

Fish Tracking, Counting, and Behaviour Analysis in Digital Aquaculture: A Comprehensive Review

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Abstract—Digital aquaculture leverages advanced technologies and data-driven methods, providing substantial benefits over traditional aquaculture practices. Fish tracking, counting, and behaviour analysis are crucial components of digital aquaculture, which are essential for optimizing production efficiency, enhancing fish welfare, and improving resource management. Previous reviews have focused on single modalities, limiting their ability to address the diverse challenges encountered in these tasks comprehensively. This review provides a comprehensive analysis of the current state of aquaculture digital technologies, including vision-based, acoustic-based, and biosensor-based methods. We examine the advantages, limitations, and applications of these methods, highlighting recent advancements and identifying critical research gaps. The scarcity of comprehensive fish datasets and the lack of unified evaluation standards, which make it difficult to compare the performance of different technologies, are identified as major obstacles hindering progress in this field. To overcome current limitations and improve the accuracy, robustness, and efficiency of fish monitoring systems, we explore the potential of emerging technologies such as multimodal data fusion and deep learning. Additionally, we contribute to the field by providing a summary of existing datasets available for fish tracking, counting, and behaviour analysis. Future research directions are outlined, emphasizing the need for comprehensive datasets and evaluation standards to facilitate meaningful comparisons between technologies and promote their practical implementation in real-world aquaculture settings.

Index Terms—Digital aquaculture, fish tracking, counting, behaviour analysis

I. INTRODUCTION

With the expansion of the global population and the degradation of the ecological environment, traditional fishing (i.e. capture fisheries) is no longer capable of meeting the growing human demand for fish products [1], [2]. Aquaculture has become the primary source of fish acquisition, and digital aquaculture is emerging as a promising approach to enhance the efficiency and sustainability of the industry [3].

Fish tracking, counting, and behaviour analysis are crucial components of digital aquaculture, playing a vital role in effective management and decision-making. Accurate monitoring of these aspects can help detect abnormal fish behaviour, estimate fish abundance, and formulate reasonable management strategies, ultimately improving fish welfare and economic outcomes in the aquaculture industry [4]. Traditional methods for fish tracking and behaviour analysis rely on the experience of human observers, and the observation results

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depend on their skills and knowledge, which are not always reliable [5], [6]. Similarly, manual fish counting methods involve removing fish from tanks, leading to stress, injury, and disease, negatively impacting fish welfare and growth [7], [8]. The implementation of intelligent tracking, counting, and behaviour analysis technologies can help overcome these limitations, reducing the risk of fish mortality, improving feeding strategies, and promoting sustainable development in aquaculture [9]–[11].

Currently, various technologies such as vision-based sensors, acoustic-based sensors and biosensors methods are used for fish tracking, counting, and behaviour analysis in aquaculture. Vision-based sensors and computer vision technology have found widespread application due to advancements in optical imaging and computer vision. However, they are limited by poor illumination, low contrast, high noise, fish deformation, frequent occlusion, and dynamic backgrounds [12]–[15]. Acoustic-based sensors and hydroacoustic methods, which are non-invasive, are particularly useful for monitoring fish in turbid water environments and overnight, but their high hardware cost limits their popularity in intensive aquaculture settings [16]–[20]. Biosensors can provide valuable information on fish physiology and behaviour, but their invasive nature and the need for individual fish tagging can be challenging in large-scale aquaculture operations [21].

Previous reviews have been conducted on fish tracking, counting and behaviour analysis [10], [12], [22]–[25]. However, most reviews focus on computer vision technology as the primary approach and relying on a single modality may not provide sufficient data for comprehensive analysis. To address this limitation, our paper systematically surveys vision-based sensors, acoustic-based sensors, biosensors, and hydroacoustic methods, facilitating a holistic discussion of tracking, counting, and behaviour analysis while identifying technology gaps in the current literature.

This article comprehensively reviews the literature on fish tracking, counting, and behavioural analysis in aquaculture over the past two decades, emphasizing the progress made in these areas and identifying potential future research directions. The remainder of this article is structured as follows: Section II explores the advancements in fish tracking techniques, while Section III discusses the various methods and applications of fish counting. Section IV discuss the behaviour analysis of fish, and Section V presents an overview of relevant public datasets. In Section VI, we examine the challenges faced by the aquaculture industry and discuss future development trends. Finally, Section VII summarises the key findings and conclusions presented in this paper.

II. FISH TRACKING

Vision-based multi-target tracking methods are increasingly used in fish behaviour analysis. However, fish tracking is challenging because of the small differences between individuals, complex environments, and variations in plankton, shapes, angles, and scales of swimming fish [26]. Fish tracking can be categorized into two-dimensional (2D) and three-dimensional (3D) tracking based on the swimming environment [27]. 2D tracking is used in shallow water containers, where fish swimming appears close to a 2D planar motion and is represented using (x, y) coordinates, but can only analyze a part of the fish behaviour. In contrast, 3D tracking considers depth information and is represented using (x, y, z) coordinates, enabling the analysis of spatial movement in natural environments.

In addition to vision-based tracking, acoustic techniques such as the Acoustic Tag System (ATS) are also used for fish tracking. ATS involves attaching acoustic tags to fish, which emit unique acoustic signals that are detected by hydrophone receivers. The position of the tagged fish can be estimated using the time difference of arrival of the acoustic signals at multiple receivers, allowing for 3D tracking of fish movement in natural habitats [28]. This section mainly analyzes the relevant literature on fish tracking methods based on visual technology (as shown in Table I) and acoustic techniques in recent years and provides a systematic summary.

A. Fish tracking based on 2-dimensional visual information

Fish tracking methods can be broadly categorized into three main approaches: classical algorithms, kernel correlation Filter algorithms, and deep learning-based tracking algorithms [25]. Each category encompasses various techniques with their strengths and limitations, which will be explored in more detail in the following subsections.

1) Fish tracking based on classical algorithm: Classical algorithms have been widely used to address the challenges of fish tracking in complex underwater environments, such as rapid posture changes, occlusion, overlap, and poor image quality. The Tracking-Learning-Detection (TLD) algorithm, which updates salient features and target model parameters through online learning, has shown promise in providing stable tracking [42]. However, its median-flow tracker may fail when fish change their swimming posture rapidly. An adaptive scale mean-shift (ASMS) algorithm, utilizing fish shape and colour features, has replaced the median-flow tracker and handled posture changes, uneven illumination, and complex backgrounds [43].

Preserving individual fish identities during occlusion and overlap remains a significant challenge. Techniques that extract head shape or body geometry features have been explored [44], [45], but their effectiveness may be limited by the rapid movement and intense geometry of fish bodies [14]. Adaptive threshold algorithms, which estimate thresholds for each pixel based on its adjacent region, have shown promise in segmenting individual fish in binarized images [46]. The global nearest neighbour algorithm with fish posture as a tracking constraint has been used to track small numbers

of zebrafish [36], but it lacks individual recognition ability, leading to track exchanges during overlap or occlusion. The Toxld algorithm addresses this issue using intensity histograms and Hu-moments to link trajectory fragments and preserve individual fish identities [47]. However, the error increases with the number of fish.

To mitigate poor image quality, retinex (MSR) based enhancement algorithms combined with object detection and Euclidean tracking have been used to improve fish detection in unclear underwater images [30], [48], [49]. Kalman Filters may not always be optimal for underwater fish tracking due to non-Gaussian noise and complex environments [50]. Mean offset technology, which models fish probability density based on colour histograms, can fail when the background colour closely resembles the fish colour distribution. Tracking algorithms based on covariance representation, which model objects as covariance matrices of pixel-based feature sets, incorporate spatial and statistical characteristics, making them more suitable for tracking fish in challenging underwater scenarios [51], [52].

2) Fish tracking based on Kalman Filter: The Kalman Filter, an efficient autoregressive filter that estimates the state of a dynamic system in an environment with uncertainties, has been widely used for fish tracking due to its versatility and robustness [33], [53]. Building upon the Kalman Filter, the SORT (Simple Online and Realtime Tracking) algorithm has emerged as a simple yet effective multi-target tracking approach [34]. SORT utilizes a Kalman Filter for frame-by-frame data correlation, and the Hungarian algorithm for correlation measurement [54]. Despite its good performance at high frame rates, SORT has limitations, such as ignoring object surface features, which makes the tracking results heavily dependent on the detection performance [55]. To address this issue, an extension of SORT called DeepSORT was developed, which leverages a CNN model trained on large-scale pedestrian datasets to extract features that enhance the network's robustness to loss and obstacle [56].

Recent literature shows that DeepSORT, an extension of the SORT algorithm, has been extensively applied in fish tracking [29]. DeepSORT combines the Kalman Filter-based SORT framework with a deep learning-based appearance feature extractor, enabling more robust tracking performance. However, challenges arise when fish undergo rapid body shape changes during fast turns, leading to blurry and difficult-to-track images [32]. To mitigate this issue, shorter exposure times and variable-size boundary boxes can be used, with the boundary boxes being estimated according to the motion state. Despite these challenges, the Kalman Filter remains a popular choice for fish tracking due to its ability to estimate the state of a dynamic system in the presence of uncertainties.

The frame rate plays a crucial role in Kalman Filter-based fish tracking performance. Low frame rates can lead to increased tracks and a higher likelihood of misidentification. Conversely, high frame rates result in more linear fish motion, enabling Kalman Filters to predict individual motion more accurately (as shown in Fig. 1). As the field continues to advance, future research should prioritize optimizing tracking schemes to minimize computing time and evaluating the long-

TABLE I: Summary of different methods in fish tracking.

Study Site	Maximum Fish Amounts	Points	Detection Methods	Tracking Methods	Tracking Metrics	Advantages	Limitation	References
Tank	13	Fish's head	YOLOv2	Kalman Filter	CIR CTR	High frame rate not necessary	Larger fish quantities increase identification losses	[29]
Tank	11	Fish center points	YOLOV3	Euclidean Distance	-	Enhance target detection in unclear water	Fish numbers are too small and done in the laboratory	[30]
Coast	-	Center of the fish head	YOLOv4	Kalman Filter	MOTA	Real-time tracking with high accuracy	Accuracy affected by different sea areas	[31]
Tank	5	Fish head and center of the fish body	Background subtraction	Kalman Filter	CIR CTR	Accurate, fast, and computational inexpensive	Fail to predict the motion state of rapidly transitioning	[32]
Tank	20	Fish head and fish body	Background subtraction	Kalman Filter	CIR CTR	Smoother resulting trajectory	Lower frame speeds lead to more track breaks and higher misidentification	[33]
Tank	5	Centroid	Background subtraction	Kalman Filter	CIR CTR	Enhances tracking performance under occlusion conditions	Abnormal water quality leads to an increased chance of fish body overlap	[34]
Tank	-	Centroids	Otsu	Manhattan Distance	-	Low cost and removable installation	Stationary fish mistaken for debris or dead	[14]
Tank	25	Fish head	DOH	CNN	Recall	Corrects trajectory errors, fills gaps, and evaluates credibility	Easy affected by floating objects, ripple reflections, fish sharp turns	[35]
Tank	10	Head feature point and central feature point	Background subtraction	Feature point matching	Precision Recall	Two-feature point model reduces tracking difficulty	Only traces a few objects for a very short process	[27]
Glass Aquarium	5	The head and tail of fish	Adaptive thresholding algorithm	GNN	Tracking errors	Accurate tracking by pose constraint, even at high speed	Unable to handle fish occlusion or attaching	[36]
Fringing Reef, Red Sea	4	Fish's body	Fast-RCNN, Inception V2	Linking consecutive frames	3D detection rate	Cost-effective, automated 2D track	Small groups of fish studied	[37]
Tank	50	Head	ResNet-101	Mahalanobis distance and cosine similarity	MOTA IDF1	Reconstruction Performance well under multiple negative factors	Bad performance of long-term tracking	[38]
Tank Pond	50	Body	Transformer	Hungarian algorithm	MOTA IDF1	Accommodates individuals with significant appearance variations.	Limitations in accurate ID matching at high stocking densities (over 50 fish)	[39]
Tank	8	Head	LSTM	Kalman Filter	Precision Recall	Cross-view more robust in high densities	Multi -view map matching is difficult, and the calculation amount is large	[40]
Tank	49	Head	Hessian (DoH) CNN	Iterative tracking strategy	Precision Recall	Tracking individuals exhibiting frequent occlusions	Requires individuals to have at least one body part that remains robust	[41]

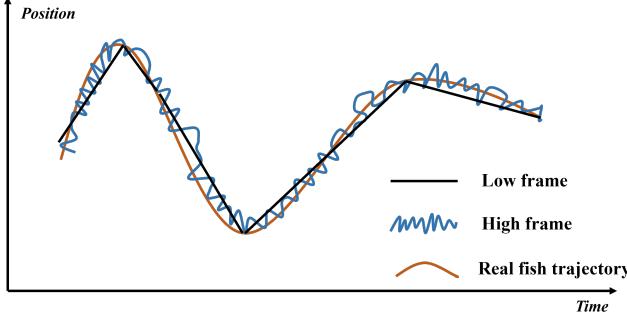


Fig. 1: Fish trajectory under different frame rates.

term tracking performance of these methods in diverse aquatic environments.

3) *Fish tracking based on deep learning*: Deep learning has emerged as a powerful tool for fish tracking, with Tracking by Detection (TBD) being the primary approach. In TBD, a deep learning model is trained on a large dataset to learn convolutional features with strong expressive power, enabling the detection and tracking of fish in video sequences. However, occlusion between fish remains a significant challenge in TBD methods, often leading to the generation of fragmented trajectories that require post-processing to link them together [57].

To address the occlusion issue, several notable multi-target tracking algorithms have been proposed, such as idTracker [58] and its upgraded version, idtracker.ai [59]. These algorithms extract unique fingerprint features from each animal in a set of videos and then identify each target in the video, enabling the tracking of individuals within a group by automatically identifying untagged animals. Although these methods have been widely used for tracking juvenile fish and small animals, the experimental setup restricted fish from swimming up and down to avoid overlapping, simplifying the task compared to real-world 3D tracking scenarios.

Further advancements in deep learning-based fish tracking have been achieved by combining CNN-based methods with other techniques, such as head detection, motion state prediction, and verification using SVM classifiers [41]. These approaches have demonstrated more robust tracking performance compared to idTracker when the fish density is higher, and the occlusion frequency increases, highlighting the potential of deep learning in handling complex tracking scenarios [35].

Despite the progress made in controlled laboratory environments, real-world marine environments pose additional challenges for fish tracking, such as light fluctuations and waves. To address these issues, To tackle these issues, researchers have developed methods like the real-time multi-class fish stock statistics method (RMCF), which uses YOLOv4 as the backbone network and adopts a parallel two-branch structure based on deep learning for detecting fish species, tracking, and counting fish [31]. Although these methods have shown promising results in complex marine environments, their recognition accuracy may vary in different sea areas due to differences in colour cast and contrast, necessitating the retraining of the network weight coefficients.

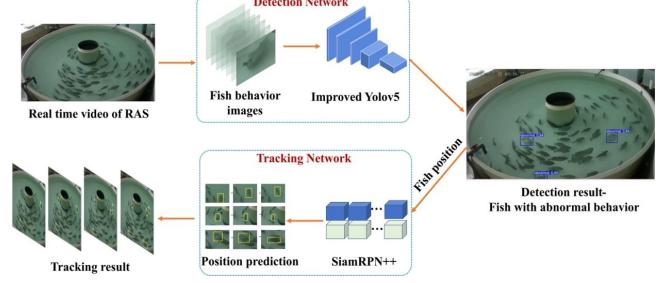


Fig. 2: Fish tracking method based on YoloV5 and SiamRPN++ [61].

Siamese network trackers have gained attention in recent years due to their exceptional tracking speed and high accuracy. The introduction of advanced algorithms, such as SiamRPN++ (as shown in Fig. 2), has further highlighted the performance of Siamese networks, surpassing the performance of tracking algorithms based on correlation filters [60], [61]. Although there are currently few articles on Siamese networks specifically for fish tracking, this approach is expected to become a new direction in the field.

Moreover, the emergence of transformer-based tracking methods has revolutionized the field of object tracking. Initially proposed for natural language processing tasks, transformers have been successfully adapted for computer vision tasks, including object detection and tracking [62]. Transformer-based trackers, such as TransTrack [63] and STARK [64], have demonstrated state-of-the-art performance on various tracking benchmarks. Transformer-based tracking methods have also shown promising results in fish tracking applications [39]. As transformer-based methods continue to advance in object tracking, they are expected to play an increasingly important role in fish-tracking applications. Future research should focus on further adapting transformer architectures to the specific challenges of underwater environments and developing efficient training strategies to handle the limited availability of annotated fish-tracking datasets.

B. Fish tracking based on 3-dimensional visual information

3-D tracking methods offer advantages over 2-D tracking algorithms, as they can be used to study the behaviour of social animals and effectively address most occlusion problems. However, 3-D tracking also presents significant challenges due to the large number of fish, similar individual appearance, occlusion, and uncertainty of stereo matching.

Two main types of 3-D tracking methods have been developed: "shadow" and "stereo" methods (as shown in Fig. 3). The "shadow" method, which requires only one camera, uses the shadow of the fish projected onto the substrate as a second view of the shoal. By calculating the 2-D positions of the fish and its shadow, the 3-D position of the fish can be obtained through triangulation. However, this method becomes increasingly difficult as the number of fish increases and shadows may be obscured, as it requires detecting each fish and its corresponding shadow.

Stereoscopic methods use multiple cameras to capture simultaneous images at different angles or a camera and a

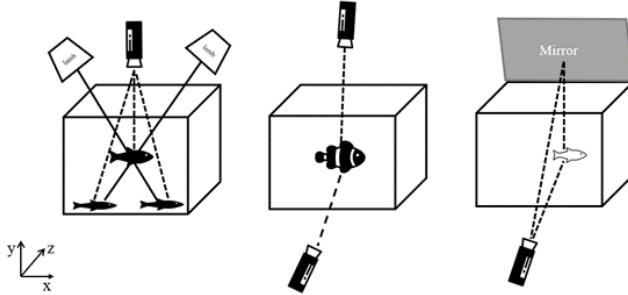


Fig. 3: Three methods to measure the 3-D position of a fish in an aquarium.

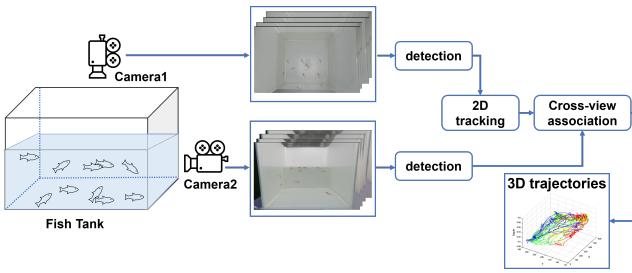


Fig. 4: Three-dimensional trajectory of multiple fish in water tank via multi video tracking.

mirror [22]. Some researchers have developed platforms that use a single camera and mirror to obtain 3-D coordinates and automatically track fish [65], [66]. These methods calculate the centre coordinates of fish and combine the association of mirror view and direct view for tracking, addressing the problem of target loss caused by occlusion. However, they require high-precision equipment and may suffer from correspondence deviations due to the pixel centres of real and virtual fish not being at the same point. Moreover, these methods are not suitable for actual production environments.

In theory, two cameras are sufficient for stereo imaging. 3-D tracking with two cameras involves obtaining the 2-D motion trajectory from the top view (larger viewing angle) and then performing 3-D matching of the top view tracking results with the feature points in the side view to obtain the object's movement in 3-D space (as shown in Fig. 4) [67]. Three or more high-speed cameras are usually required to capture synchronous videos to track many objects, solve ambiguities, and avoid errors between objects. A study by [68] determined the location of fisheye under the top and side views using mixed Gaussian and Gabor models, respectively, and then obtained the 3-D motion trajectories of the objects by associating the top-view tracking results with the trajectories of two side views [40]. However, the detection effect has poor performance due to the difficulty in distinguishing the eye area characteristics of fish. Furthermore, analyzing fish movement behaviour in three views leads to complex equipment installation and reduces the accuracy of association and stereo matching [67].

Occlusion remains one of the main challenges in 3D fish tracking, as it is in other MOT (Multiple Object Tracking) tasks. However, the frequency of occlusion has not been adequately measured in the current literature, with the complexity

indicator of the datasets used in existing studies typically being the number of fish rather than an assessment of fish occlusion events. For instance, a demo video in [27] shows only 4 occlusion events within 15 seconds for a group of 10 fish.

Current system evaluations assess parameters such as ID swaps, fragments, precision, and recall for the generated 2-D and 3D tracks without describing how these indicators are calculated. The lack of uniform indicators makes it difficult to fairly compare the methods presented in various studies. Furthermore, most of the literature does not provide open-source code and annotated data, limiting the repeatability of the results. A recent study by [38], [69] introduced a standard MOT evaluation framework for fish tracking, providing a good model for multi-target fish tracking. A unified evaluation standard should be introduced to ensure the fairness of fish multi-target tracking comparisons and facilitate progress in this field.

C. Fish tracking based on acoustic tag system

The Acoustic Tag System (ATS), a passive acoustic method of acoustic monitoring technology, has become an important means of monitoring fish trajectories and studying fish behaviour [70]. Unlike vision-based tracking methods, which rely on clear water conditions and sufficient lighting, ATS can provide reliable tracking data in challenging underwater environments, such as turbid waters or low-light conditions [71]. The appropriate acoustic tag (also called an acoustic signal transmitter) type and parameters are selected according to the size of the fish and the research period (as shown in Fig. 5) [72]. The application of the acoustic tagging system mainly includes the abundance assessment of fish resources, the swimming pattern of fish, the evaluation of habitat characteristics, the spawning site of fish, the survival situation of fish, and the behaviour differences of fish [73], [74]. However, acoustic tag monitoring technology is rarely used in aquaculture and has broad application prospects.

Using acoustic tag monitoring technology to monitor fish movement and behaviour trajectories, obtain real-time three-dimensional movement trajectory coordinates of the fish, and perform related data analysis and application is an advanced technique [75]. Compared with vision-based monitoring technologies, acoustic tag monitoring technology has the advantages of in-situ observation and simple data processing methods. However, this technology determines the location of the fish by receiving the sound wave signal sent by the acoustic tag on the fish, and the fish may die during the data monitoring process [76], [77]. Therefore, technicians must conduct real-time monitoring and data processing and analysis of monitoring data promptly to ensure the continuity and accuracy of the data.

Acoustic tag monitoring technology and vision-based tracking methods have their unique strengths and limitations. Vision-based methods can provide detailed information about fish appearance, shape, and motion, but they are limited by water clarity and lighting conditions. In contrast, acoustic tag monitoring technology can provide reliable tracking data in

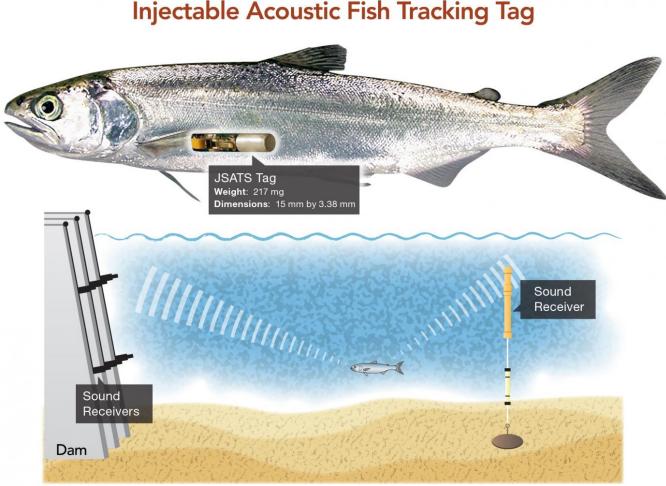


Fig. 5: Fish tracking method based on acoustic tag [78].

challenging underwater environments, but it lacks detailed visual information about fish appearance and behaviour. Combining these two modalities can help overcome their limitations and provide a more comprehensive understanding of fish behaviour and movement patterns.

D. Tracking evaluation metrics

Multi-target tracking evaluation indices directly reflect an algorithm's tracking ability, and the MOTchallenge official multi-objective tracking evaluation indicators [79] provide a standardized framework for assessment. Key metrics include Multiple Object Tracking Accuracy (MOTA) and Multiple Object Tracking Precision (MOTP).

The MOTA combines three sources of errors to evaluate a tracker's performance, follow as:

$$MOTA = 1 - \frac{\sum_t (FN_t + FP_t + ID_{SW_t})}{\sum_t GT_t} \quad (1)$$

where FN_t , FP_t , ID_{SW_t} , GT_t represent the number of false negatives, false positives, identity switches, and ground truth targets in frame t correspondingly.

The MOTP is used to measure misalignment between annotated and predicted object locations, defined as:

$$MOTP = \frac{\sum_{i,t} d_t^i}{\sum_t c_t} \quad (2)$$

where d_t is the distance between the localization of objects in the ground truth and the detection output c_t is the total matches made between ground truth and the detection output.

Identification-Score (IDF_1) comprehensively considers Identification Precision (IDP) and Identification Recall (IDR) rate:

$$IDF_1 = \frac{TP}{TP + 0.5FP + 0.5FN} \quad (3)$$

where True Positive (TP), False Positive (FP), and False Negative (FN) involved in IDF_1 all consider ID, so the indicator is more sensitive to the accuracy of ID information.

To better capture the specific challenges of tracking fish populations, some literature has introduced additional metrics, such as Correct Tracking Ratio (CTR) and Correct Identification Ratio (CIR). CTR measures the percentage of correctly tracked frames for individual fish.

$$CTR = \frac{\sum(\text{NumberOfCorrectFramesOfSingleFish})}{\text{NumberOfFish} \times \text{NumberOfFrames}} \quad (4)$$

CIR represents the probability of correctly identifying all fish after an occlusion event:

$$CIR = \frac{\text{TimesThatAllFishGetCorrectIdentityAfterOcclusion}}{\text{NumberOfOcclusionsEvents}} \quad (5)$$

In addition to those metrics, tracking speed is another important factor to consider when evaluating fish-tracking algorithms, especially for real-time applications. Some common metrics for measuring tracking speed include frames per second (FPS) and processing time per frame. FPS indicates the number of frames a tracking algorithm can process in one second while processing time per frame measures the average time taken to process a single frame. Higher FPS and lower processing time per frame are desirable for efficient and real-time tracking performance. These metrics offer a valuable foundation for evaluating fish tracking performance, comprehensively assessing various errors, fish-specific challenges, and tracking speed. However, they may not always capture the full complexity of fish-tracking scenarios and can be limited by the lack of widespread adoption and the need for detailed ground-truth annotations.

To drive advances in this field, researchers should work towards developing more specialized metrics and evaluation protocols that consider the specific requirements and challenges of fish tracking applications. By combining these metrics with careful consideration of the diverse underwater environments in which fish tracking algorithms must operate, researchers can work towards more comprehensive and standardized evaluation practices that fully characterize the robustness, generalizability, and efficiency of these algorithms.

III. FISH COUNTING

A. Fish counting methods based on sensor technology

Sensor-based counting devices are usually divided into resistance counters and infrared counters. Infrared counters detect infrared signals, which are electromagnetic waves with wavelengths between 760 nm and 1 mm [80]. Counting based on infrared counters requires a tunnel structure to limit the movement of the fish. When a fish passes between the infrared transmitter and the receiver, the counting is completed [81], [82]. Although infrared sensors can count in smaller areas of space, their performance is affected by water depth and turbidity. At a depth of 17.9 centimetres (cm) in pure water, the intensity of the infrared light drops to 50% [83], and the presence of suspended particles can further degrade the performance of infrared counting at high turbidity levels [84]. In addition to environmental factors, the accuracy of infrared sensor counting devices is susceptible to the pass rate of fish, often resulting in an underestimation of the number of fish

[85], [86]. This may be due to the slow swimming of some fish, confusion when two or more fish enter the scanner unit simultaneously, and the reluctance of some fish to leave the device after entering the light tunnel, resulting in repeated scanning. Despite these limitations, infrared light can work in the dark, and the accuracy of counting can be improved by subsequent software algorithms, such as multiple object tracking (MOT) algorithms, which can solve false counting from multiple targets [84], [87], [88].

Resistivity counters, another type of sensor-based counting method, work by detecting changes in resistance when a fish passes between two electrodes [89], [90]. Like infrared sensor counting devices, electronic resistivity counters require the fish to pass through a specific tunnel and have similar disadvantages, such as repeat counts when a fish swims multiple times in the channel and missing counts when the number of fish is large [91]. However, electronic resistivity counters are suitable for limited lighting and long, narrow river channels while detecting non-destructively and without requiring specific lighting conditions [92].

Although both infrared and resistivity fish counters have limitations and may underestimate fish pass rates, they offer valuable tools for non-invasive fish counting in various environments. Future research should focus on developing and improving these technologies to enhance their accuracy and reliability. Potential avenues for improvement include modifying resistivity counters and exploring alternative sensors [93]. By addressing the current challenges and refining these sensor-based counting methods, researchers can provide valuable tools for effective fishery management and conservation efforts.

B. Counting methods based on computer vision technology

Accurate fish biomass assessment is crucial for optimizing management strategies and reducing feeding costs in the aquaculture industry [94], [95]. Computer vision-based fish counting has gained prominence among various methods due to its non-invasive nature, low cost, and high efficiency [96], [97]. However, the complexity of underwater environments, including varying light conditions, backgrounds, and fish swimming patterns, poses challenges for accurate fish counting [98]–[100].

This section summarizes and analyzes the current computer vision-based fish counting aquaculture methods, focusing on two main categories: image-based counting and video-based counting. The summary of the computer vision-based methods can be seen in Table. II. The subsections delve into the details of each category, discussing the advancements, challenges, and future directions in the field. By bridging the gap between laboratory-based experiments and real-world applications, computer vision-based fish counting can become an indispensable tool for sustainable aquaculture management.

1) *Image-based counting method:* Image-based fish counting methods can be broadly categorized into two main approaches: detecting-based methods, which aim to detect all fish in a region, and density-based methods [101], [102], which estimate the number of fish by analyzing the distribution of fish schools [103], [104].

Early studies focused on detecting-based methods, which rely heavily on the accuracy of fish image segmentation from the background [117]. These methods, such as artificial neural networks (BPNN) [118], showed potential for automatic fish counting in scenarios with a limited number of fish. However, they often struggled with complex adhesions in fish images and overlapping fish [111], [119]. To address the challenges of overlapping fish, adaptive segmentation algorithms were developed to extract the geometric features of fish [114]. Combined with machine learning models like LS-SVM, these algorithms showed improved counting accuracy compared to BPNN models, particularly in scenarios with similar fish sizes and low stocking densities. However, the performance of these models declined when faced with high fish densities and changing geometric shapes due to fish overlap [120]. Further advancements in fish image segmentation were made by introducing more general adaptive thresholding methods and skeleton extraction-based methods to handle overlapping fish [112]. While these methods performed well under controlled laboratory conditions, their accuracy diminished in real-world aquaculture environments, where factors such as high fish school density, poor visibility, and insufficient light posed significant challenges [113].

Efforts to mitigate issues related to light, noise, and feature recognition led to the development of segmentation methods that combined local normalized filters and iterative selection thresholds [110]. Although these methods demonstrated high performance in correcting non-uniform lighting, reducing noise, and identifying features, the unique challenges posed by aquaculture settings, such as fish shadows caused by water refraction and continuous movement of shoals, continued to affect segmentation accuracy and limit the effectiveness of traditional computer vision methods for fish counting [111].

The introduction of deep learning techniques has opened new avenues for fish counting in aquaculture. With the increasing availability of fish datasets, deep learning models have been applied to this domain, offering strong adaptability and easy transformation without requiring complex feature extraction work [107], [121]. Convolutional neural networks (CNNs) have been shown to achieve high accuracy in detecting and counting fish of different sizes by adjusting different thresholds [109].

Density-based methods, which estimate the number of fish by mapping input images to corresponding density maps, have also shown promise in fish counting applications. These methods provide additional information about the spatial distribution of fish, which can be valuable for various purposes [122]. Hybrid neural network models, such as those combining MCNN and DCNN architectures, have been proposed to improve fish counting accuracy, outperforming traditional CNNs and MCNNs [97], [105].

Despite the advancements made in fish counting methods, several challenges remain. Density-based methods are sensitive to the degree of occlusion, with higher fish densities leading to greater errors. Moreover, variations in water quality, light conditions, camera angle, water depth, and surface refraction can cause significant differences in the appearance of fish across different farming environments, affecting the

TABLE II: Different counting methods based on computer vision.

Study Cite	Amount	Dataset	Model	Count points	Evaluation index	Results	Advantages	Limitations	References
Tank	100	786	MAN	Center	Accuracy	97.12%	Better generalization ability	larger error for areas with high fish density	[105]
Tank	-	4000	DG-LR	Fish-Connected Area	R ²	96.07%	No need to detect every fish	No complex environments	[7]
Net Cage	214	1501	Hybrid Neural Network	Center points	Accuracy	95.06%	Improves model performance without losing resolution	Does not describe the distribution of fish school gathering and dispersing Repeating detection and wrong detection in high contrast areas	[106]
Cage	62	200	RCNN	Bounding Box	Accuracy	92.4%	Reduce count errors due to repeating detections	No detailed analysis of the number of fish in the system per unit time	[107]
Counter	1000	1500	Background Subtraction Kalman filter	Blob	average precision	97.47%	Automatic counting, low cost	Threshold adapts to different numbers of fish	[108]
Containers	600	4000	CNN	Contours	Accuracy	99.17%	Pure white background, no noise	[109]	
Dishpan	100	-	Local Normalization Filter	Pixel Area	Accuracy F-measure	99.8% 98.83%	automated system.	Small sample size	[110]
Aquarium	350	1000	Background Subtraction	Contours	Accuracy	95.57%	Portable, low cost	Need a fixed size of fish and a certain area	[111]
Aquarium	9	-	Adaptive Thresholding	Skeleton	Average counting error	6%	Solve the overlapped-fish problem cleverly	Only adapted to relatively small fish densities	[112]
Net Cage	250	1000	PTV	Centroid	Detection rate	90%	Potential application or industrial aquaculture	Affected by background noise sensitivity	[113]
Aquarium	100	600	LS-SVM	Skeleton	Accuracy	98.73%	Good generalization	Assume that the size of fish is similar	[114]
Aquarium	300	3200	MSENet	Centroid	MAE	3.33	Lightweight and low computation costs	limited to a scene with a fixed viewpoint	[115]
Long Channel	300	1318	YOLOv5-Nano	Bounding Box	Average Counting Precision	96.4%	Solves the problem of missing fish fry	Occlusion still causes some fish to be incorrectly detected	[116]

accuracy and generalization ability of counting models. To address these challenges, future research should create more comprehensive and diverse datasets that capture the variability encountered in real-world aquaculture settings. Efforts should also be directed towards improving counting accuracy, model generalization ability in high-density areas, and maintaining accuracy under different pond conditions.

2) *Video-based counting method:* Video-based counting methods offer a more efficient alternative to counting objects in single images, enabling the development of reliable and inexpensive systems for counting fish in sequential videos [123]. However, directly applying current automatic detecting and counting frameworks in underwater environments presents several challenges. Firstly, underwater cameras are susceptible to contamination by impurities in the water, leading to

deterioration of video quality. Additionally, current communication technology and cost limit underwater video real-time transmission technology, resulting in delays that impact real-time detection [124]. Secondly, underwater videos suffer from colour shift and contrast degradation due to light absorption and scattering in the water, making object detection and segmentation more difficult than in land-based applications [125].

To address these issues, numerous image enhancement algorithms have been proposed to improve the quality of underwater images [126]. These algorithms aim to restore the real colour and improve the contrast of underwater images. However, the effectiveness of these enhancement techniques varies greatly depending on the environment and lighting conditions [127]. Furthermore, the detection and segmenta-

tion results directly depend on the image enhancement and segmentation performance, which can be time-consuming.

Despite these challenges, video-based counting methods find applications in various aquatic environments, such as aquaculture and fisheries management. In aquaculture, these methods can be used to estimate fish catch and abundance statistics, reducing the time and effort required for manual recording by fishermen [128], [129]. In the context of stream fish research and management, video technology provides a new strategy for estimating fish abundance, although its effectiveness may vary depending on the age and behaviour of the fish species being studied [130], [131].

As technology advances and more robust algorithms are developed, video-based counting methods are expected to play an increasingly important role in accurately assessing fish populations in various aquatic environments. Combining video methods with machine learning models promotes powerful new directions for river fish research, management, and protection. Future research should focus on improving the reliability and efficiency of these methods while addressing the specific challenges posed by underwater video acquisition and analysis, such as image quality degradation, real-time transmission limitations, and the need for effective image enhancement techniques. By tackling these issues, video-based counting methods can provide valuable insights into fish populations and support sustainable fisheries management practices.

C. Counting methods based on acoustic technology

Acoustic technology for fish counting can be divided into two main categories: acoustic imaging and hydroacoustic methods. While underwater visible imaging suffers from limitations due to light attenuation caused by water absorption and scattering, resulting in blurred images and reduced image quantity as shooting distance increases, acoustic-based counting methods offer a viable alternative. Sound waves can travel far through water without significant attenuation, making them suitable for situations where visual counting is inappropriate or ineffective.

1) *Acoustic imaging methods:* Multi-beam imaging sonar such as Adaptive Resolution Imaging Sonar (ARIS) and Dual-frequency Identification Sonar (DIDSON) are normally used to monitor migratory fish in rivers [132]. These systems produce high-resolution underwater sonar video output without the need for underwater light, allowing for fish counting and measuring directly from the footage, even in turbid waters and overnight [133].

DIDSON, developed by the Applied Physics Laboratory at the University of Washington [134], is a multi-beam sonar system frequently used to acquire underwater acoustic images for fish identification and counting. As DIDSON uses sound instead of light, it is not affected by water turbidity and can collect data during both day and night [135], [136]. However, studies have shown that manual counting of DIDSON data can be time-consuming and prone to errors, with large deviations between operators [137], [138]. This may be because Echoview repeatedly calculated nearly stationary horizontal positions within the DIDSON field of view [139].

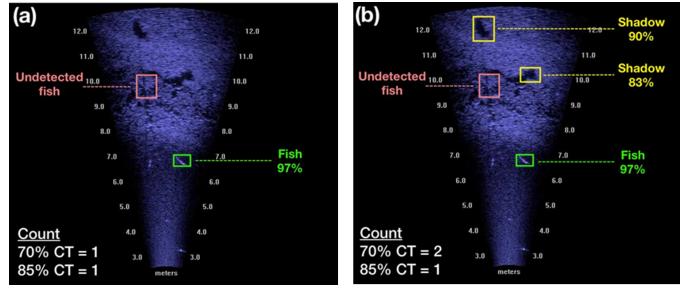


Fig. 6: Example of DIDSON image counting [140].

To reduce the time and cost of DIDSON data processing, various subsampling methods can be employed, with automation-assisted subsampling being the best method to reduce the cost of estimating migratory fish populations in rivers [18]. Multi-beam echogram processing software, such as Echoview or DIDSON Control and Display software, can partially perform fish detection and counting functions [141], [142]. Echoview uses a Component Object Model (COM) interface that allows users to build customized pre-processing and post-processing scripting modules, streamlining the processing method and providing the ability to refine fish counting using various fish detection parameters [143], [144]. However, the echograms of the video-like data files generated by DIDSON require manual counting, which is tedious, time-consuming, and can produce large errors for large datasets [145]. Semi-automatic post-processing of imaging sonar data is possible using existing software (e.g., Echoview Software Pty Ltd., Hobart, Australia) [141], [146], but the process still requires manual calibration for non-fish target noise, which is cumbersome and inefficient. Furthermore, post-processing software can be very expensive, limiting its accessibility for many researchers and practitioners.

Digital image-processing technology offers an inexpensive and rapid alternative that has been successfully applied in various scientific fields. Several studies have focused on the automatic processing of fish targets in imaging sonar data. For example, K-nearest neighbour background subtraction with DeepSort target tracking to track and count fish automatically [147] and GPNet, a novel encoder-decoder network with global attention and point supervision, to boost sonar image-based fish counting accuracy [148].

The new generation of acoustic cameras includes Adaptive Resolution Imaging Sonar (ARIS) (Sound Metrics Corp, WA, USA), which operates at higher frequencies compared to DIDSON, offering greater flexibility and improved image resolution [149], [150]. A comparison of fish monitoring data based on the ARIS sonar system and the GoPro camera showed that the detection rate of the sonar-based system was 62.6% (compared to the amount captured by the net), exceeding the 45.4% of the camera-based system [151].

While sonar imaging counting methods are powerful tools for gathering fish abundance estimates in difficult-to-observe, structurally complex, chaotic, and dark environments, they can still be disturbed by various types of underwater noise. Additionally, sonar imaging equipment is relatively expensive and

TABLE III: A comparison of different methods based on acoustic imaging.

Site	Technology	Software	MHz	Metrics	Results	Advantages	Limitations	References
River	ARIS	Echoview	1.1MHz frequency	Accuracy	84%	Distinguishes downstream moving fish from other objects	Results vary among operators	[16]
Lagoon	ARIS	Sound Metrics	1.8MHz	R^2	0.99	Consistent results with manual	The results varied greatly among different operators	[137]
River	ARIS	ARIS software Fish	1.8MHz	F1-scores	75%	Faster and no post-processing	Underestimates total fish count	[154]
Reservoir	ARIS	KNN background subtraction and DeepSort	1.8MHz	Accuracy	73%	Automatic calibration saves data processing time	Unable to identify fish in bottom background, long processing time	[147]
River	ARIS	ARISfish	3.0MHz	Detection Rate	62.6%	Counts fish > 100 mm in night and turbid conditions	May not detect small fish	[151]
River	DIDSON	Echoview 6.0	1.8MHz	Accuracy	83.7%	Avoids manual counting errors and biases	Time-consuming calculations	[18]
River	DIDSON	Sound Metrics	1.8MHz	F1 scores	79%	Performs well using direct, shadow, and combined detections	Low fish densities in each image	[140]
Reservoir	DIDSON	NN-EKF2/Echoview	1.8MHz	Error compared with the manual detection results	Less than 5%	Less calculation and easy to implement Estimates	Inaccurate when targets overlap	[153]
River	DIDSON	Sound Metrics/Echoview	1.2MHz	Accuracy	90% (upstream) 41% (downstream)	potamodromous fish passage in large lakes Not limited by surface disturbances or turbidity	High processing times and costs	[139]
River	DIDSON	Manual counting	1.8MHz	Average Percent Error (APE)	5.4%	Better acoustic target identification and resolution	Shadowing from passing fish	[138]
River	DIDSON	Hand-counter	1.8MHz	Coefficient of Variation (CV)	9.63%		Data loss on small fish in highly turbulent environments	[152]

requires professional personnel to conduct analysis, making it more suitable for investigating fish abundance in ocean fishing and river ports [152], [153].

These recent advancements in digital image-processing techniques showcase the growing interest in developing efficient and accurate methods for automatic fish tracking and counting in sonar data. By leveraging the power of deep learning and computer vision algorithms, these approaches aim to overcome the limitations of manual processing and provide more reliable and scalable solutions for aquaculture monitoring and management. However, while these methods show promising results, they still face challenges such as dealing with occlusions, varying fish densities, and the need for large annotated datasets for training. Future research should address these limitations and develop more robust and generalizable algorithms that can be easily adapted to different sonar imaging systems and underwater environments.

Table III summarizes the advantages and disadvantages of sonar imaging counting methods in aquaculture and their practical applications. Despite the limitations, acoustic counting methods remain valuable for monitoring fish populations in challenging underwater environments where visual counting

methods may be impractical or ineffective.

2) *Hydroacoustic methods:* Acoustic echo-sounding is one of the most popular methods for estimating fish abundance due to their simplicity and non-invasive nature [155]. These methods rely on the physical characteristics of the target and the water medium. When an echo sounder's transducer emits an acoustic wave, it spreads through the water and encounters the target object. Due to the difference in acoustic impedance between the object and the water medium, the object scatters the incident acoustic wave, and a portion of it is backscattered to the transducer, known as the echo signal [156], [157].

The target's depth can be measured according to the interval between the acoustic emission and the reception of the target's echo. By analyzing the strength and structure of the echo signal, the intensity, number, and distribution of the target can be estimated. The Echo Integration method is one of the main methods for underwater acoustic assessment of fish stocks. It calculates the number of fish by dividing the integral value of the echo intensity of fish in the sampling unit area by the ultrasonic reflectance of individual fish (target intensity, TS). Several studies have used the echo integration technique to estimate the number of fish based on the backscattering echoes

observed with an echo sounder [158], [159].

Although the sound intensity reflected by a shoal is related to the number of fish [160], the use of echo sounders in fish tanks and cages presents several challenges [161]. Reverberation in a cage can occur due to the echo of an acoustic signal from the boundary, necessitating the removal of the cage boundary signal during counting [162]. Another issue with acoustic estimation of fish populations is shadow utility, which is needed to compensate for the attenuation of echo strength when dense shoals are in focus [157]. To investigate the possibility of using commercial echo sounders for real-time fish counting in offshore cages, a study by [163] employed an echosounder and echo-integration technology. The experimental results showed that the proposed method could achieve more than 90% estimation accuracy [164], indicating its reliability for future fish management decisions.

Despite the increasing use of underwater echo sounders in fishery research, their application is subject to interference from various factors, such as differences in instrument performance, the blind area of the echo sounder itself, external environmental factors, and the evasive behaviour of fish in response to survey ships and sound waves [165], [166]. Furthermore, echosounders are expensive and technically demanding, making them unsuitable for factory aquaculture needs. Future research should focus on reducing the cost of instruments or developing alternative instruments suitable for promotion to meet the actual needs of aquaculture.

IV. FISH SCHOOL BEHAVIOUR ANALYSIS

Fish behaviour, a direct result of the living environment and growth state, includes both normal (i.e. feeding behaviour, swimming behaviour, reproduction behaviour, gathering behaviour) and abnormal behaviours (i.e. disease behaviour, hypoxia behaviour, cannibalism behaviour) [167]–[169]. Poor water quality and management in aquaculture can cause fish stress behaviour [170], leading to immune suppression, slow growth, and reduced productivity and welfare [171]. Traditional fish behaviour analysis, relying on human observers, is often unreliable, time-consuming, and labour-intensive [5], [6]. Accurate estimation of fish behaviour is crucial for optimizing resource use, controlling water quality, and improving fish welfare and economic benefits [172]. The following sections will explore the latest advancements in fish behaviour analysis, focusing on computer vision-based methods for assessing fish school behaviour and feeding behaviour, providing insights into the current state of the art and potential future directions for research and application in this field.

A. Fish school behaviour analysis based on computer vision

1) *Fish feeding behavior:* In intensive aquaculture, feeding is the main expenditure [173], and feeding optimization is crucial for improving efficiency and reducing costs [174]. Traditional feeding methods based on farmers' experience are limited by low efficiency and high labour intensity, and they cannot accurately address the problems of overfeeding or underfeeding [175]. The intensity and amplitude of changes in fish behaviour can directly reflect fish appetite. Computer

vision technology can effectively quantify fish feeding behaviour, optimize feeding strategies, and reduce feeding costs.

Many researchers have used traditional methods, such as background subtraction and optical flow, to extract target features for determining feeding indices [176]. While these methods can accurately capture fish feeding behaviour, they require complex foreground segmentation processes that may decrease computational efficiency and are easily affected by water surface fluctuations and reflective areas [20]. With its advantages of automatic feature extraction and large-capacity modelling, deep learning has been widely used in aquaculture [177].

Existing approaches mainly use digital cameras to capture the corresponding images as input and characterize the fish behaviour with discrete feeding intensity (e.g., “None”, “Weak”, “Medium” and “Strong” [178]–[181]) as a classification problem, modelled by Convolutional Neural Networks (CNNs). However, fish-feeding behaviour is a dynamic and continuous process. Single images are insufficient to capture the context of fish feeding intensity [177], [182]. As an alternative, video-based methods have been proposed to exploit spatial and temporal visual information for FFIA, which offers rich context for capturing fish feeding behaviour. Raw RGB videos were converted into optical flow image sequences and fed into a 3D convolutional neural network (3D CNN) to evaluate fish feeding intensity, achieving a very high accuracy [183], [184].

While recent advancements in computer vision and deep learning have shown promise in analyzing fish feeding behaviour, some limitations still need to be addressed. One major challenge is the discrepancy between the ideal environments in which fish-feeding datasets are collected and the real-world conditions found in aquaculture settings. Factors such as water turbidity, fluctuating light levels, and variable camera angles can significantly impact the performance of these models when deployed in real-world farms.

Another limitation is the computational complexity of video-based models, which often require substantial computational resources, making them difficult to deploy on resource-constrained devices commonly used in aquaculture. The large size of these models can also hinder their real-time performance, which is crucial for timely decision-making in aquaculture management. Furthermore, the limited generalizability of current models to new fish species is a significant challenge. Many existing models are trained on species-specific datasets, and their performance often drops significantly when applied to new or unseen species due to differences in morphological features, colour patterns, and behavioural characteristics.

To address these limitations, future research should focus on developing more robust, adaptable, and species-agnostic models that can effectively handle the variability encountered in real aquaculture environments. This may involve collecting more diverse and representative datasets, exploring domain adaptation, transfer learning, and few-shot learning techniques, and optimizing models for efficient inference on edge devices.

2) *Hypoxia behavior:* Hypoxia, a common issue in aquaculture systems, can significantly impact fish mortality and lead to substantial production losses [185]. Fish exhibit various behavioural responses to hypoxic conditions, such as changes

in ventilatory frequency (VF), swimming activity, surface respiration, and vertical habitat [186]–[189]. To provide early warning of hypoxia in aquaculture, it is essential to evaluate the specific behavioural responses of fish when oxygen levels in the water drop sharply.

Image processing algorithms have been proposed to quantify the hypoxia behaviour of fish in aquariums [190]. However, these methods often rely on complex foreground segmentation processes, which can decrease computational efficiency and are easily affected by water surface fluctuations. Deep learning methods, such as YOLO object detection, have emerged as powerful tools for transforming and upgrading fish farming practices by quickly detecting fish behaviour with high accuracy [173].

Despite the progress made in recognizing fish hypoxia behaviour, most experiments have been conducted under laboratory conditions, which may not accurately reflect the challenges encountered in actual production systems. Factors such as water turbidity, uneven illumination, and high fish density can make it more difficult to identify individual fish and their specific behaviours in real-world settings. Furthermore, inducing hypoxia through human intervention in laboratory experiments can compromise animal welfare and cause irreversible damage to fish health.

To address these limitations, future research should focus on developing more robust and adaptable methods for detecting fish hypoxia behaviour in real-world aquaculture systems. Moreover, integrating multiple data sources, such as water quality sensors and video monitoring systems, could provide a more comprehensive understanding of fish behaviour and enable early detection of hypoxia-related issues. By combining advanced computer vision techniques with domain expertise in aquaculture and fish physiology, researchers can develop more effective and practical solutions for monitoring and managing fish health in real-world settings.

3) Other abnormal behavior: Abnormal fish behaviours, such as aggression, fear, stress, illness, parasitic infection, and cannibalism, can have significant impacts on aquaculture production (as shown in Fig. 7), fish welfare, and population balance [169], [191]–[193]. While less common than feed-

ing and hypoxia behaviours, these abnormalities still play a crucial role in aquaculture warning operations. Detecting and localizing abnormal behaviours, particularly those occurring within small groups or individuals, remains challenging in computer vision. To address this challenge, researchers have adapted techniques from human behaviour analysis, such as motion-effect maps and deep learning algorithms, to detect, localize, and recognize abnormal fish behaviours in intensive aquaculture systems [194], [195]. These methods have shown promising results in identifying specific behaviours and evaluating various health and environmental factors. However, further research is needed to investigate the complex interplay between local and global abnormal behaviours and develop robust, multi-target tracking systems that operate efficiently in real-world aquaculture settings.

Monitoring and protecting fish during critical life events, such as spawning aggregations, is essential for maintaining population balance and preventing overfishing [196], [197]. Computer vision techniques, including stereoscopic video analysis and 3D neural networks, have been employed to quantify fish reproductive behaviour and classify complex behaviours [198], [199], providing valuable tools for baseline studies and long-term monitoring.

While computer vision and image processing technologies offer economical and effective means for monitoring abnormal fish behaviour, the relative scarcity of abnormal behaviour data has hindered in-depth research. Most existing studies have been conducted in controlled laboratory environments, which may not accurately represent the complex factors in real-world aquaculture settings [200], [201]. Overcoming the challenges posed by complex water environments, uneven lighting, large numbers of individuals, and intricate fish movements is crucial for developing robust and reliable multi-target abnormal behaviour monitoring and tracking systems in computer vision [61].

B. Fish school behaviour analysis based on Trajectory analysis

Visual-based monitoring systems for detecting abnormal fish behaviour often rely on known scenes and predefined



Fig. 7: Abnormal behaviors: “Turning-over behavior”, “Frightening behavior”, “Feeding behavior”, “Hypothermia behavior”, “Hypoxic behavior”, “Cannibalism behavior”.

movement models, which can be subjective and lack adaptability to different environments [202]. Analyzing many target trajectories in a specific scene can reveal behaviour patterns and construct effective motion behaviour models with greater universality and applicability [182].

Using visual monitoring systems, researchers can obtain 3D time-varying trajectory data (location and time information) of fish. Studies have tracked zebrafish using YOLOV2 and Kalman filters, obtaining movement trajectories that showed significantly faster swimming, greater agitation, and agglomeration in the centre of the aquarium during feeding periods [29]. Other researchers have developed semi-automatic in situ tracking systems to reconstruct synchronized 3D movement trajectories of individual reef fish in social groups, analyzing their behaviour when capturing plankton prey [37].

However, relatively few studies on abnormal fish behaviour use trajectory analysis in aquaculture. This scarcity can be attributed to the limited availability of open datasets on abnormal fish behaviour and the rare occurrence of such behaviours, making data acquisition challenging. Moreover, fish trajectories inherently contain information about position, speed, and direction, and the definition of an abnormal trajectory may encompass multiple aspects. In the past decade, track-based anomaly detection methods have primarily relied on traditional clustering methods or focused on statistical models of trajectories. In contrast, the representation of trajectories remains an open problem [203], [204].

To address these challenges and advance aquaculture, future research should draw inspiration from the successful application of abnormal trajectory behaviour analysis methods in other fields, such as crowd and vehicle monitoring. By adapting these techniques to fish's unique characteristics and environments, researchers can create more powerful and flexible models for identifying and comprehending abnormal fish behaviour in various aquaculture contexts.

C. Fish behaviour analysis based on passive acoustic monitoring

Passive acoustic monitoring (PAM) has emerged as a non-invasive and increasingly accessible remote sensing technology for monitoring underwater environments [205], [206]. With approximately 1,000 out of the 35,000 known fish species confirmed to produce sounds underwater [207], [208], PAM offers a unique opportunity to analyze fish behaviour through the sounds they generate (The example of fish abnormal behaviour is shown in Fig. 8).

Fish can produce a series of sounds during feeding, and the frequency spectrum of these sounds can be used to analyze their feeding behaviour. For example, turbots generate feeding sounds that vary with food intake intensity, ranging from 15 to 20 dB in the frequency range 7–10 kHz [209]. Similarly, feeding sounds produced by various fish species, such as rainbow trout (0.02–25 kHz) [210], Japanese minnow (1–10 kHz) [211], Atlantic horse mackerel (1.6–4 kHz) [212], yellowtail (4–6 kHz) [213], have comparable frequency ranges.

The Fish feeding behaviour analysis based on audio was initially proposed by [4], [214], the audio signal is first trans-

formed into log mel spectrograms and then fed into a CNN-based model for FFIA. Subsequent work [215], [216] have further demonstrated the feasibility of using audio as input for FFIA. Audio-based methods offer advantages such as energy efficiency and lower computational costs compared to vision-based methods [217], [218]. However, audio-based models have lower classification performance than video-based FFIA due to their inability to capture full visual information and sensitivity to environmental noise [219]. Moreover, rapidly swimming predatory fish, such as brown and rainbow trout, often combine forward swimming with feeding, accompanied by splashing sounds and strong tail patting [172]. The rapid pellet capture by these species superimposes feeding sounds, and pellet impacts pose a challenge in obtaining accurate feeding sound data.

To overcome these challenges, future research should focus on developing advanced signal processing techniques to separate feeding sounds from ambient noise and other interfering sounds. Additionally, exploring the integration of audio and visual data could help improve the overall classification performance and robustness of fish behaviour analysis systems.

D. Fish behaviour analysis based on biosensor technology

Biosensor technology has shown great potential in collecting individual animal information, such as individual trajectory, acceleration, velocity, respiration frequencies, heartbeat frequency, and tail beat frequency [221], [222]. In recent years, accelerometers have been increasingly used in marine biology research to study the feeding behaviour of aquatic animals.

The feeding behaviour of most fish leads to characteristic changes in acceleration that differ from their normal movement patterns [223]. These characteristic changes in acceleration can be effectively used to distinguish feeding behaviour patterns from other behaviour patterns [224]. For example, [225] used accelerometer tags to investigate the feeding behaviour of Atlantic cod (*Gadus morhua*) in the wild. The authors found that the accelerometer data could accurately identify feeding events and provide insights into the foraging ecology of this species. Similarly, a study by [226] used a combination of accelerometers and gyroscopes to analyze the feeding behaviour of captive yellowtail kingfish (*Seriola lalandi*). The authors demonstrated that the sensor data could be used to classify different types of feeding behaviour, such as biting, chewing, and swallowing, with high accuracy.

In addition to feeding behaviour, biosensors have been used to study other aspects of fish behaviour, such as swimming activity and energy expenditure. For instance, [227] used accelerometers to investigate the swimming behaviour and energy expenditure of wild Atlantic salmon (*Salmo salar*) while migrating to spawning grounds. The authors found that the accelerometer data provided valuable insights into the swimming performance and energy costs of this species in natural conditions.

However, using biosensors in fish behaviour analysis also presents some challenges and concerns. Biosensors are typically surgically attached or implanted into the fish's body, which can lead to the direct death of the fish or cause

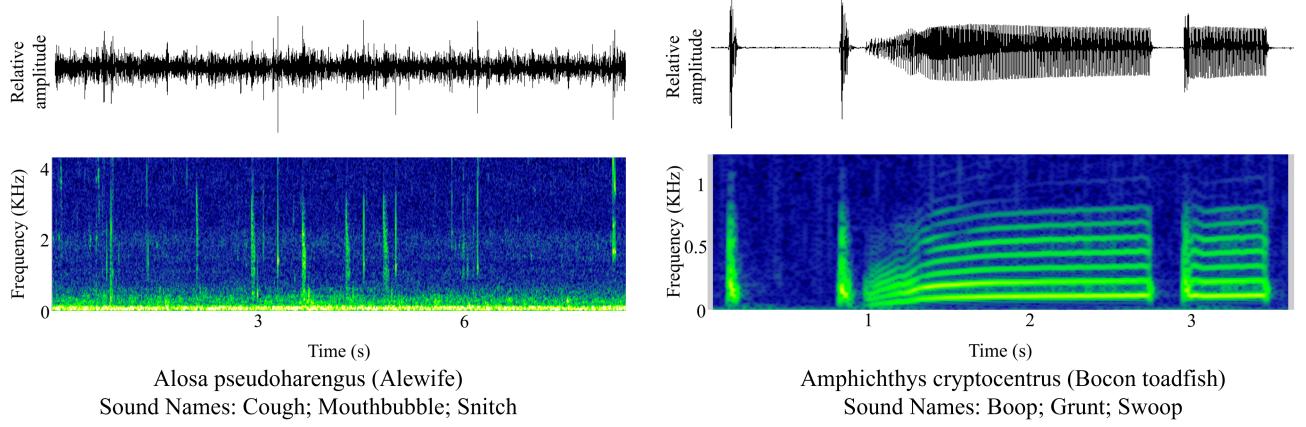


Fig. 8: The audio spectrum of different fish abnormal behaviours [220].

behavioural changes that may affect the results of experiments. Moreover, this method may cause irreversible harm to the fish and compromise animal welfare. To address these issues, researchers should focus on developing minimally invasive or non-invasive biosensor technologies that can be safely attached to or removed from fish without causing undue stress or harm. Furthermore, ethical considerations should be prioritized when using biosensor technology in fish behaviour analysis.

Despite these challenges, biosensor technology offers a promising approach to studying fish behaviour at the individual level, providing valuable insights into the feeding ecology, swimming performance, and energy expenditure of various fish species. By combining biosensor data with other monitoring techniques, such as passive acoustic monitoring and vision-based methods, researchers can develop a more comprehensive understanding of fish behaviour in both captive and wild settings. As biosensor technology continues to advance, it is essential to balance the potential benefits of these tools with the need to ensure the welfare and ethical treatment of the fish being studied.

V. PUBLIC DATASET

High-quality public datasets are crucial for developing and evaluating computer vision and deep learning methods for fish detection, tracking, and behaviour analysis. However, despite the growing popularity of deep learning, there are still relatively few public datasets specifically focused on underwater fish scenes. This scarcity has led many researchers to conduct their analyses and behavioural studies under ideal or controlled conditions. Table IV summarizes the available public fish datasets.

VI. CHALLENGES AND FUTURE PERSPECTIVES

Fish tracking, counting, and behaviour analysis play a crucial role in the intelligent development of aquaculture production. While computer vision technology is currently a popular method for these tasks, it faces several challenges due to the unique characteristics of aquaculture environments, such as high fish density, complex water backgrounds, and irregular fish movement. These factors can lead to interference between

multiple targets, false detections, missed counts, and tracking failures.

Acoustic methods offer an alternative approach that enables automatic and rapid fish counting and tracking in low-light and turbid water conditions. However, underwater noises, high equipment costs, and the need for professional expertise make acoustic methods more suitable for large-scale operations like marine fishing rather than factory or pond farming environments. To further increase the level of intelligence in aquaculture, we predict several different trends for future development:

1) Massively available datasets: The wide application of intelligent technology in aquaculture, especially the success of deep learning algorithms in image processing [15], has highlighted the need for large-labelled datasets. Although available datasets are gradually increasing, most are limited to identifying and detecting fish species. Open data on fish tracking, counting, and behaviour analysis is scarce. Passive acoustic monitoring (PAM) is also gaining popularity for underwater listening [206], [239] and public sound data of underwater fish (e.g., Fishsound) are emerging. However, the sample size of these datasets has not yet reached critical mass. In the future, developing an international platform for sharing images and acoustic data will be essential to promote sustainable aquaculture development.

2) Audio-visual multi-modal techniques: Fish tracking, counting, and behaviour analysis methods are limited to single modalities (acoustic or computer vision). However, the complex aquaculture environment leads to one-sided data that cannot fully capture all fish information [214]. Multimodal machine learning aims to establish models that process and associate data from multiple modalities. With the development of multimodal machine learning, crowd tracking and behaviour analysis based on audio-visual data have attracted extensive attention. Multimodal learning for fish is still in its infancy, but combining video data, sonar imaging data, and active acoustic data can better model fish tracking, counting, and behaviour quantification tasks, further improving the level of intelligence in aquaculture.

3) On-device machine learning: Most current fish tracking, counting, and behavioural analysis models are performed in

TABLE IV: Summary of the various fish datasets.

Dataset	No. of videos/image	Resolution	Number of labeled fish	Tasks	Reference
Fish4-Knowledge	700,000 videos with 10 min each clip Training set: 20 videos and 20,000 images, Test set: 73 videos	320 × 240 640 × 480 320 × 240	- 9000	Classification, Detection and Tracking Classification, Counting	[228] [229]
SeaCLEF 2016	16,915 images (3,777 training, 13,138 testing) 30 videos sequence with 537 images Training Set: 54052 images, Test Set: 32400 images	1920 × 1080	10000	Detection, classification and counting	[230]
Sonar image counting dataset	360 × 360	-	Counting	[231]	
3D-ZeF20	2704 × 1520	86452	Tracking	[69]	
Automated Fish Tracking	189 videos of varying durations (1- 30 seconds)	1920 × 1080	8700	Detection, Tracking	[232]
DeepFish	39,766 images	1920 × 1080	3200	Segmentation, counting and Classification	[233]
FISHTRAC	14 videos	1920 × 1080	3449	Tracking and detection	[234]
BrackishMOT	98 videos each lasting about 1 minute	2704 × 1520		Tracking	[235]
CFC Mullet Schools Dataset	527215 SONA images over 100k SONA images	288 × 624 to 1086 × 2125 320 × 576	515933 500	Detection, Tracking and Counting Detection Counting	[236] [237]
Fish Sounds	115 different fish sound clips	64kbps	-	Behaviour analysis	[238]
AV-FFIA	27000 video and sound clips	1086 × 2125 256kbps	All	Feeding Behaviour analysis	[214]

the cloud or on high-performance GPUs. However, many aquaculture tasks require real-time responses, such as fish feeding and abnormal behaviour detection. Cloud-based models may struggle to guarantee this real-time performance, and many devices in remote and harsh aquaculture environments may not have consistent internet connectivity. On-device models can greatly reduce exercise pressure and make devices more intelligent, providing users with a better experience. However, terminal devices have processing power, power consumption, cost, and volume limitations. Future developments could focus on reducing the complexity of computing and storage by optimizing neural network algorithms or compressing network models using techniques like knowledge distillation to enable direct running on device chips.

4) Integration of fish tracking, counting, and behaviour analysis: Most research addresses fish tracking, counting, and behaviour analysis as separate tasks. However, these tasks are often interconnected in real-world aquaculture scenarios and must be performed continuously in the same environment. Developing a joint model that can handle all three tasks simultaneously would be more memory-efficient and suitable for practical applications in aquaculture. A joint model would leverage the shared features and information among the tasks, reducing redundancy and improving overall performance. For

example, accurate fish tracking can provide valuable information for counting and behaviour analysis, while behaviour analysis can help identify and resolve tracking challenges such as occlusions and interactions between fish. Researchers can develop more comprehensive and efficient systems for monitoring and managing aquaculture farms by integrating these tasks into a single framework. This approach would also reduce the computational resources required, making it more feasible to deploy such systems in real-world settings. Future research should focus on developing novel architectures and training strategies that can effectively combine fish tracking, counting, and behaviour analysis tasks.

5) Integration of large language models (LLMs) and artificial general intelligence (AGI): Recent advancements in LLMs and AGI have the potential to revolutionize fish tracking, counting, and behaviour analysis. LLMs, such as GPT-4 [240] and LLaMA [241], can be fine-tuned on aquaculture-specific datasets to generate accurate descriptions and analyses of fish behaviour from textual data. AGI systems, like DeepMind's Gato [242], which can perform a wide range of tasks using a single model, could be adapted to integrate multiple modalities (e.g., vision, acoustics, and text) for comprehensive fish monitoring and management. By leveraging the power of LLMs and AGI, aquaculture researchers and practitioners can develop

more intelligent and adaptable systems for understanding and optimizing fish welfare and production.

VII. CONCLUSION

This review provides a comprehensive analysis of the current state of digital technologies in aquaculture, including vision-based sensors, acoustic-based sensors, and biosensors, for fish tracking, counting, and behaviour analysis. These technologies offer valuable tools for optimizing production efficiency, fish welfare, and resource management in aquaculture. However, each technology has its own limitations, such as the sensitivity of vision-based sensors to environmental conditions, the high cost and complexity of acoustic-based sensors, and the potential invasiveness of biosensors. Despite the advancements made in these technologies, significant challenges remain, including the scarcity of comprehensive fish datasets, the lack of unified evaluation standards, and the need for more robust and adaptable systems that can handle the complexities of real-world aquaculture environments. To address these challenges and drive progress in the field, future research should focus on developing diverse and representative datasets, establishing standardized evaluation frameworks, and exploring the integration of multiple technologies to create more comprehensive and reliable monitoring systems. Furthermore, emerging technologies such as multimodal data fusion, deep learning, and edge computing present exciting opportunities for advancing digital aquaculture. By leveraging these technologies, researchers can develop more accurate, efficient, and practical solutions for fish tracking, counting, and behaviour analysis, ultimately contributing to the sustainable growth and development of the aquaculture industry.

VIII. AUTHOR CONTRIBUTIONS

Meng Cui: Conceptualization; writing – original draft.
Xubo Liu: Investigation; validation; methodology; data curation.
Haohe Liu: Validation; writing – original draft; data curation; formal analysis.
Jinzheng Zhao: Validation; writing – review and editing.
Daoliang Li: Funding acquisition; validation; project administration.
Wenwu Wang: Funding acquisition; validation; project administration; resources; writing – review and editing.

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X. DATA AVAILABILITY STATEMENT

Since this is a review paper, there is no data available. All information can be found in the cited references.

XI. CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest.

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