Visual-Based System for Fish Detection and Velocity Estimation in Marine Aquaculture

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Abstract

As global aquaculture continues to expand to meet the rising seafood demand, optimization of feeding remains a crucial issue for the industry to address to achieve sustainable development. This study proposed a visual-based system for estimating fish velocity, which is to be integrated into a farmer's feeding operation to determine the optimal feed amount. The YOLOv8 algorithm was utilized to detect fish in underwater videos, enabling precise monitoring of fish behavior. The results indicate a successful fish detection with an accuracy of 85%. The fish velocity estimation approach demonstrated the difference between the hungry fish and the normal fish behavior. The findings suggested that integrating fish velocity data into feeding operations can significantly enhance feed efficiency, reduce waste, and promote sustainable aquaculture practices, ensuring optimal fish growth while minimizing environmental and economic impacts.

Keywords: YOLOv8, Aquaculture, Fish Detection, Velocity Estimation.

1. Introduction

With the increasing demand for seafood and declining marine fishery stocks, aquaculture has continued to expand into becoming the major contributor to seafood production worldwide. In 2022, aquaculture production has surpassed the production by capture fisheries, accounting for 51% of aquatic animal production [1]. However, the expansion of the industry also came with sustainability issues, most brought on by poor management practices. If not properly addressed, these issues could get out of control and cause harm not only to the aquatic environment but also to aquaculture production itself [2]. One of the most important issues in the industry is the optimization of feeding. In many aquaculture operations, feeds make up one of the largest, if not the largest portion of the production costs [3]. To maximize the fish growth, farmers estimate the amount of feed supplied and the timing of the feeding, mostly by observing the fish feeding behavior. However, the estimation is based on the farmers' own intuition and their subjective experiences. This results in a notable difference in quality between the fish fed by veteran farmers and those fed by novice farmers. The inferior quality of novice-fed fish could be attributed to the farmers' inefficiency in supplying feed. While underfeeding results in slower growth, overfeeding results in uneaten feed decomposing in water, leading to water pollution affecting the health and growth of fish, resulting in poor quality of fish [4]. In addition, they incur more feeding expenses without producing a substantial increase in the weight and quality of the fish. In the end, the farmers would make less profits or even incur losses from their operation. By applying digital transformation (DX) on fish farms, farmers can get a more accurate estimation of fish feeding behavior and optimize their feeding regime. This in turn can help improve the growth of the fish, potentially resulting in increased margins. With the ubiquity of digital cameras, computer vision (CV) has become one of the most widely used technologies in aquaculture [5]. With the recent emergence of machine learning and artificial intelligence, it has been used for intelligent recognition of fish activity [6]. However, application in most research works is focused on feeding behavior recognition in environments where lighting conditions and water clarity are controlled. Varying conditions in marine cages pose many difficulties in estimating fish feeding behavior. On top of visibility challenges underwater, non-fish objects also hamper the ability of vision systems to recognize fish behavior. This paper presents an underwater imaging system for recognizing fish-feeding behavior in marine fish cage environments. Here we present our approach to enhancing videos of fish activity captured underwater and then tracking their movement. This paper then discusses the relation of the estimated fish motion to the farmer's feeding regime to determine the optimal amount of feed to be supplied.

2. Methodology

Measuring the fish velocity is the key to understanding the fish behavior toward the effective management and optimization of fishery operations. The biggest challenges in underwater video analysis are poor visibility, different lighting conditions, noise, and color distortion due to wavelength-selective water absorption. These challenges result in difficulty in fish detection and tracking. The research aims to track the fish from the video from the fish cage and estimate their velocity. This is critical for maintaining sustainable and productive fishery practices. The study is divided into three mains objectives shown in Figure 1.

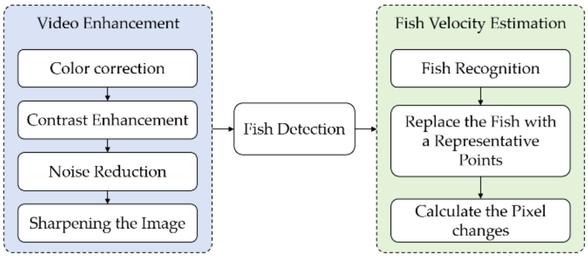

Figure 1. The flowchart of visual-based fish motion tracking

2.1. *Video Enhancement*

Enhancing underwater video is challenging due to the unique condition of the water. The wavelength-dependent absorption result is a color distortion [7]. The blue color travels longest in the water while the red color faces higher attenuation over short distances. Furthermore, image degrading is strongly affected by light attenuation and scattering [8]. Addressing these issues is an essential process for improving video quality, it is also promising to facilitate more accurate fish detection and tracking. Several steps were applied to enhance the underwater video: color correction, contrast enhancement, noise reduction, and sharpening. Figure 2 shows the snapshot of the video enhancement.

Figure 2. Image enhancement result

2.2. *Fish Detection*

Fish detection is critical for monitoring and analyzing fish behavior. You Only Look Once (YOLO) algorithm is a well-known object detection algorithm, especially in complex environments. Its versions are widely used for different applications such as face recognition, small object detection, and underwater object detection [9]. In this research, YOLOv8 was applied to detect the fish in the video by breaking the video into individual frames, then, applying the detection algorithm, and finally recombining the frames to make the video with the detection information.

The datasets were collected from the video in an underwater real environment for Yellow tail fish aqua-cage. The camera was set at depths of 3.4m to continuously capture a video before, during, and after feeding processing. Afterward, the video frames were extracted to make training and validation dataset images. The dataset consists of 150 augmented images, divided into 71% for training, 20% for validation, and 10% for testing. The training iterations were set to 150 epochs, at each epoch, a careful analysis of the model performance such as precision and recall was applied. Using hyperparameters such as learning rate and batch size, the model has been adjusted to optimize detection accuracy. The model was fine-tuned to balance sensitivity with specificity to minimize false positives which is particularly challenging in a complex environment like underwater.

2.3. *Fish Velocity Estimation*

Several methods, such as optical flow, Kalman filter, and DeepSort, can be applied to estimate the fish velocity in the aqua-cage. However, in complex environments such as underwater, where lighting significantly affects pixel brightness, traditional tracking techniques become more complicated due to difficulties in extracting features from the object to be tracked. In this research, we proposed a novel method to simplify the issue of motion tracking and velocity calculation.

Tracking the fish motion in the sequencing frames involves tracking the whole fish by extracting fish features and calculating the pixel displacements among every two frames. Nevertheless, the changes in the light condition of the sequencing images, and unexpected fish directions and poses make it more difficult to apply the tracking methods to the fish directly. Therefore, replacing the fish with representative points is an essential step

3. Results and discussion

With the enhanced video, the YOLOv8 was trained using 500 images, the trained model then was applied on separate images to evaluate its performance. To evaluate the level of video enhancement, the trained model was applied on two test sets; 50 images before enhancement and the same 50 images after enhancement. Table 1 illustrates the dataset partitioning for the training, validation and testing, the comparison of the mean average perdition (mAP-50), and the system accuracy between the video before and after enhancement.

Table 1. The dataset partitioning for training YOLOv8 and model mAP-50

	Before enhancement	After enhancement
Dataset	150	
Training set	106	
Validation set	30	
Test set	14	
mAP-50 best	0.874	0.864
Test accuracy	70.3%	73.2%

The table showed a slight decrease in the mAP, but increasing in the test accuracy, indicating the need for further analysis of the images. The testing set was carefully checked for better understanding. Table 2 summarizes the comparison results of the deep analysis of the testing dataset before and after enhancement.

Table 2. Comparison results of the deep analysis of the testing dataset before and after enhancement.

parameter	value
# of testing images	14
# of images with the same detection rate	3
The model detected more fish before enhancement than after	5 images
The model detected more fish after enhancement than before	6 images
Total number of fish in the testing images	104
# of detected fishes in the images before enhancement, (detection rate)	77, (74%)
# of detected fishes in the images before enhancement, (detection rate)	80, (76.9%)

The table shows a slight improvement in detection. The detection rate of the images before enhancement was 74%, while after enhancement, it was 76.9%.

To track the fish's motion, the trained model of YOLOv8 was first applied to detect the fish and then replaced the detected fish with representative dots. Figure 3 illustrates a snapshot from a video demonstrating velocity estimation of fish movement.

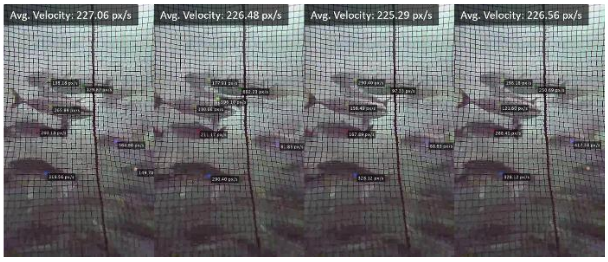

Figure 3. Estimated fish velocity

The calculation is conducted based on the distance between corresponding pixels in consecutive frames, frame (i) and frame (i+1) successively, for each detected fish. This method allows tracking of the movement of individual fish. For each frame, the approach calculates and provides the average velocity of all the fish present within the frame, offering an overall measure of their movement.

The proposed method is employed in two videos, the case of normal fish movement, and the second the case during fish feeding. Choosing two different videos has two purposes:

1- To determine the difference in the detection of YOLOv8 since the fish's random and high-velocity movement might affect the detection due to the quality of the video.

Figure 4 illustrates the number of detected fish in the two described cases.

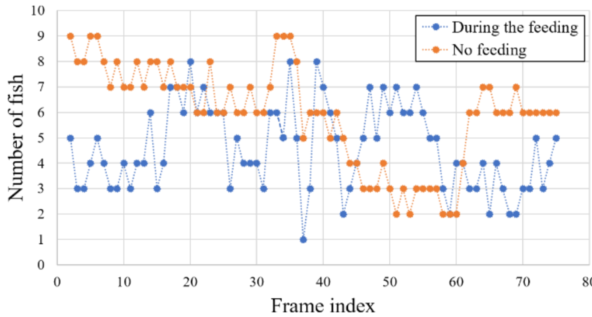

Figure 4. Number of detected fish in two cases (during the feeding presses and without feeding)

From the figure, the number of detected fish during the feeding is higher than in the case of no feeding. The reason is the direction of the fish. During the feeding, the fish is hungry, thus they move in random directions, also the direction camera view axis, in this case, the detection algorithm failed to detect these fish. In addition, the high speed of the fish decreased the video quality resulting in frailer detection.

2- To evaluate the velocity estimation approach with different fish velocities. Figure 5 illustrates the fish velocity estimation for the two videos: During the feeding and no feeding.

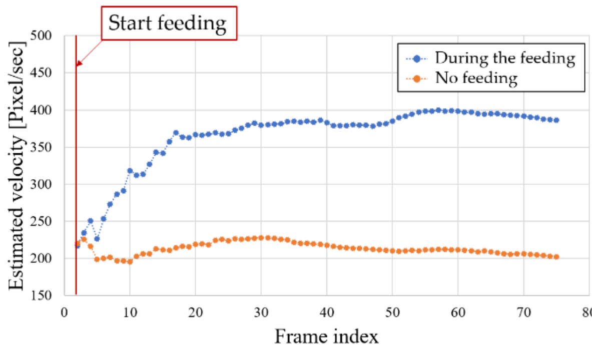

Figure 5. Estimated fish velocity

The orange line in Figure 5 represents the case when the fish are behaving normally without feeding. The blue line represents the case when the feeding process started. The estimated fish velocity when feeding is going is higher than the normal case. This estimated velocity was calculated by pixel per second

4. Conclusion

This study proposed a visual-based system for optimizing feeding strategies in aquaculture by underwater imaging, fish detection, and velocity estimation. The video enhancement process addressed several challenges such as color distortion, poor visibility, and noise, resulting in improved fish detection accuracy from 70.3% to 73.2%. YOLOv8 was utilized for fish detection, trained with 106 underwater images, and tested on 14 images. Despite a slight decrease in mAP-50, the in-depth analysis of the test images demonstrates that detection was better after enhancement by 2.9%. Track fish velocity was conducted by pixel displacement which is a simplified optical flow technique. The system proved that fish velocity significantly increased during feeding, offering a potential approach for optimizing feeding schedules.

This research highlights the potential for integrating image enhancement, machine learning, and velocity tracking to promote sustainable aquaculture. It offers a pathway to reduce feed waste, lower production costs, and improve profitability while supporting sustainable and efficient fish farming practices.

Future work will expand the dataset and refine detection models, for accuracy improvement. Developing an algorithm that analyzes both videos before and after enhancements will enable dynamic adjustments of detection performance.

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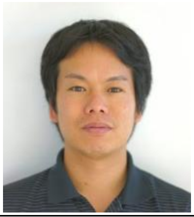

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