Assessment of Motion Activity of a School of Rainbow Trout in Underwater Video Surveillance System

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***Abstract*—Video Surveillance Systems (VSS) are progressing towards the digitalization of industry. In this demo, we apply the Artificial Intelligence (AI) technology to assess the motion activity of a school of rainbow trout. The practical need is to detect and react on too low and too high activity. The input data come from stereo cameras installed around the pool. The activity recognition used the specifically trained YOLO-Pose neural network (NN). Our first algorithm assesses the speed of a rainbow trout based on averaging the individual fish activity parameters. Our second algorithm assesses the angle of an individual rainbow trout to detect the fish in bad health state. Our early experimental study of the algorithms demonstrates their applicability for monitoring the fish health and condition, feeding management, water quality control and fish behavior control in aquaculture.**

I. Introduction

Video Surveillance Systems (VSS) have become an integral part of modern industry, providing valuable insights for diverse applications. Particularly, in aquaculture, these systems are increasingly being used for real-time monitoring of fish behavior, health, and environmental conditions. As this field continues to digitize, the application of Artificial Intelligence (AI) technologies such as the YOLO-Pose neural network (NN) presents an opportunity to revolutionize fish surveillance and management.

In this context, our goal is to develop algorithms capable of determining fish behavior over time, focusing specifically on the motion activity of a school of rainbow trout. These algorithms serve practical needs to detect and react to both excessively low and high activity levels, aiding in the identification of fish health state, feeding management, water quality control, and fish behavior control.

Our approach involves using stereo cameras installed around the pool to gather input data, which is then processed by the specifically trained YOLO-Pose NN. Two algorithms have been developed as part of this research. The first assesses the speed of individual rainbow trout by averaging the activity parameters, while the second examines the angle of each fish to identify potential health issues.

The preliminary experiments using these algorithms have demonstrated their potential applicability for monitoring fish health and behavior, thereby contributing towards more effective and sustainable aquaculture practices.

The rest of this paper is organized as follows. In Section II we discuss the importance of feeding management in aquaculture and how video analytics can be used to optimize this process. In Section III we provide a comprehensive review of existing methods for assessing motion activity. Section IV details our specific solution for evaluating the motion activity of a school of rainbow trout. In Section V we share the results from our preliminary experiments, discuss the integration of our algorithms into the Fishgrow Platform, and reflect on the accuracy, performance, and potential improvements of our solution.

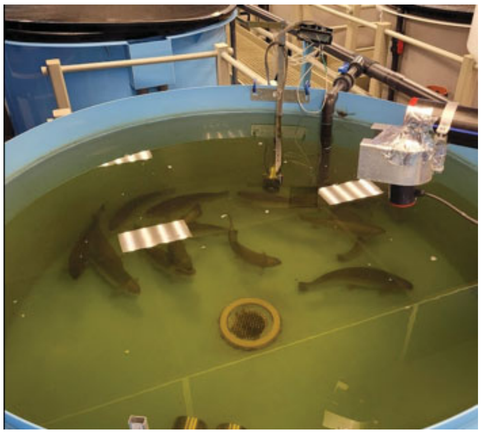

Fig. 1. Pool with school of rainbow trout

Fig. 2. Stereo camera

II. Videoanalytics of a School of Fish

In the realm of aquaculture, video analytics has emerged as a powerful tool for understanding, managing, and optimizing fish populations. This technology, when combined with machine learning and artificial intelligence, can provide unprecedented insights into the behaviors, health, and well-being of fish schools. Let's delve into the practical tasks of video analytics of a school of fish, while defining our specific task requirements and conditions.

- Behavior Analysis;
  Video analytics can capture and interpret the movement patterns of fish, allowing researchers to monitor schooling behavior, feeding habits, and responses to environmental changes. Understanding these patterns can help optimize feeding schedules, improve habitat design, and even predict disease outbreaks.

- Health Monitoring;
  By observing the swimming patterns and behavior of individual fish, video analytics can potentially identify signs of stress, disease, or injury. Unusual swimming patterns, changes in speed, or erratic behavior could all be indicators of health issues.

- Feeding management;
  It is a crucial aspect of aquaculture, significantly impacting the health of the fish, the efficiency of the operations, and ultimately, the productivity of the farm. Traditional methods of feeding management often rely on visual observations and manual interventions, which can be time-consuming and prone to error. With the advent of video analytics, however, these processes can be significantly optimized.

- Water Quality Assessment.
  Changes in fish behavior can often indicate issues with water quality. By monitoring fish movements and behaviors, video analytics can provide early warnings of potential water quality problems, such as changes in temperature, pH levels, or oxygen content.

Our specific task is to utilize video analytics to assess the motion activity of a school of Rainbow Trout in an aquaculture setting. The requirements for this task include a high-resolution underwater video surveillance system capable of capturing detailed footage from multiple angles. The system must be able to function effectively in varying light conditions and water clarity levels. The conditions include a controlled environment where factors such as feeding times, water temperature, and water quality are maintained within optimal ranges for Rainbow Trout.

The primary goal of this task is to develop algorithms that can effectively assess the speed and angle of individual Rainbow Trout. This data will be used to identify potential health issues, optimize feeding schedules, and enhance the overall management of the school of fish. The video analytics system will be paired with a specifically trained YOLO-Pose neural network, which will process the video data and provide the information necessary to achieve these goals.

III. Methods for Assessing Motion Activity

A wide array of methods exists for assessing motion activity, applicable to a variety of subjects, including fish and other objects. The review of these methods provides the foundation upon which our unique solution is built.

In the context of marine biology, several studies have utilized video-based tracking systems to monitor and analyze the movement of aquatic species. For instance, "Aquatic Toxic Analysis by Monitoring Fish Behavior Using Computer Vision: A Recent Progress" by Chunlei Xia. et al. (2018) [1], provides a comprehensive overview of computer vision-based tracking and its application to marine life. In this study, a speed calculation method was used, similar to the one we employ for assessing individual fish speed.

In the broader field of motion analysis, methods have been developed to track not only the speed but also the direction of moving objects. A widely referenced approach is discussed in "Tracking of Moving Objects from a Moving Vehicle Using a Scanning Laser Rangefinder" by Robert A. MacLachlan et al. (2006) [2]. This work introduces the concept of using distance measurements from multiple points of view, which can be extrapolated to our method of determining the angle of the fish using stereo cameras and 3D spatial points.

The Kalman filter, a recursive algorithm used for estimating the state of a dynamic system from noisy measurements, is a commonly used tool in motion analysis. "Using the Kalman Filter for Human Motion Tracking in Video Surveillance" by Caius Suliman et al. (2010) [3], shows how it can be used to filter out noise and improve the accuracy of motion tracking data. This method can be applied to smooth out erratic data in fish motion activity caused by abrupt changes in direction or speed.

When it comes to objects beyond marine life, methods for assessing motion activity also span across different industries. For example, in "Video Analytics for Business Intelligence" by Caifeng Shan et al. (2012) [4], computer vision and motion tracking are used to analyze customer behavior in retail environments. Although the context is different, the principles of motion tracking and behavior analysis could be applicable to our study.

In conclusion, the existing body of research offers a variety of methods for assessing motion activity, each with its own advantages and potential applications. By integrating and adapting these methods, it is possible to develop a robust and accurate system for assessing the motion activity of a school of Rainbow Trout, ultimately contributing to the advancement of aquaculture management and research.

IV. Assessment of Motion Activity of a School of Rainbow Trout

Our solution for assessing the motion activity of a school of Rainbow Trout leverages the power of Artificial Intelligence, specifically the YOLO-Pose algorithm, and borrows methods from existing literature on motion activity assessment.

The choice of YOLO-Pose as the primary algorithm is driven by its ability to detect and differentiate multiple points on individual fish, including the mouth, eye, dorsal fin, adipose fin, tail, anal fin, ventral fin, and pectoral fin. This high degree of granularity facilitates detailed analysis of fish motion, which aligns with our requirements as outlined in the ”Videoanalytics of a School of Fish” section.

To train the YOLO-Pose algorithm, we prepared a dataset primarily sourced from our stereo cameras. This dataset was annotated using the COCO-annotator [5], a tool widely used for creating training datasets for object detection algorithms.

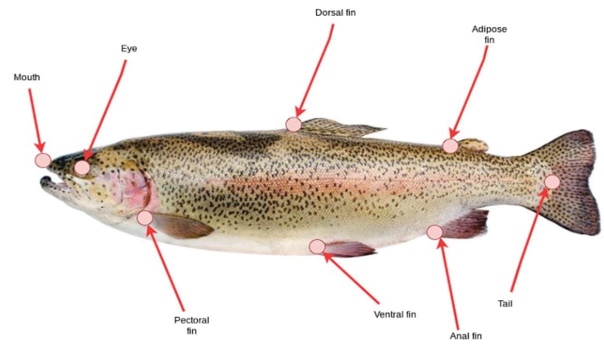

Fig. 3. Detected fish points

For assessing fish speed, we employed a method inspired by [1]. We calculate the mean or median speed of each detected point on individual fish, then calculate the mean or median of these measurements to obtain the overall speed of the fish. To mitigate the effect of sudden jumps in speed data, we apply the Kalman filter, as suggested in [3].

To calculate the angle of the fish, we use the 3D spatial points provided by YOLO-Pose and specific algorithms for calculating distance from stereo cameras. A method similar to this has been utilized in [2]. The horizontal angle is calculated as the angle between the tail-mouth vector and the plane of the pool, while the vertical angle is determined between the fish plane and the pool plane.

The fish plane is determined using a least squares solution, a method commonly employed for fitting a plane to a set of points in 3D space. A similar method has been used in ”The Research about the Point-Cloud-Plane Fitting Based on Penalized Least Squares” by MENG Qingnian et al. (2015)[6].

By integrating these methods and tools, we have developed a comprehensive solution for assessing the motion activity of a school of Rainbow Trout. This solution not only meets our specific requirements but also offers potential for further refinement and application in broader contexts.

V. Use case: Early Experiments and Integration in Underwater VSS

Our initial experiments with the designed solution offer compelling insights into its potential and areas for further refinement. Two distinct feeding experiments were conducted under varying water conditions to test the speed calculation algorithm.

The experimental setup involved capturing video footage of the school of Rainbow Trout 15-20 minutes before feeding, followed by a similar duration of recording after feeding. This allowed us to compare the fish motion activity before and after the feeding intervention, thereby testing the algorithm’s effectiveness at detecting changes in fish activity. The results were promising, confirming the algorithm’s ability to analyze fish activity in alignment with the problems defined in the ”Videoanalytics of a School of Fish” section.

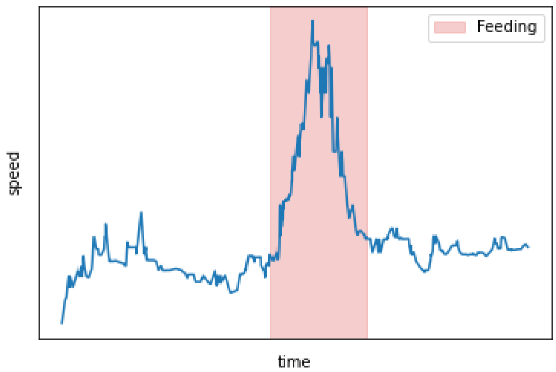

Fig. 4. Measurement of fish speed during feeding

A parallel line of experimentation focused on the algorithm for calculating the angle of fish. The current version of the YOLO-Pose algorithm tends to interpret upside-down fish as if they are swimming normally. This misinterpretation is attributed to the lack of upside-down fish data in the training set. To address this issue, we have already begun collecting and annotating video footage of upside-down fish to enhance the YOLO-Pose’s detection accuracy. Despite this limitation, the current algorithm is still capable of providing valuable insights into fish health, albeit with potential inaccuracies in vertical angle measurements. The horizontal angle calculation, however, is not affected, as the YOLO-Pose successfully detects the Tail and Mouth points.

Fig. 5. Example of a sick fish

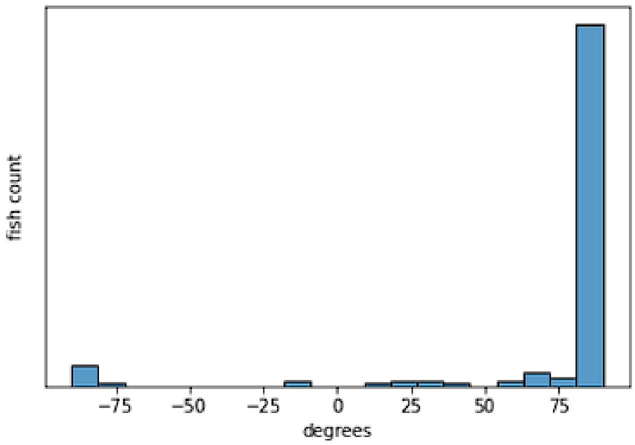

Fig. 6. Vertical angle measurements

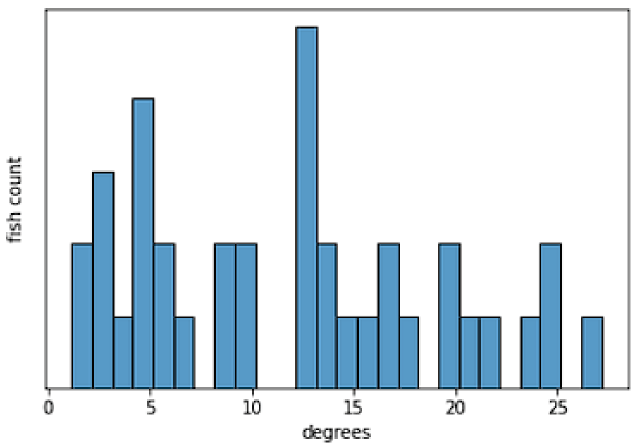

Fig. 7. Horizontal angle measurements

The developed algorithms for calculating speed and angle have been successfully integrated into the Fishgrow Platform, a comprehensive software-hardware complex designed for aquaculture. This integration enables real-time monitoring and analysis of fish activity, opening up new possibilities for managing and optimizing aquaculture operations.

VI. Use of Existing Technologies

Let us summarize the existing technologies and underlying algorithms.

- Stereo cameras
  - Hikvision DS-2CD2683G2-IZS
  - Linovision IPC608
- Neural network based on PyTorch [7] and YOLO-Pose [8] for detecting up to 8 points of individual fish.
- OpenCV [9] library of programming functions for computer vision.
- Message protocol ZeroMQ [10] for message exchange.
- Python 3.8 [11] programming language with libraries for the implementation of the basic video processing modules and interaction with above technologies.

VII. Conclusion

Our research has highlighted the promising potential of artificial intelligence and video analytics in aquaculture. The algorithms we developed for assessing fish speed and angle have shown effectiveness in identifying activity levels and potential health issues in a school of rainbow trout. Their integration into the Fishgrow Platform underscores the viability of this approach and its potential to revolutionize aquaculture operations.

However, areas for refinement remain. The current limitation of the YOLO-Pose algorithm in detecting upside-down swimming fish points to the need for more diverse training data. Moving forward, we aim to optimize these algorithms for various species and environmental conditions, thereby expanding their applicability. This study not only advances the use of AI technologies in aquaculture but also sets the stage for future innovations aimed at boosting operational efficiency and sustainability.

Acknowledgment

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References

[1] C. Xia, L. Fu, Z. Liu, H. Liu, L. Chen, and Y. Liu, “Aquatic toxic analysis by monitoring fish behavior using computer vision: A recent progress,” *Journal of toxicology*, 2022.

[2] R. MacLachlan and C. Mertz, “Tracking of moving objects from a moving vehicle using a scanning laser rangefinder,” *IEEE Intelligent Transportation Systems Conference*, pp. 301–306, 2006.

[3] C. Suliman, C. Cruceru, and F. Moldoveanu, “Kalman filter based tracking in an video surveillance system,” *Advances in Electrical and Computer Engineering*, vol. 10, 05 2010.

[4] C. Shan, F. Porikli, T. Xiang, and S. Gong, *Video Analytics for Business Intelligence*. Berlin: Springer Berlin, Heidelberg, 2012.

[5] J. Brooks, “COCO Annotator,” https://github.com/jsbroks/coco-annotator/, 2019.

[6] M. Qingnian, Z. Dehua, and X. Yezhang, “The research about the point-cloud-plane fitting based on penalized least squares,” *jgg*, pp. 420–423, 2015.

[7] “PyTorch.” [Online]. Available: https://www.pytorch.org

[8] D. Maji, S. Nagori, M. Mathew, and D. Poddar, “Yolo-pose: Enhancing yolo for multi person pose estimation using object keypoint similarity loss,” *CVPR*, pp. 2637–2646, 2022.

[9] “Home - OpenCV.” [Online]. Available: https://opencv.org/

[10] “ZeroMQ.” [Online]. Available: https://zeromq.org/

[11] “Python.” [Online]. Available: https://www.python.org/