the community will accept this research's application well. In order to compare the accuracy results, this research used the same apparatus as earlier studies, as follows:

- 1) Software
 - a. Mac OS Sierra
 - b. Anaconda (Python)
 - c. OpenCV
- 2) Hardware
 - a. Laptop MacBook Air Core i5 processor (1.40 GHz)
 - b. Intel SSD 128 GB
 - c. DDR3 4 GB Memory
 - d. 11" Monitor
 - e. Oppo F7, Vivo V9, dan Vivo V15 Cellphone
 - f. Clarco specialized larval container

B. Model Description

The special Clarco (Crab Larva Counter) container is made with used materials so that later it can be purchased and used by the cultivation community at a low price, while the

application hardware uses a cellphone with a camera above 8 Mega Pixel which is currently used by most people.

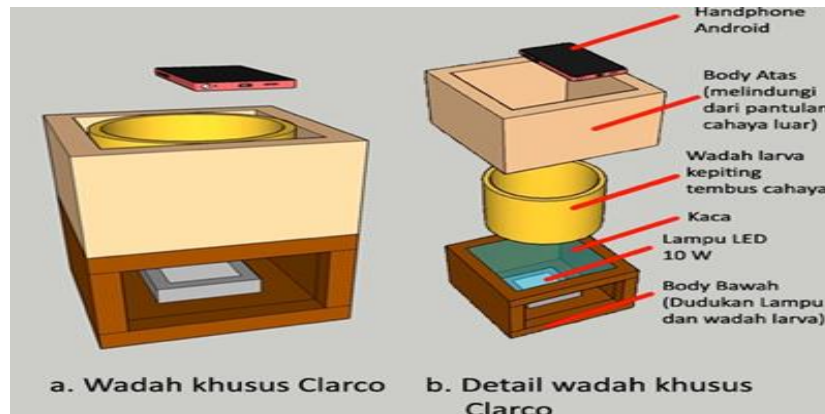


Figure 4. Clarco (Crab Larva Counter) container model

In simple terms, this research method model can be described as follows:

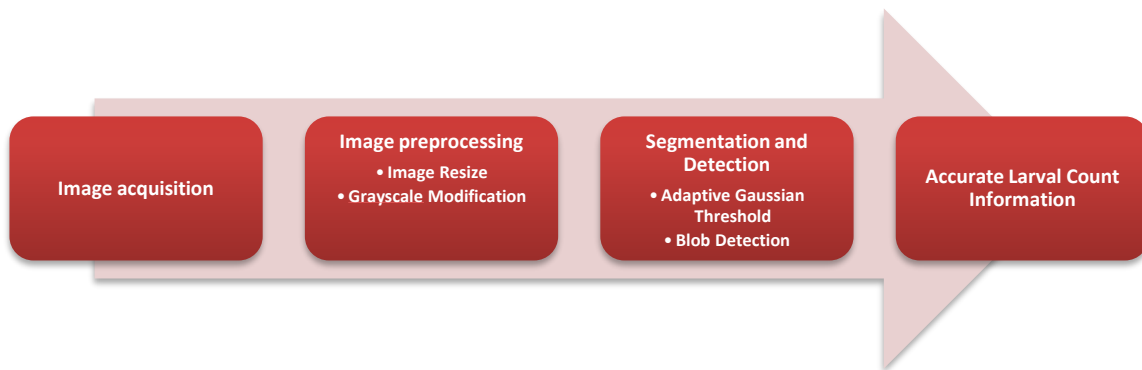


Figure 5. Research Method Model

C. Image Preprocessing

1) Resize Picture

The first step is to resize the image so that its dimensions are as desired and its pixel count does not negatively impact the memory performance of the mobile device.

2) Grayscale Modification

At this stage, the captured image is converted from image pixels containing three red, green and blue color data contents worth 0 - 255 each (R,G,B) into color pixels containing only one color data 0 - 255 (grayscale).

D. Detection and Segmentation

1) Adaptive Gaussian Filter

The following is the openCV library used to perform Adaptive Gaussian Threshold.

```
th3=cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,\n cv2.THRESH_BINARY,11,5)
```

2) Blob Detection Technique

In this research, blob detection is given several filter parameters to improve the accuracy of blob detection for larva counting, namely:



a. Filter by Area

In this filter, blobs are detected based on a specified size, so objects smaller than the larvae such as larval food (artemia) are not detected and counted. In the OpenCV library, filter by area is used with the command:

```
params.filterByArea = True params.minArea = 1
```

b. Filter by Convexity

A picture is worth a thousand words. Convexity is defined as (Blob area/Convex area). In the OpenCV library, filter by convexity is used with the command:

```
params.filterByConvexity = True params.minConvexity = 0.1
```

c. Filter by Circularity

This filter calculates the object's proximity to the blob detection circle. From the OpenCV library, the filter is used with the command:

```
params.filterByCircularity = True params.minCircularity = 0.5
```

d. Filter by Inertia

This filter measures how long a shape is. For example, for circles, this value is 1, for ellipses it is between 0 and 1, and for lines it is 0. In the OpenCV library, these filters are used with the command:

```
params.filterByInertia = True params.minInertiaRatio = 1
```

Once the parameters of the filter are determined, the blob will be detected according to the set parameters. In the openCV library, the blob detection technique is written using the If condition command.

```
ver = (cv2.__version__).split('.')
if int(ver[0]) < 3 : detector = cv2.SimpleBlobDetector(params)
else : detector = cv2.SimpleBlobDetector_create(params)
# Detect blobs.
keypoints = detector.detect(im) im_with_keypoints = cv2.drawKeypoints(im, keypoints,
np.array([[]], (0,0,255), cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)
text = "Jumlah Larva Zoea: " + str(len(keypoints))
nblobs = len(keypoints)
```

4. RESULTS AND DISCUSSION

Adaptive gaussian threshold algorithm and blob detection technique were used to capture and process image data of larval samples in order to count the number of crab larvae in the three different crab larval phases, namely zoea-2, zoea-3, and zoea-4. In the life cycle of crab larvae, the zoea phase is an extremely critical time. Overall, the results from combining the blob detection technique with the adaptive gaussian threshold algorithm were satisfactory. Nearly all crab larvae can be accurately spotted, as seen in one example of larval detection in Figure 6.

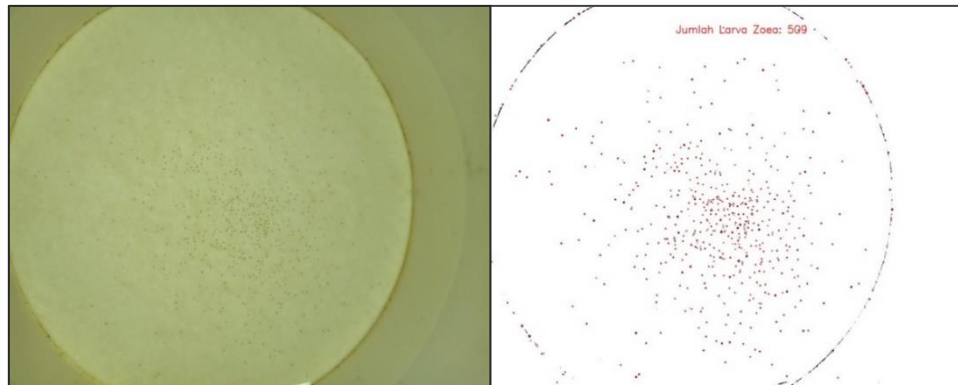


Figure 6. Comparison of the original image with the results of adaptive gaussian filter and blob detection

The technique is being tested with 45 photos of various types of larvae. Confusion Matrix is used for test validation, with the following test accuracy results:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where,

- TP is the quantity of observations of larvae that were identified as such with accuracy
- TN is the quantity of observations not of larvae
- FP is the quantity of non-larvae that are identified as larvae
- FN is the quantity of larvae that could not be found

Table 1. Confusion Matrix

n = 38747	Prediction = True	Prediction = False
Aktual = Benar	TP = 37931	FN = 815
Aktual = Salah	FP = 88	TN = 0

$$Accuracy = \frac{37931 + 0}{38834} = 0,9767$$

The table shows that, on average across all samples, the presentation accuracy of the data for larval detection is 97.67%.

Table 2. Some sample testing results

Image Name	Manual Calculation	Crab Larvae Counter App	Accuracy (TP+TN/TP+TN+FP+FN) %
oz421	231	237	97,47
oz422	233	239	97,49
oz423	236	241	97,93
oz424	229	230	99,57
oz21	511	503	98,63
oz22	522	499	95,59
oz311	206	206	100,00
oz314	201	207	97,10

In Table 2 are some test results on several samples of different larval types where the accuracy results using the confusion matrix as shown in Table 1 are at an average accuracy of 97.67%.

Table 3. Accuracy of detection results of each larval type

Type of Larva	Average Accuracy
Zoea-2	97,22
Zoea-3	97,01
Zoea-4	98,80

In Table 3. it can be seen that the presentation of accuracy using the confusion matrix of the four types of larval phases calculated, the highest accuracy is in the Zoea-4 phase with an accuracy of 98.80% where Zoea-4 is the largest size of the four types of larval types while the lowest accuracy is in the Zoea-3 phase with an accuracy of 97.01%, slightly different from the accuracy results in the Zoea-2 phase with an accuracy of 97.22%. Accurate larval detection is affected by a number of factors, including defective containers, camera focus, light reflection, water level, and the distance of the larvae from the water's surface.

5. CONCLUSIONS AND SUGGESTIONS

A. Conclusions

The calculation of the number of crab larvae in the Zoea-2 to Zoea-4 phase using the Adaptive Gaussian Threshold algorithm and blob detection techniques has a very good accuracy on Zoea-4 with an accuracy of 98.80% with an average accuracy of Zoea-2 to Zoea-4 is 97.67%, better than the previous study with different methods of using segmentation algorithms, where in the previous study only used grayscale modification standards on Zoea-1 with an accuracy of 89.88%.

B. Suggestions

In this study, to get the object of research in the form of crab larvae is still quite difficult to find due to the lack of crab hatcheries in the research area, only in a few government-owned research centers there are crab hatcheries, so it is hoped that in the future there will be more crab hatcheries for future research and cultivation. For this study, the larvae had to be taken from the hatchery tank because image capturing was also carried out in a unique container with a finite amount of water. Future studies are expected to concentrate on image capture and direct counting via mobile applications on the hatchery container utilizing advanced image recognition and more accurate intelligent algorithms.

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