Smart Media Journal / Vol.12, No.3 / ISSN:2287-1322
https://dx.doi.org/10.30693/SMJ.2023.12.3.112

Size Estimation for Shrimp Using Deep Learning Method

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Abstract

Shrimp farming has been becoming a new source of income for fishermen in South Korea. It is often necessary for fishers to measure the size of the shrimp for the purpose to understand the growth rate of the shrimp and to determine the amount of food put into the breeding pond. Traditional methods rely on humans, which has huge time and labor costs. This paper proposes a deep learning-based method for calculating the size of shrimps automatically. Firstly, we use fine-tuning techniques to update the Mask RCNN model with our farm data, enabling it to segment shrimps and generate shrimp masks. We then use skeletonizing method and maximum inscribed circle to calculate the length and width of shrimp, respectively. Our method is simple yet effective, and most importantly, it requires a small hardware resource and is easy to deploy to shrimp farms.

Keywords: computer vision | instance segmentation | image processing | AI application

I. INTRODUCTION

Recent years have seen the increase of shrimp demand in South Korea, and shrimp farming is an important source of financial for local people. Normally, the farming cycle of shrimps is about 5 to 6 months. During this period, the size of shrimps needs to be measured several times, for the purpose to obtain the growth information of shrimp and determine the feed amount for breeding shrimps[1,2]. Over-feeding may cause high costs for farmers and pollution of the growing environment of shrimp due to excessive food accumulation, while under-feeding will result in growth depressions and cannibalism[3]. Traditional methods for estimating size of shrimps are mostly relied on human measurements of shrimp samples with a ruler or by empirical observations, which is time consuming and needs a huge amount of labor resource, increasing the breed costs. Furthermore, these methods are tended to miss the best time for harvest, due to the rough measurement. Therefore, it is much urgent to develop a technology to automatically monitor the growth of shrimps for the aquaculture field.

To deal with this situation, this paper proposes to use deep learning method to estimate the size of shrimps, which can free shrimp culturist, greatly reducing shrimp farming costs. In particular, a deep neural network that can achieve instance segmentation on shrimp is first trained. This network is based on Mask RCNN[4], where we do the fine-tuning to update the

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* This research was supported by Korea Institute of Marine Science & Technology Promotion (KIMST) funded by the Ministry of Oceans and Fisheries (20210460).

Manuscript: 2022.10.07
Revised: 2022.12.01, 2022.12.27
Confirmation of Publication: 2023.03.08
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parameters for shrimp instance segmentation. Then, based on the masks, some morphological operations in image processing algorithms are utilized to estimate the length and width of shrimps. For length estimation, an edge detection method is used to generate an edge for the mask and then a skeleton extraction method is applied to thin the shrimp contour, obtaining the center line of mask, and use the length of center line as the length of the shrimp. For width estimation, the first step is also to extract a contour of the mask, and then find a maximum inscribed circle inside the contour. The diameter of this circle is considered as the width of shrimp. There are many alternative ways to decide the length and width for shrimps. We use the above principles to define them, because of the simplicity and efficiency.

The remainder of this paper is as follows. A brief review on the related papers for size estimation of shrimp is presented in Section II. A detailed description of the proposed method is provided in Section III. In Section IV, the results of our method are discussed and Section V concludes the whole paper.

II. RELATED WORK

For size estimation of shrimp, Harbitz[5] proposed an image analysis method to automatically estimate length of shrimp. He firstly segmented the shrimp from the background by using intensity threshold, and then used a linear model to link log-log scale of length and pixel area. His method ran with a speed less than 0.01s per image while it had a precision of 0.43 mm. However, this method needs to bring the shrimps from water and take a picture, which is also time consuming. Zhou[6] proposed to estimate size of shrimp in 3D space. This method firstly uses instance segmentation method to obtain masks, and then back-projects the 2D masks into 3D space, producing point clouds for each mask with multi-view geometry knowledges. It can only reconstruct surface point clouds, and is easy to measure the length, while not effective for width, due to the bad quality of reconstruction. Furthermore, it's really hard to capture depth information from underwater shrimps because of the water scattering. This method needs to use stereo vision to compute the depth, increasing the complexity. On the contrary, this paper proposes measure size of shrimp based on instance segmentation masks, considering from effectiveness and convenience. Our method only needs small amount of computing resources with fast speed to give size estimation for shrimps.

III. PROPOSED METHOD

The architecture of the proposed method is shown in Fig. 1. It contains instance segmentation and morphological operations. Due to that size estimation is based on shrimp mask, an instance segmentation deep neural network is first trained based on Mask RCNN[4]. This deep neural network is a famous instance segmentation model. It takes a RGB image as input and output the category, the coordinates of bounding box, and segmentation mask for each object in the image. Compared with the previous segmentation algorithm, it can treat several objects of the same category as different instances.

We do the fine-tuning to the original Mask RCNN model. The pre-trained weight file is trained on several popular public datasets, such as COCO dataset[9] and Pascal VOC dataset[10]. The experimental section provides the performance of this model on COCO dataset. In detail, the parameters of network layers in feature extraction module, RPN module, and fully convolution layers except the last classify layer are frozen. The fine-tuning process updates the parameters of a few of layers, to make the model can recognize and localize the shrimp class. Through the fine-tuning process, the customized Mask RCNN model can finish instance segmentation task on each given image, producing bounding boxes and masks, which is the basement for size estimation.

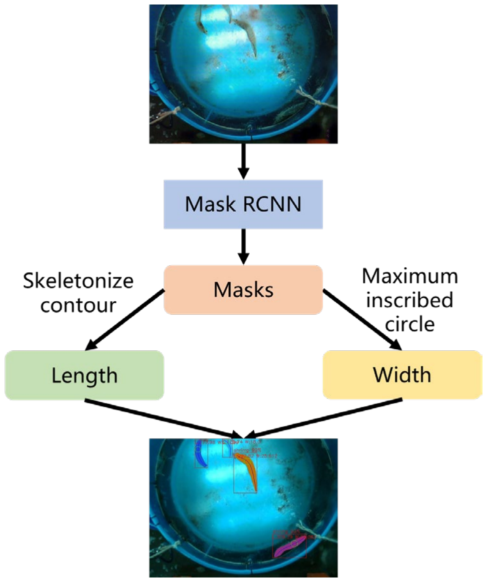

Fig. 1. The diagram of the proposed method. An instance segmentation network is first trained based on Mask RCNN [5], and then length and width of shrimp are estimated based on masks.

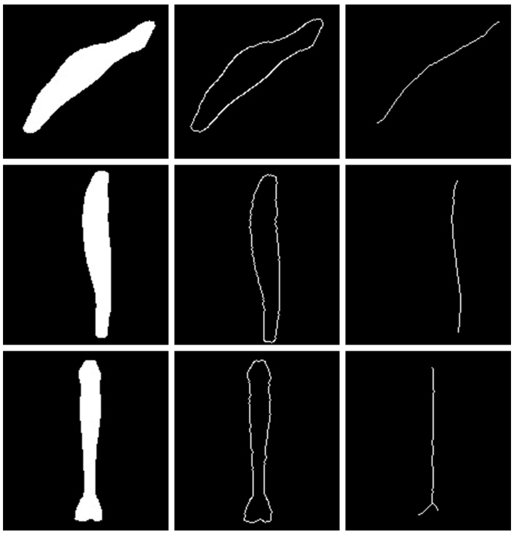

Fig. 2. Skeletonizing process. From left to right are mask, contour, and center line.

Based on the shrimp masks generated by Mask RCNN model, a method involving skeletonizing contour of mask is applied to estimate the length of shrimp. This skeletonizing method is based on[7], which can achieve extraction of center line of a contour. In particular, a contour of the shrimp mask is first extracted and then the contour is thinned by skeletonizing method. The center line can effectively represent the real length of a contour, especially for the situations that there is a reverse curvature of the contour, compared with the length in bounding boxes. An example is shown in Fig. 2.

Table 1 Algorithm for width estimation

Algorithm 1: Find maximum inscribed circle
Input: The contour of a shrimp mask **Output**: The maximum inscribed circle **1**: Choose a pixel inside the contour and compute the distance of each pixel to the contour edge; **2**: Draw circles for each pixel using distance as radius, and check whether the circle tangents to the contour. If so, save that circle; **3**: Repeat step 1 and 2, until all pixels inside the contour are traversed; **4**: Compare the radius of all saved circles and find the circle with largest radius; **5**: Output the circle that has the largest radius as the max inscribed circle.

For width estimation, we consider taking the diameter of the maximum inscribed circle as the width of the contour. We argue that the shrimp shape is non-rigid and the width in this shape is different from head to tail. It's hard to define the width for the shrimp. Therefore, we compute each width from head to tail and choose the largest width, which is most representative for the growth of shrimp. To achieve this goal, we search inscribed circles inside the contour iteratively, and take the diameter of the largest inscribed circle as the width of the shrimp. The specific process is shown as Table 1. Some examples are visualized in Fig. 3.

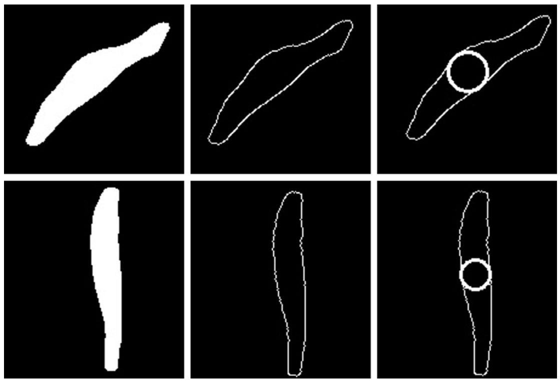

Fig. 3 The visualizations of find the maximum inscribed circle in a contour. Left: instance segmentation mask. Right: maximum inscribed circle for the contour.

Ⅳ. EXPERIMENTAL RESULTS

We provide our experimental results and discussions on our method in this section. The experimental setups and dataset used for fine-tuning are first introduced and performance on instance segmentation is presented. Then results of size estimation of shrimp are visualized. Finally, some discussion about experimental results and the proposed method are given.

Our experiments are conducted in Ubuntu 18.04 system with 3 Nvidia RTX TITAN graphics. The Pytorch and OpenCV library are used for implementing our method. The base learning rate is set as 0.00025 and the number of output class is set as 1. The Adam algorithm is used for optimization. The dataset is constructed by the images collected from a shrimp farm in Sinan Island, Republic of Korea. The camera we use is RealSense D435i from Intel Inc. Because the water scattering has distortion impacts, and water is much dirty, most raw images suffer several image distortion and blurring. When collecting images, we use an equipment to lift shrimps close to water surface, to obtain clear images. This equipment makes sure the height of camera to shrimps is the same every time when the camera takes a photo. If the water is clear enough, the shrimp images can be picked directly under the water.

We choose 450 high quality images, which are relatively clearer from over one thousand images for instance segmentation experiment, where 300 images are used for fine-tuning and 150 images for testing.

The fine-tuning of Mask RCNN is implemented on open-source codebase Detectron2[8], in which only a few of layers' parameters are trained for shrimp class, keeping most layers' parameters frozen. The instance segmentation results are shown in Table 2. The performance on COCO dataset[9] is directly borrowed from the codebase.

As shown in Table 2, our fine-tuning results have much larger improvements than the results on COCO dataset. Shrimp indicates our own 450 shrimp images. AP means the average precision of the model, which is one of the key metrics for comparing the performance of instance segmentation models. AP_{50} and AP_{75} indicate AP value when the threshold of IOU set as 0.5 and 0.75, respectively. AP_S and AP_L validate the performance from a multi-scale point, meaning that AP value of small and large objects. The values of AP_s in our method are extremely small because there are few small shrimps.

Table 2 Instance segmentation results

Metrics	IOU of Bounding box		IOU of Mask	
	Shrimp	COCO	Shrimp	COCO
AP	76.6	39.8	68.1	31.37
AP_{50}	84.2	62.3	83.2	60.0
AP_{75}	82.2	43.4	76.5	39.4
AP_S	1.1	22.1	0.1	16.9
AP_L	91.3	51.2	81.3	53.5

Our customized model has large improvements in other metrics except that term. Comparing the performance of our results with the public ones is less meaningful, because there is only one class in our experimental dataset, and the number of shrimps in one image is relatively small. While as long as there is no serious occlusion, even shrimp density is high, we believe this model can effectively generate shrimp masks with sufficient data, according to that Mask RCNN is used in all kinds of vision tasks. Therefore, our method can still calculate the shrimp size.

The results in Table 2 proves that our fine-tuning process is successful, and based on the instance segmentation results, the size estimation of shrimp is explored. The instance segmentation results are shown in Fig. 4.

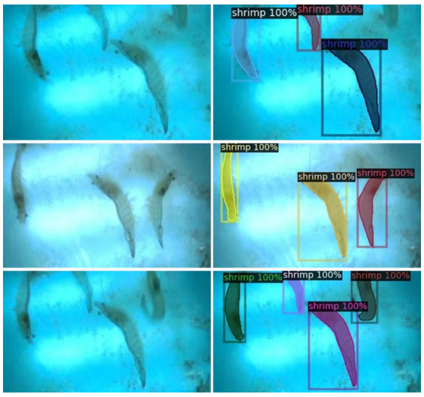

Fig. 4 The visualizations of instance segmentation results. Left: original images. Right: results.

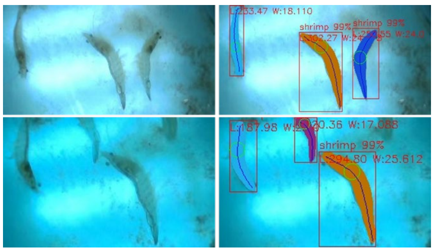

Fig. 6 The visualizations of size estimation results. Left: original images. Right: results.

To calculate the real size of shrimp, we need a reference stuff whose actual size is known, because our realsense camera cannot get accurate depth due to the water scattering. The details of calculation process are as follows. The Fig. 5 below shows pinhole camera model.

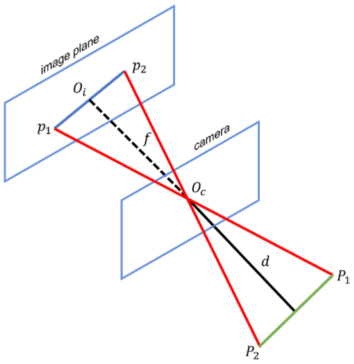

Fig. 5 Pinhole camera model

Assume that the length of P_1P_2 that is real stuff in 3D space is known as L. O_i and O_c are image plane center and camera center respectively. p_1p_2 is the project of P_1P_2 in image plane, whose length is l. f is the focus of camera and d is the distance of P_1P_2 to camera center, which can be measured by depth camera. Note that P_1P_2 is perpendicular to the camera. According to the Principle of Similar Triangles, we have the scale,

$$scale \triangleq \frac{l}{L} = \frac{f}{d} \tag{1}$$

Because the shrimp is under the water, the depth d here cannot be measured accurately. But through the reference stuff, we can get the scale that presents the actual length of a pixel unit. Once we get the pixel size of shrimp, we can then calculate the real size through the scale.

Specific to our project, if we want to calculate the real size of shrimp, we need to find out the length of the projection of reference stuff in every image. It's much travail for our project. The proposed measurement is yet efficient enough for tracking the growth change of shrimps, although it is calculated in pixels. Because we usually sample shrimps from breeding pond, taking pictures, measuring their size, and calculate mean size information of the whole shrimps in the pond, and do it several times during the breeding season. It means that the method should be simple and easy to deploy. Our method just needs a camera and can be deployed to the NVIDIA Jetson Nano, with fast speed and relatively high instance segmentation performance. From this point, the proposed method can effectively finish this task.

Fig. 6 shows the size estimation of shrimp, based on instance segmentation masks. The texts above the bounding boxes in the figure indicate class, confidence score, length, and width. These size values are in pixels, not actual length.

The calculation of width and length in our method is not predicted by the network. Their calculations are based on masks produced by instance segmentation. Length is computed by skeletonizing contour of the corresponding mask and width is calculated by finding the maximum inscribed circle inside the contour. Both these operations belong to morphological category. There is no uncertainty in these operations. Given a certain mask, length and width are the only determined values. Therefore, the accuracy of the mask is the only uncertain factor. In other words, our method can be evaluated by the performance of instance segmentation, which is referred to Table 2.

For our project, the pixel size is enough to track the growth changes of shrimps. We can convert the pixel size into real size through the method proposed in the paper but is trivial for our project. It's a demonstration for other researchers who are interested in computing real size. Our method belongs to the application of deep learning methods. Therefore, the common challenges in this area also exist in our method, such as small-scale dataset, occlusions et al. But especially for our project, the image quality is really bad due to the underlying image distortion, dust scattering and dirty water. The dataset scale and image quality are the main challenges. Therefore, it is necessary to continuously collect pictures, expanding the dataset.

V. CONCLUSION

We propose a method based on deep learning techniques to estimate the size of shrimps in this paper. We use fine-tuning to update the Mask RCNN model, enabling it segmenting the shrimps. We then use skeletonizing and maximum inscribed circle knowledges to get the length and width of shrimp. The proposed method is simple and easy to deploy on the farm. Through this method, the growth of shrimps can be monitored conveniently.

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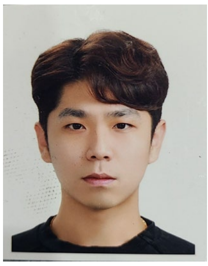

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