A Computer Vision Approach to Counting Farmed Fish in Flowing Water

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Abstract: Aquaculture is an expanding industry that depends on accurate fish counting for effective production management, including growth monitoring and feed optimization. Manual counting is time-consuming and labor-intensive, while commercial counting devices face challenges such as high costs and space constraints. In ecology, tracking animal movement trajectories is essential, but using devices on small organisms is impractical, prompting the adoption of video and machine learning techniques. In contrast to traditional biological studies that often rely on offline analysis, real-time fish counting is vital in aquaculture. This study introduces a fish count method based on a Multiple Object Tracking (MOT) algorithm explicitly tailored for aquaculture. The method prioritizes counting accuracy over precise movement tracking, optimizing existing techniques. The proposed approach provides a viable solution to count fish in aquaculture and potentially other fields.

1 INTRODUCTION

Aquaculture is a rapidly growing industry where accurate fish counts are crucial for managing growth, feed, and production(FAO, 2024). Manual counting is impractical, and while ICT-based systems(of Japan, 2022) automate tasks like feeding and measuring, commercial counting devices face challenges such as high costs and space requirements.

In ecological research, tracking organism movement provides insights into behavior and group dynamics(A. I. Dell and Brose, 2014). However, using GPS or sensors for small organisms is often impractical. Instead, video-based methods using machine learning have become common(Mathis et al., 2018; Pereira et al., 2022), enabling tracking via object detection and association in video frames, a process central to Multiple Object Tracking (MOT).

Conventional MOT systems for biology focus on offline analysis, prioritizing accuracy over speed. In aquaculture, real-time counting is essential for tasks like transferring or shipping fish. This study proposes a fish-counting method using MOT, designed for aquaculture. Unlike traditional MOT, it emphasizes accurate counting rather than precise movement trajectories.

The method involves detecting fish in each frame and associating them across frames to avoid double counting, even with standard cameras operating at 60 fps. Experiments conducted at aquaculture sites demonstrated the method's accuracy across various conditions, outperforming conventional MOT and detection-only approaches.

This method offers a practical solution for aquaculture and similar scenarios requiring real-time, accurate counts of individual organisms.

2 RELATED WORK

2.1 Object Detection

Object detection methods are categorized as one-stage and two-stage approaches. One-stage methods, like YOLO (Redmon et al., 2016), directly estimate object locations and classifications, making them ideal for real-time applications. In contrast, two-stage methods, such as Faster R-CNN (Ren et al., 2015), first identify candidate regions and then classify them, offering higher accuracy at the cost of slower performance. Recent advancements include methods like

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DETR (Carion et al., 2020), leveraging large language models.

This study adopts a one-stage approach using YOLOv8, chosen for its effectiveness in detecting small objects like juvenile fish, ensuring suitability for real-time applications.

2.2 Object Tracking

There are several approaches to object tracking. One standard method is tracking by detection, which associates detected objects by using algorithms such as the Hungarian Algorithm to link detection results and track objects. Examples of this approach include SORT (Bewley et al., 2016), ByteTrack (Zhang et al., 2022), and OC-SORT (Cao et al., 2023).

2.3 Fish Tracking and Counting

Recent advances in computer vision have enabled significant progress in fish tracking. Wang et al. (Wang et al., 2019) used TLD and ASMS for high-accuracy tracking based on fish color and shape. Tools like idTracker (Pérez-Escudero et al., 2014) and idTracker.ai (Romero-Ferrero et al., 2019) reduce ID switches caused by occlusions or group interactions.

For counting, computer vision methods balance cost and efficiency. Systems like LDNet (Li et al., 2024) handle high-density environments, and segmentation-based approaches (Lilibeth Coronel and Namoco, 1970) measure from single images, though they struggle with noise. Video-based approaches, such as Mask R-CNN (Tseng and Kuo, 2020), offer better accuracy and efficiency but often focus on tanks or static environments. Few methods address fast-moving fish in waterways.

3 PROPOSED METHOD

3.1 Problem Definition and Overview of Proposed Method

Although fish can be counted through detection alone, there are several issues. In the footage used in this study, the fish exhibit fast and complex movements, leading to false and missed detections. Additionally, because the fish are being carried by water, the system is affected by noise from the water itself. Unlike pedestrians, whose appearance can be distinguished by clothing, fish have slight variation in their external features and generally look very similar. As a result, it becomes challenging to differentiate fish that have already been counted, leading to double counting, misdetection of water as fish, or counting multiple fish passing simultaneously as a single one. This can result in overcounting.

Narrowing the detection area can reduce overcounting but increases the risk of missing fish. Thus, setting the detection range appropriately is crucial. Additionally, methods like SORT use IoU (Intersection Over Union), which measures the overlap between the predicted and detected bounding boxes, for tracking. However, in the case of fast-moving objects, the IoU can drop to zero, causing tracking failures and reducing the accuracy of fish counting.

The proposed method to solve these issues is illustrated in Figure 1. In this method, (a) similar to the standard SORT, object detection is performed on each frame using YOLO to detect the fish. Then, (b) the Kalman filter is applied to the detected positions from the previous time step to predict the current position. Next, (c) the predicted position is associated with the detected position at the current time step. Instead of using IoU, the association is made simply based on the shortest Euclidean distance. (d) The tracked objects are considered individual fish and are counted accordingly. Each of these steps is explained in detail below.

3.2 Detection

YOLOv8 is used for detection. YOLO is a one-stage object detection model that can perform both classification and object detection simultaneously. Its architecture is composed of a backbone, a neck, and a head. Improvements in the new architecture and convolutional layers enable advanced detection while maintaining excellent real-time performance. The fish targeted in this study are relatively small, with a body length of 3 to 5 cm, making them appear small in the footage. However, YOLOv8 is capable of detecting even small objects effectively.

3.3 Prediction

The Kalman filter is used to predict the movement of fish. It estimates the tracked object's position, velocity, and acceleration over time, making it effective for predicting states from noisy data. The Kalman filter has also been widely used in recent tracking applications. Using the Kalman filter makes it easier to predict the next position of the tracked object. Since real-time prediction is essential for fish counting and tracking, the Kalman filter was chosen for its real-time capabilities and computational efficiency.

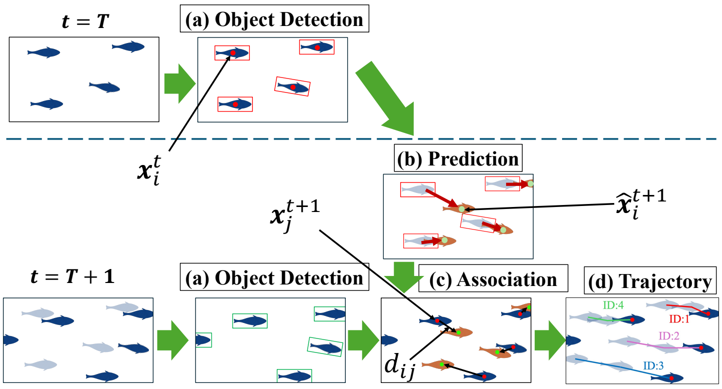


Figure 1: Illustration of the proposed method. After inputting the video, (a) object detection is performed, followed by (b) predicting the positions of the detected fish. (c) The predicted position is then associated with the detection result at the subsequent frame by calculating the Euclidean distance between the center coordinates of the prediction and the detection result, with the closest match being selected. (d) The fish are tracked, and IDs are assigned. The number of tracked objects, identified by their IDs, is then counted.

3.4 Association

In the video used in this study, the distance the fish move between frames is significant, making it unsuitable to use IoU-based association methods like SORT, as it lowers the accuracy of fish counting. IoU-based association is weak in handling occlusions, and tracking fast-moving objects often fails. As a result, objects assigned an ID in one frame may be assigned a different ID in the next frame, leading to an inflated count.

To address this, the association between fish is made based on the Euclidean distance between the center coordinates of the bounding boxes predicted by the Kalman filter and the bounding boxes detected by YOLO.

First, fish detection is performed at each time step t, and the bounding boxes of the detected fish are obtained, with the center of the bounding box considered as the position x_i^t of the fish, where i is the index representing individual fish. Next, state estimation is performed using the Kalman filter, which estimates and updates the state over time. The position information of the object in the next frame is predicted based on past position information and the prediction model as $\hat{x}_i^{t+1} = F(x_i^t)$. Then, the Euclidean distance between each predicted position and the detection result in the next frame $d_{ij} = ||\hat{x}_i^{t+1} - x_j^{t+1}||^2$ is calculated, and if the distance is smaller than a predetermined threshold D_T, the objects are considered to be associated. Although this process is quite simple, as shown in later experiments, it allows for sufficiently accurate association even for fast-moving objects.

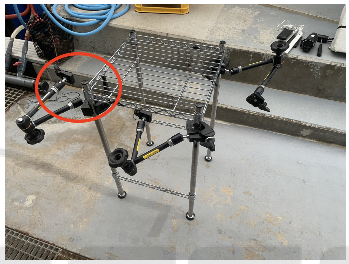


Figure 2: Equipment for Experiments.

3.5 Tracking

After the association step, tracklets are created, and IDs are assigned to them. Then, the prediction for each tracklet is matched with new detections to continue tracking. If an object fails to be tracked, it is considered a tracking failure, and the Kalman filter is used to predict the object's position from the point of failure. In the next frame (t+1), the association is re-established if the new detection result is within the threshold of the predicted position from the Kalman filter. If a tracklet remains in a failed tracking state for a certain number of frames, it is deleted. This method aims to achieve real-time counting by improving computational efficiency, making fast fish counting feasible.

4 EXPERIMENT

4.1 Datasets

For the experiment, a setup was constructed as shown in Figure 2, with a camera mounted on the camera arm at the location marked in red, and the shooting

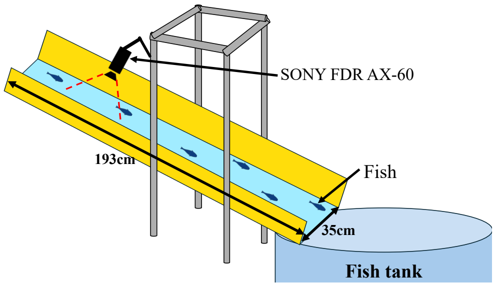


Figure 3: Filming Condition.

environment was arranged as shown in Figure 3. The camera was positioned perpendicular to the waterway to ensure that the size of the fish remained consistent throughout the footage. The fish were released into the water and recorded the fish being directed to a different tank through a waterway. The video was recorded using a SONY FDR-AX60 camera, and the shooting conditions are listed in Table 1. The target fish had body lengths of 3 to 5 cm. The recording took place at the Oshima Hatchery, Kindai University Aquaculture Technology and Production Center.

To evaluate the method under various conditions, we used the following three datasets:

4.1.1 Dataset 1: YOLO Training Dataset

To train the YOLO object detection model, images were randomly extracted from videos of fish flowing through a waterway recorded at different times of the day. 488 images containing fish were selected and randomly divided into training and validation datasets. Manual annotation provided ground-truth data for training.

4.1.2 Dataset 2: Dataset for Fish Counting Evaluation

The first dataset for fish counting experiments was recorded in the same waterway environment with a uniform yellow background, as used for YOLO training. A total of 27 videos were prepared to count the number of fish passing through the waterway. This environment is well-suited for evaluating the performance of the detection model and the essential accuracy of the MOT-based counting method.

Among these videos, 18 were recorded at different times on the same day, while the remaining nine were recorded on separate days, introducing subtle environmental changes. This dataset is referred to as Dataset 2. Videos recorded on the same day are labeled with letters (e.g., 2-A, 2-B, 2-C), while videos recorded on different days are labeled with numbers (e.g., 2-1, 2-2, 2-3). Sample images of Dataset 2 are shown in Figure 4.

Table 1: Specifications of the Camera and Video Used for Experiments.

Camera	SONY FDR AX-60
Resolution	1920×1080 pixel
Frame Rate	60fps
Bit Rate	50Mbs

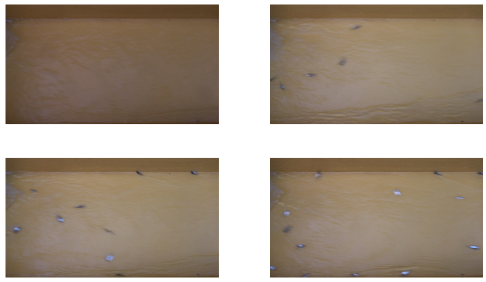


Figure 4: Sample Frames of Video Used in Dataset 2.

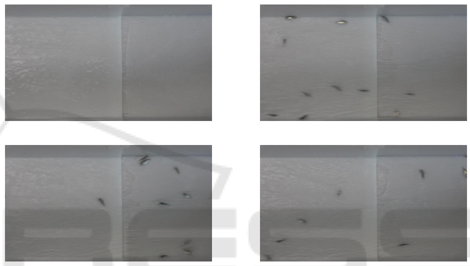


Figure 5: Sample Frames of Video Used in Dataset 3.

4.1.3 Dataset 3: Dataset for Fish Counting Evaluation with Different Backgrounds

A separate set of four videos with a white background was prepared to evaluate the impact of background color as Dataset 3. This dataset was used to assess the performance of the proposed method under different conditions. Although the videos were recorded on dates different from those in Dataset 2, the waterway conditions were similar. Sample images of Dataset 3 are shown in Figure 5.

Using these datasets, we conducted three major experiments. The results are presented below.

4.2 Experiment 1: Fish Detection

In Experiment 1, since the proposed method follows the tracking by detection paradigm of MOT, poor detection accuracy by YOLO can significantly impact the accuracy of fish counting. By verifying the accuracy of YOLOv8, we aim to confirm whether YOLOv8 can detect fish accurately.

To build a model for detecting fish using YOLOv8, we used Dataset 1, which were recorded

Table 2: YOLOv8 Training Parameters.

Epochs	50
Number of Images for Training	390
Number of Images for Verification	98
Batch Size	16
Network	YOLOv8n

Table 3: Object Detection Results of YOLOv8.

Precision	Recall	AP
95.4	93.8	95.6

under the same conditions as the fish-counting footage Dataset 2 but from a different time. 390 images were prepared for training and 98 images for validation. The training conditions are outlined in Table 2.

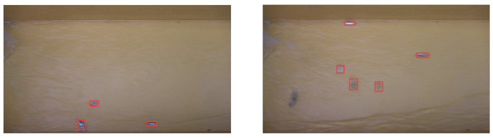
The results of detection using YOLO are shown in Table 3. The evaluation metrics used were Precision, Recall, and AP. Precision represents the proportion of objects predicted as fish that were recognized as fish. Recall represents the proportion of actual fish that were correctly detected as fish. AP (Average Precision) is the average precision across various parameters, indicating the overall detection performance.

All three evaluation metrics exceeded 93%, indicating that YOLOv8 can detect small fish with high accuracy. However, there were some issues, such as false detections of water, missed detections, or failing to distinguish between two fish and detecting one fish as two. Additionally, in cases where fish were occluded, the system sometimes detected more fish than were present. Figure 6 shows examples of missed and false detections. However, we believe these issues can be improved by adding temporal information, increasing the number of training data, and extending the training iterations.

4.3 Experiment 2: Fish Counting

In Experiment 2, we examined whether accurate fish counting could be achieved. The ground truth for the number of fish was obtained by manually counting the fish in the footage, and the results were compared.

In the proposed method, it is necessary to set the distance threshold D_T. First, we evaluate the results under various threshold values. Then, we assess the method's performance using the prepared diverse datasets to evaluate its robustness and generalizability.



(a) (b)

Figure 6: Examples of Incorrect Detections.

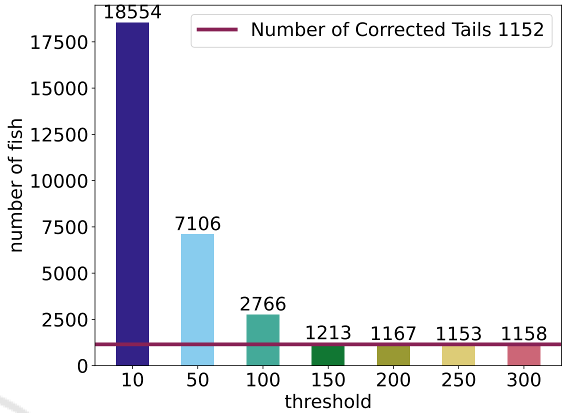


Figure 7: Results of Varying the Distance Threshold for Dataset 2-A.

4.3.1 Evaluation of Impact of Euclidean Distance Threshold on Association

Figure 7 shows the impact of varying the distance threshold D_T for Dataset 2. If this threshold is set too low, the number of failed associations will increase, leading to a higher count. Conversely, if the threshold is too high, objects that should not be associated may be linked, resulting in a lower count.

The results show that when the threshold D_T is small, the estimated fish count is significantly higher, which aligns with the abovementioned discussion. However, once the threshold exceeds 150, the count stabilizes near the correct value, indicating that increasing the threshold does not lead to many unnecessary associations. In other words, this threshold is not highly sensitive, and setting it above a particular value ensures accurate results.

The estimated result of the proposed method was 1,153 fish, with a difference of only one fish compared to the ground truth of 1,152. While there were instances of missed detections, tracking failures, and double counting, these errors offset each other, resulting in a value close to the actual count. This demonstrates that the proposed method is effective for fish counting and serves its purpose well.

Figure 8 shows the results of the same experiment conducted on Dataset 3-1, respectively. The result reveals a similar trend, with values very close to the ground truths of 1262. Notably, for Dataset 3-1,

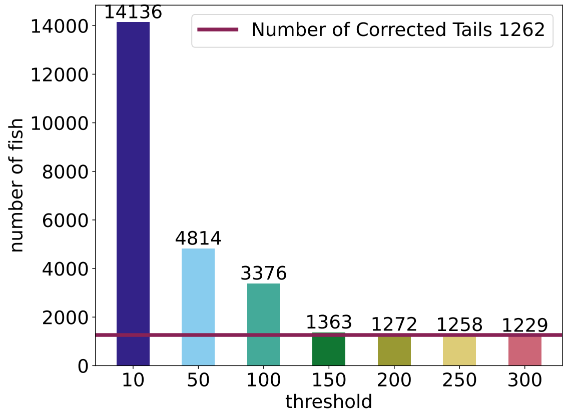


Figure 8: Results of Varying the Distance Threshold for Dataset 3-1.

which features a background color different from the images used for YOLO training, good results were achieved without being affected by the background color.

4.3.2 Evaluation of Fish Counting Under Various Conditions

From the results in the previous section, it was found that setting the distance threshold D_T greater than 150 generally produces favorable results. Therefore, we evaluated fish counting on all prepared datasets using D_T values of 150 and 250, where stable results were observed.

Table 4 presents the experimental results. GT refers to the counting results obtained through manual annotation, and the fish counts obtained using the two different D_T values are also shown.

For Dataset 2-A to 2-R, most videos showed a tendency for the fish count to exceed the ground truth by 5–10% when $D_T = 150$, whereas the error was around 3% when $D_T = 250$. This is because, at $D_T = 150$, there were some instances where fish with large movements were not correctly associated. In contrast, at $D_T = 250$, the associations were more successful, reducing the likelihood of overcounting.

In 2-G, which had the highest number of fish (9,441), the count with $D_T = 150$ was 9,857, approximately 4.4% higher than the ground truth. However, with $D_T = 250$, the count improved to 9,315, reducing the difference to about 1.4%. This indicates that accurate counting can still be achieved even in high-density conditions with a large number of fish.

For Dataset 2-1 to 2-9, both $D_T = 150$ and $D_T = 250$ showed a tendency for the counting results to exceed the ground truth. However, with $D_T = 250$, the error remained within the acceptable range at around 10%. One observed cause of this overcounting is that fish passing along the edges of the waterway can reflect off the walls, leading to multiple counts. This issue could potentially be addressed by revising the recording conditions.

Table 4: Counting Results Across All Datasets.

Data	GT	$D_t = 150$		$D_t = 250$	
2-A	1,152	1,213	+5%	1,153	+0.1%
2-B	934	980	+4.9%	945	+1.2%
2-C	836	880	+5.3%	843	+0.8%
2-D	4,616	4,927	+6.7%	4,627	+0.2%
2-E	5,066	5,242	+3.5%	4,992	−1.5%
2-F	516	546	+5.9%	514	−0.4%
2-G	9,441	9,857	+4.4%	9,315	−1.4%
2-H	594	652	+9.8%	604	+1.7%
2-I	308	338	+9.7%	320	+3.9%
2-J	562	600	+6.8%	570	+1.4%
2-K	1,084	1,166	+7.6%	1,101	+1.6%
2-L	1,006	1,079	+7.2%	1,018	+1.2%
2-M	208	240	+15%	223	+7.2%
2-N	682	723	+6.0%	695	+1.9%
2-O	365	381	+4.4%	376	+3.0%
2-P	667	711	+6.6%	678	+1.7%
2-Q	717	790	+10%	728	+1.5%
2-R	3,469	3,799	+9.5%	3,374	−2.8%
2-1	576	653	+13%	608	+5.6%
2-2	283	303	+7.1%	295	+4.2%
2-3	237	274	+16%	258	+8.9%
2-4	73	83	+13%	77	+5.5%
2-5	260	271	+4.2%	272	+4.6%
2-6	120	133	+10%	128	+6.7%
2-7	115	128	+11%	121	+5.2%
2-8	801	872	+8.9%	836	+4.4%
2-9	3,936	4,272	+8.5%	4,009	+1.9%
3-1	1,262	1,357	+7.5%	1,261	−0.1%
3-2	1,345	1,438	+6.9%	1,362	+1.3%
3-3	1,680	1,875	+11%	1,675	−0.3%
3-4	1,567	1,760	+12%	1,558	−0.6%

Dataset 3 involved significantly different conditions, yet the error trends were similar to those observed in Dataset 2-A to 2-R. This indicates that the proposed method can perform stable fish counting even when the environment changes.

4.4 Detailed Evaluation

Additional experiments were conducted to verify the effectiveness of the proposed method. All subsequent experiments were conducted using Dataset 2-1. And, the threshold D_T was set to 250.

Table 5: Comparison with Counting Using Detection Results Alone.

Method	Number of Fish
YOLOv8 alone	45,845
Proposed Method	1,153

Table 6: Comparison of Conventional MOT Methods.

Detector	Tracking	Number of Fish
YOLOv8	SORT	1,883
	OC-SORT	1,726
	ByteTrack	2,268
	Ours	1,153
Ground Truth		1,152

4.4.1 Comparison with Counting Using Detection Only

The results obtained using only YOLOv8 for detection and counting are presented in Table 5. In other words, this approach does not perform temporal tracking but rather sums the number of detections in individual frames, and these results are compared.

As shown in Table 3, fish in a single image can be detected with sufficient accuracy. However, when counting detections from consecutive frames as separate individuals, the count increases significantly. To prevent this, narrowing the detection range is undesirable, as it increases the risk of missed detections.

4.4.2 Comparison with Tracking Methods Typically Used in MOT

The proposed method was compared with traditional tracking methods used in existing MOT techniques. All detectors were based on the YOLOv8 model used in Experiments 1 and 2. The results are shown in Table 6.

The results show that the proposed method achieved a lower fish counting error rate than IoU-based association methods. First, in the case of SORT, it assumes that the movement between frames is slight and uses IoU for tracking. As a result, it often fails to re-identify objects once they are lost, considering them as separate individuals, which likely led to the observed results.

Next, OC-SORT consists of three components. ORU reduces error accumulation during occlusion, OCM enhances directional consistency for nonlinear movements, and OCR recovers lost tracks after short-term occlusions. These features contributed to lower errors compared to SORT. However, using IoU-based association for fast-moving objects increases the difficulty.

Table 7: Verification of the Kalman Filter's Effect.

Prediction	Number of Fish
Kalman Filter	1,153
without Kalman Filter	1,731

Lastly, ByteTrack utilizes low-confidence detection results, which can lead to errors when tracking fast-moving objects, as motion blur often occurs. Additionally, since it associates detection results with high-confidence detection, discrepancies between predictions and detection results can cause misassociations or unmatched tracks.

4.4.3 Verification of Effectiveness of Kalman Filter

To verify the effectiveness of the Kalman filter's predictions, we compared two approaches: one where no motion prediction was performed between frames and the detection results from frame t and frame $t+1$ were directly used for the association, and another where the Kalman filter was applied. The results are shown in Table 7.

The Kalman filter makes it easier to associate objects by filtering based on past position and velocity information, making it less susceptible to noise and allowing for movement-aware predictions. Without the Kalman filter, the association of detection results between frames becomes more prone to errors due to sudden object movements or the influence of noise, such as water. This can lead to tracking failures and frequent ID switches, which is likely the cause of the increase in the fish count.

4.4.4 Evaluation of Impact of Frame Rate

Finally, we evaluate the fish count results when varying the frame rate. The higher the frame rate, the smaller the fish movement between frames, making tracking easier and improving the accuracy of fish counting. From an accuracy perspective, a higher frame rate is preferable. Still, as mentioned in Section 1, there are situations where real-time processing is required, and higher frame rates make real-time processing more difficult. Therefore, we evaluated with a lower frame rate. We generated 30, 15, and 12 fps footage from the 60fps footage. The same method is applied to the generated footage. The results are shown in Table 8.

When $D_T = 150$, reducing the frame rate to 30fps caused the fish count to increase compared to the ground truth of 1152. However, at 15fps, the count decreased, and it dropped further at 12fps. This is because, at 30fps, the increased fish movement between frames leads to association failures, resulting in

Table 8: Counting Results with Different Frame Rates.

Frame Rate	$D_t = 150$	$D_t = 250$	$D_t = 300$
60 fps	1,213	1,153	1,158
30 fps	1,618	1,190	1,178
15 fps	1,270	721	834
12 fps	995	650	487

an overestimation of the count. At lower frame rates, fewer fish are captured in the images, as the frame rate becomes too low to record their presence effectively.

A similar trend was observed for $D_T = 250$ and $D_T = 300$. At 60fps, all three threshold values provided satisfactory results. However, at 30fps, it was found that DT must be set to 250 or 300 to achieve reliable results. The conditions for $D_T = 150$ at 60fps and $D_T = 300$ at 30fps can be considered nearly equivalent, and indeed, the fish counting results were almost identical under these settings.

As stated in Section 1, real-time processing is required in aquaculture settings, making lower frame rates more desirable. In such cases, it is necessary to consider the movement speed of the fish and set an appropriate D_T value.

5 SUMMARY

In this paper, we proposed a method for counting fast-swimming fish to apply in aquaculture settings. Since real-time counting is considered, we employed simple techniques, but the method has achieved sufficient accuracy. Future challenges include conducting detailed evaluations in different environments and with various fish species and developing a real-time system.

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