AI-assisted Automated Pipeline for Length Estimation, Visual Assessment of the Digestive Tract and Counting of Shrimp in Aquaculture Production

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Abstract: Shrimp farming is a century-old practice in aquaculture production. In the past years, some improvements of the traditional farming methods have been made, however, it still involves mostly intensive manual work, which makes traditional farming a neither time nor cost efficient production process. Therefore, a continuous monitoring approach is required for increasing the efficiency of shrimp farming. This paper proposes a pipeline for automated shrimp monitoring using deep learning and image processing methods. The automated monitoring includes length estimation, assessment of the shrimp's digestive tract and counting. Furthermore, a mobile system is designed for monitoring shrimp in various breeding tanks. This study shows promising results and unfolds the potential of artificial intelligence in automating shrimp monitoring.

1 INTRODUCTION

Aquaculture production of whiteleg shrimp, namely *Penaeus vannamei*, is steadily increasing (Boone, 1931) and accounts for more than half of the worldwide crustacean production (FAO, 2020). The average farming cycle, e.g. the time to raise the animals from larvae to adult shrimp, has a duration of 5 – 6 months. During this cycle, the shrimp remain in their production system until they reach a harvest weight of 25 – 30 grams. However, due to their high sensitivity, manual growth measurements are only possible to a limited extent and in addition, it is hardly feasible to gauge the exact number of animals in the system. Nonetheless, the knowledge of stocking densities or quantity of shrimp is important for optimized feeding and to determine the optimal harvest period (Harbitz, 2007). These parameters are crucial for avoiding non-adequate feeding during production and assessing the growth and health development of the shrimp. For example, erroneous or missing knowledge of shrimp count and densities in the production system may lead to over-feeding, resulting in higher costs and a decline in water quality due to higher waste. Contrarily, under-feeding might result in growth depressions and cannibalism. (Roy et al., 2012).

Therefore, it is inevitable to adjust the feeding rates based on control measurements (e.g. average length or weight of shrimp samples) and counting for achieving optimal growth and survival rates. As feed takes approximately 60 minutes to pass through the gut (Beseres et al., 2005), the degree of filling of the digestive tract is an appropriate discernible and measurable criterion for assessing the state of the feeding rate. However, the currently employed methods for assessing feeding status and quantities involve time-consuming manual work and are therefore prone to human-error.

In this paper, the potential of artificial intelligence in automated shrimp monitoring is assessed. To increase the efficiency of the shrimp farming process, we propose the following:

- A flexible and easy to install monitoring system for various shrimp production systems.

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- An approach for estimating the length of shrimp with the aid of instance segmentation.
- An approach that combines instance segmentation and image classification for efficiently assessing the shrimp's digestive tract.
- A multi-feature shrimp counting approach, which reduces the problems with overlapping shrimp.

By means of this automated monitoring approach, a time- and cost-efficient shrimp production can be achieved. The structure of the paper is as follows. In Section 2, the related work is analyzed. In Section 3, the monitoring system, the dataset and the automated shrimp monitoring pipeline are presented. In Section 4, the results of the different approaches are discussed and Section 5 concludes the paper.

2 RELATED WORK

2.1 Counting

Shrimp counting has been an interest for researchers over recent years. Most of the methods focus on conventional image processing techniques to automate the shrimp counting process.

Khantuwan and Khiripet (2012), took gray-scale images of shrimp larvae and improved the contrast of larvae edges using Laplacian and Median filters followed by adaptive thresholding for reducing non-uniform illumination. They determined a statistical measure in the form of a histogram for a first stage counting and used template matching for a second stage counting. Kaewchote et al. (2018) automated the counting of post larvae shrimp by extracting features using Local Binary Patterns followed by identifying objects using a Random Forest classifier. Another study by Awalludin et al. (2019) proposed combining anisotropic diffusion with a canny edge detector followed by blob analysis for counting shrimp larvae. Solahudin et al. (2018) applied thresholding and dilation to estimate the count of whiteleg shrimp. Similarly, Yeh and Chen (2019) applied image thresholding for extracting contours to be used for counting.

Most of these methods are restricted to a specific application setup. Extending them to a different setup requires a reconfiguration of the applied techniques, like adjusting the threshold values if the lighting differs or if the color degrades due to a different production tank. This would require an input from the user and would thus be prone to more errors and the automatic process might be impaired.

An alternative to conventional image processing techniques is deep learning, which enables feature learning from the input data and which is robust to noise and illumination variations. Deep learning outperforms traditional image processing techniques and surpassed its limitations (O'Mahony et al., 2019). However, there are hardly any studies for the application of deep learning in shrimp counting.

In a recent study by Nguyen et al. (2020), a deep learning-based method for whiteleg shrimp larvae counting has been applied. They prepared a dataset of shrimp in a glass container with low water level to minimize overlaps. This dataset was used to train an instance segmentation network based on a two-phase Mask R-CNN to detect shrimp larvae in regions with overlaps. Their approach works well with a small number of overlapping shrimp, however, the accuracy substantially decreased with more overlaps.

In our method, we focus on detecting two major features of the shrimp using a deep learning object detection network to reduce the problems with overlapping shrimp and increase the accuracy of automated shrimp counting.

2.2 Length Estimation

Harbitz (2007) segment shrimp automatically based on an intensity threshold. Afterwards, objects are identified and their pixel areas are calculated, which in turn are used for separating shrimp objects based on an area threshold. This separation enables identifying shrimp based on centroid values. Then the length is estimated by linking each shrimp's area with a corresponding caliper measurement. The estimation of shrimp length by Harbitz (2007) is dependent on multiple analysis and values prediction, which in return make it hard to generalize and be robust to changes.

To achieve a robustness to change, our approach for automated length estimation utilizes the results from instance segmentation, while being facilitated by our monitoring system.

2.3 Digestive Tract Assessment

To our knowledge, no research has yet been done on the visual assessment of the digestive tract of shrimp. In shrimp, the digestive tract is a straight tube running dorsally, which is divided into three regions: the foregut, the midgut, which begins at the junction of the hepatopancreas, and the hindgut (Franceschini-Vicentini et al., 2009; Davie et al., 2015). It is externally identifiable when filled, and therefore well suited for image analysis.

In this paper, we present a methodology for automatically assessing the digestive tract's condition.

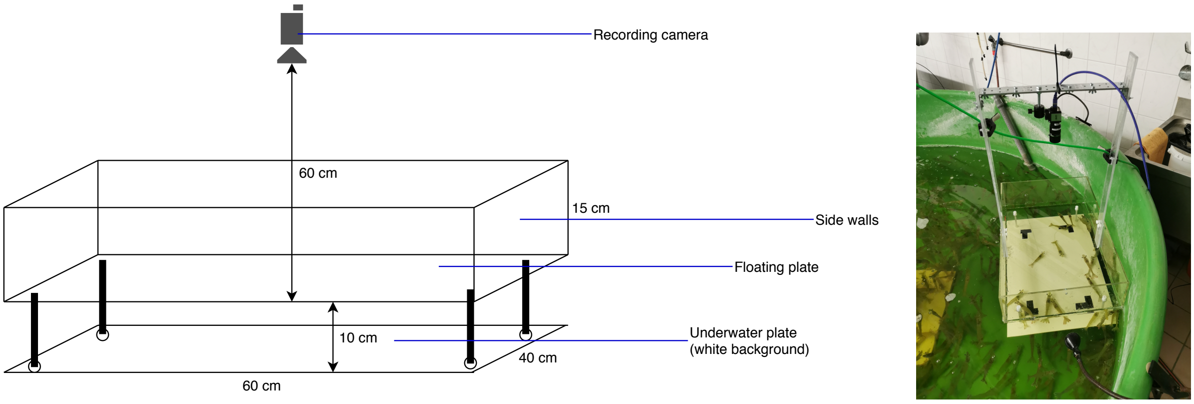

Figure 1: Shrimp monitoring system. Left: Sketch of the system design. Right: The installed system in an experimental tank.

3 METHODOLOGY

3.1 Monitoring System Design

There are various types of shrimp production tanks. Therefore, the scenarios differ, for example, in water depth, water quality or tank shape. As part of this study, a mobile system was designed for recording images of shrimp in an area of interest, which enables the application of the proposed methodology to various scenarios.

Figure 1 presents a sketch of the designed system along with the installed setup used for automated shrimp monitoring. The system consists of a floating box made of transparent perspex (top is open) and an underwater plate made of white plastic, reducing the water column to 10 cm. The dimension of the floating box is $60 \times 40 \times 15$ cm, whereas the underwater plate's dimension is 60×40 cm. This setup allows only a small number of shrimp in the water column and therefore, reduces the number of overlapping shrimp by design. The underwater plate is equipped with markings for an area of interest of dimension 40×20 cm, where analysis and evaluation are based on. The shrimp can swim freely through the monitoring system. The camera is placed orthogonal at a height of 60 cm on top of the floating box, capturing images through its transparent bottom. This prevents image distortions due to a wavy water interface and allows a clear view into the water column, regardless of the external factors of the experimental tank. This provides a good prerequisite for the proposed monitoring approaches even in challenging tank environments.

3.2 Dataset

Images were taken of the shrimp with a resolution of 3088×2076 pixels, where various focal lengths and exposure times had been tested. At that point, most of the shrimp had sizes between 9 and 12 cm. Figure 2 shows a sample of the recorded images and the corresponding cropped area of interest based on the measured markings on the underwater plate. As can be seen, the shrimp images can be considered as high quality.

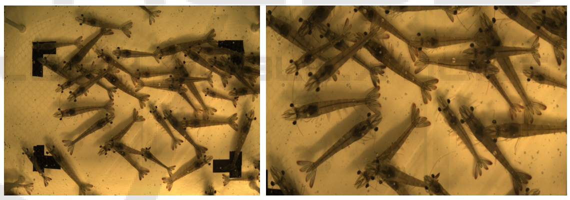

Figure 2: A sample image of the monitoring system (left) and the cropped area of interest (right).

The recorded images were divided into several datasets. For the instance segmentation and object detection network, the recorded high resolution images were split into 4 equally sized images with a resolution of 1544×1038 pixels. The classification dataset was obtained from the instance segmentation network predictions, which will be discussed in the next section. The overall number of images used for the instance segmentation, object detection and classification networks were 898, 410, and 292, respectively. Finally, 150 images were cropped to the defined area of interest and used for evaluating the results of the automated monitoring approach. Table 1 illustrates the datasets used for each deep learning network and for evaluation.

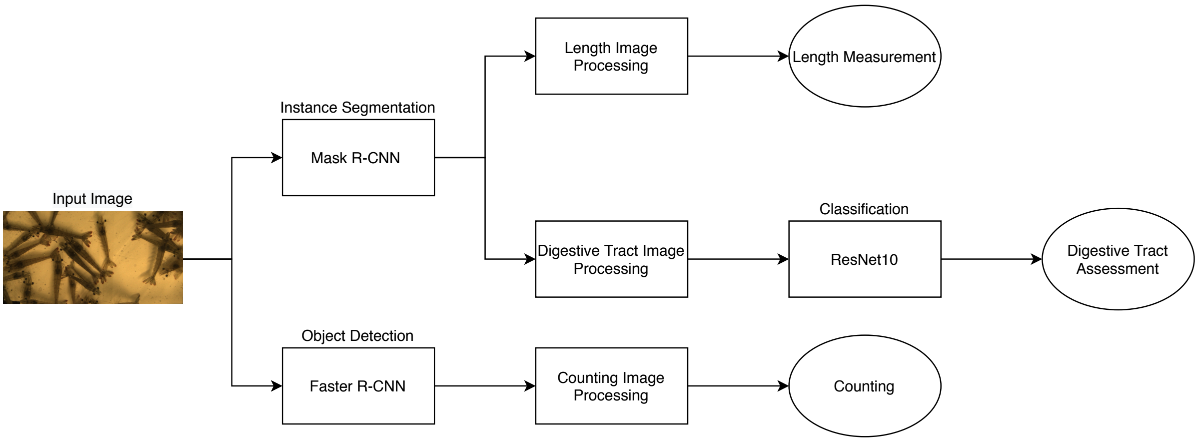

Figure 3: The proposed pipeline for length measurement, digestive tract assessment and counting.

Table 1: Number of images used for each category.

	Training	Validation	**Overall**
Instance Segmentation	701	47	**898**
Object Detection	234	26	**410**
Classification	212	40	**292**
Evaluation			**150**

3.3 Automated Shrimp Monitoring

The captured images were processed by our pipeline for automated shrimp monitoring (Figure 3). The pipeline consists of two main branches. The upper branch begins with an instance segmentation network, namely Mask R-CNN (He et al., 2017), with a combination of Feature Pyramid Network (FPN) (Lin et al., 2017) and deep residual network (ResNet) (He et al., 2016) for feature extraction, which is used for detecting and segmenting individual shrimp. The length is then determined by processing the outputs of the instance segmentation network, whereas the image classification network (ResNet (He et al., 2016)) is used for assessing the digestive tract of a shrimp. The lower branch consists of the Faster R-CNN network (Ren et al., 2017) for detecting two unique body parts of each shrimp. Afterwards, the detected body parts are processed for shrimp counting.

3.3.1 Length Estimation

The shrimp were assumed to be located approximately at the same distance from the camera as the underwater plate. Therefore, the measured markings on the plate were used to obtain a scale factor to convert between pixels and centimeters. Upward swimming shrimp violate this assumption and hence were excluded from the annotation. This exclusion does not distort the overall monitoring process, since the major swimming direction of the shrimp is horizontal and since not each individual shrimp needs to be measured to get a significant length distribution. Since the length of shrimp in this study is calculated from the top of the rostrum (beak) to the end of the telson (fin), only horizontally swimming, non-overlapping, completely visible shrimp were annotated and used for training of the instance segmentation network. This was a crucial step for forcing the network to detect and segment measurable shrimp only.

The trained instance segmentation network was used for predicting a bounding box and a segmentation mask for each individual shrimp. Figure 4 illustrates the processing steps. The predicted segmentation mask was converted into contours and the extreme left, right, top and bottom contour points were deduced (Figure 4 (b)). The pair of deduced extreme points with the longest distance were assumed to form a line passing through the rostrum and the telson. The two intersecting points of the line and the shrimp's bounding box were used to calculate the length of the shrimp in pixel (Figure 4 (c)). Finally, the scale factor was used to get the length estimate (Figure 4 (d)).

3.3.2 Digestive Tract

The main goal was to analyze the condition of the shrimp's digestive tract. More precisely, the degree of filling of the digestive tract. For that, the inferred segmentation masks of the instance segmentation network were used for extracting a dataset. Therefore each segmented shrimp was cropped from the original image and then rotated and translated to the same orientation (Figure 5). This dataset was used for training the classification network, which eventually should classify the shrimp into two categories: *full* and *other* shrimp. The amount of visible shrimp in test data didn't allow for more categories. Figure 5 shows the two different shrimp categories based on the degree

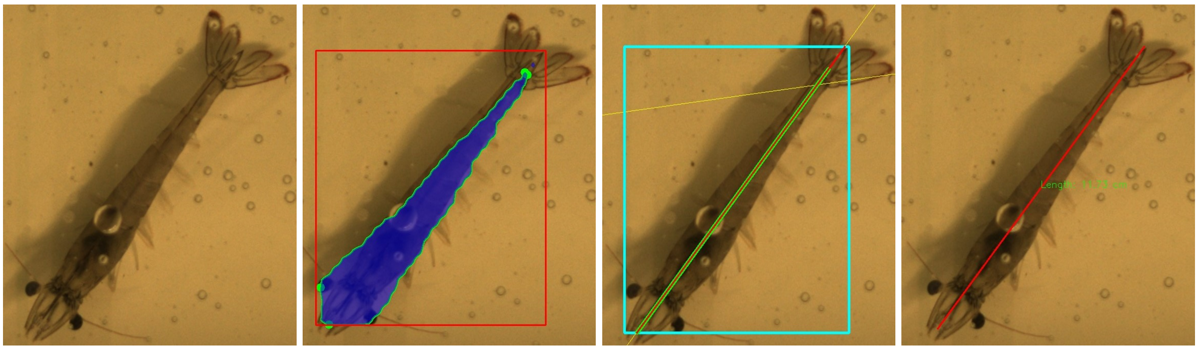

Figure 4: Length estimation approach: *from left to right* (a) Original. (b) Inferred results and extreme points. (c) Derived line and intersecting points. (d) The estimated length in centimeters.

of filling of the digestive tract. As can be seen in the images, shrimp with a sharp filled line are considered as *full*, whereas the ones with light or no filled line are considered as *other*. Within our pipeline for automated shrimp monitoring (Figure 3), after an image passed the instance segmentation network, the inferred results were forwarded for image transformation and classification. Finally, the predicted classification results were used to assess the condition of the shrimp's digestive tract.

3.3.3 Counting

A separate branch in the pipeline was used for the counting task, since it is independent of the previous results. An object detection network was trained on two body parts of the shrimp, namely the pair of eyes and the hepatopancreas, since most of the time, one of these is visible even in overlapping situations. The results of the object detection were forwarded for further processing. The processing included calculating the shortest distance between a centroid of a predicted hepatopancreas bounding box and each eye pair bounding box. If this distance didn't exceed 165 pixels (2.3625 cm), the corresponding hepatopancreas and eye pair bounding boxes were considered as belonging to one object. The distance value was chosen heuristically. Otherwise, the corresponding boxes were considered as belonging to two separate shrimp and were counted as two objects. Afterwards, both centroids are removed and the process is continued iteratively. Figure 6 shows an overview of the counting process. The bounding boxes in blue color (Figure 6 (b)) are considered as one object, whereas the ones in red color are considered as separate individual objects.

4 RESULTS AND DISCUSSION

4.1 Length Estimation

For evaluation of the length estimation, a comparison with manual measurements was performed. Therefore, 625 horizontally swimming, non-overlapping, completely visible shrimp have been manually measured in a set of 150 evaluation images. The same evaluation images were used for predicting individual shrimp using the trained instance segmentation network, and ultimately, measuring the length. To have a feasible evaluation of the measurement accuracy, distributions of the manual and predicted measurements were calculated. Figure 7 shows the length distribution of both the manual (ground-truth) and the predicted measurements. In contrast to the ground-truth (625 shrimps), only 401 shrimp could be detected and measured by our pipeline for automated shrimp monitoring. Looking at the distribution, shrimp below approximately 9 cm were not detected very often. This implies that the instance segmentation network has a weakness in detecting small shrimp, which is probably due to an imbalanced dataset. A more balanced dataset with more diverse training data would be a solution for addressing this issue. Nonetheless, the predicted length distribution matches the ground-truth one, where most shrimp have a length value between 9–12 cm. Both resemble a normal distribution.

4.2 Digestive Tract

At the time of capturing, most of the shrimp showed a high degree of filling of their digestive tract (category *full*). This made it hard to collect enough data for the *other* category and impossible to define further categories, which would lead to a more significant analysis of the feeding status. We tried to maintain a relatively small balanced dataset instead of a

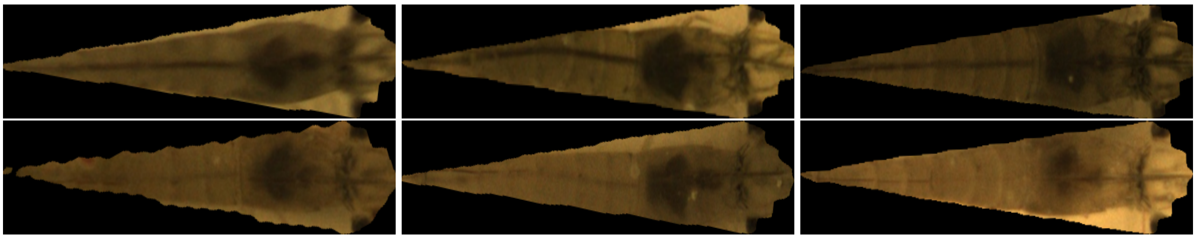

Figure 5: Dataset for training the classification network. Top row: *Full* category. Bottom row: *Other* category.

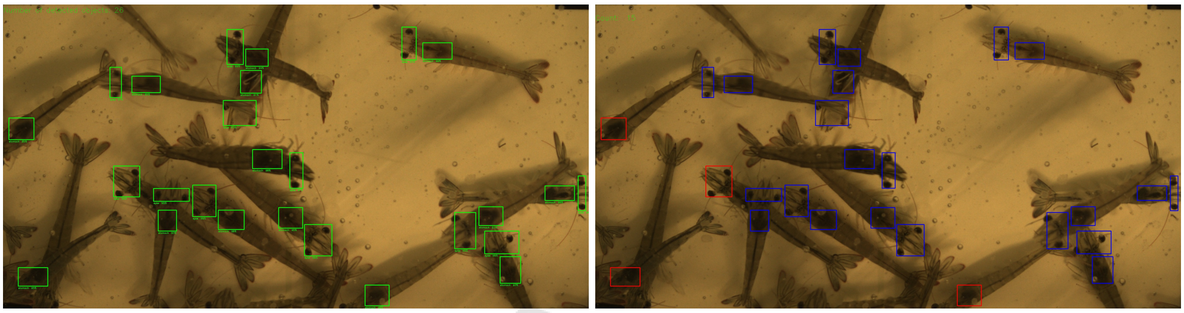

Figure 6: Counting approach: Left: Object detection inference. Right: Counting Result.

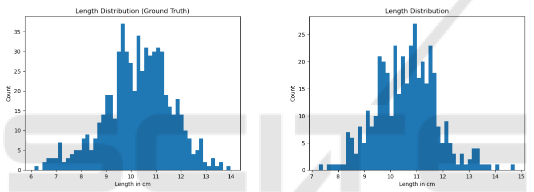

Figure 7: Calculated distribution of shrimp length estimation in 150 evaluation images. Left: Ground-truth length distribution. Right: Predicted length distribution.

large imbalanced one. Table 2 shows the confusion matrix of the trained classification network. It can be seen that 51 shrimp of the *full* category were correctly classified out of 52, whereas 45 shrimp of the *other* category were correctly classified out of 52. As was expected, the network didn't perform as well on the *other* category as on the *full* one. Having a larger dataset with more shrimp in the *other* category would boost the performance of the classification network. Since there is a direct relation between the instance segmentation results and the classification network, improving the results of the former would lead to a better training dataset for the latter and ultimately better performance.

Table 2: Confusion matrix of the digestive tract classification network.

		Predicted		
		Full	**Other**	**Sum**
Actual	**Full**	**51**	1	52
	Other	7	**45**	52
	Sum	58	46	104

4.3 Counting

For the evaluation of the automated counting task, three different people counted the shrimp in the set of 150 evaluation images manually. Compared to the manual counting, the mean percentage error over the evaluation images amounted to 6.6 %, with a highest counting percentage error of 23.8 %. After interpreting the results, the drawn conclusions read as follows: 1. Captured images with many overlapping shrimp cause the network to miss some of them. 2. The reason for that is a partially hidden hepatopancreas and/or pair of eyes. 3. As a solution for addressing this problem, a third body part of the shrimp could be added to the detection problem along with the hepatopancreas and the pair of eyes. 4. Alternatively, partially hidden body parts should be annotated as well to improve the network's performance in overlapping situations. With this approach the shrimp count can be estimated in an area of interest. If that area can be considered as a representative, the counting can be utilized for extrapolation to the whole tank. However, the utilized area turned out to be too small. Therefore, the present results are considered as proof of concept of the proposed approach.

5 CONCLUSION

This paper shows the feasibility of utilizing artificial intelligence in automated shrimp length estimation, digestive tract assessment and counting. Furthermore, a flexible and easy to install monitoring system for various shrimp production systems was presented. By means of the proposed automated monitoring approach, a more time and cost efficient shrimp production can be achieved to increase the efficiency of the shrimp farming process. Certainly, as mentioned in the previous section, there is room for improvement within all three mentioned use-cases. This could be a subject for future research. Additionally, it became clear that the designed system should cover a significantly larger area than 40×20 cm. Approximately 100×100 cm would be a better fit, which would make the counting task more meaningful. In addition to all the considered use-cases, an automated detection of anomalies in the external appearance of shrimp could be an interesting use-case for future works.

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