Underwater Insights: Computer Vision Techniques for Fish Behavior Detection

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***Abstract*— This paper presents a comprehensive review of computer vision techniques for detecting fish behavior in underwater environments. The study systematically analyzes methodologies across image processing, object detection, and motion tracking to enhance the clarity, precision, and dynamic observation of fish activities. By employing a robust literature search strategy and applying rigorous inclusion criteria, studies with strong methodological rigor, clear reporting of results, and demonstrated effectiveness in real-world underwater settings were selected. Key parameters such as accuracy, robustness, scalability, computational efficiency, and generalizability are used to evaluate these techniques. The findings highlight the advancements in adaptive algorithms, semi-supervised learning, and edge computing solutions that enhance real-time analysis and reduce dependency on extensive annotated datasets. This review provides a foundational understanding of the current state and future directions in underwater fish behavior detection, emphasizing the need for integrated multimodal data and collaborative research efforts.**

Keywords—Computer Vision, Fish Behavior Detection, Underwater Imaging, Deep Learning, Marine Ecology

I. INTRODUCTION

Understanding fish behavior in their natural underwater environments is crucial for various applications, including marine ecology, fisheries management, and environmental conservation. Traditional methods for studying fish behavior, such as direct observation and manual tracking, are often invasive, labour-intensive, and limited in scope. Recent advancements in computer vision technology offer powerful tools to analyze fish behavior with greater accuracy and efficiency, transforming the field of marine biology (Boudhane and Nsiri, 2016).

Computer vision techniques leverage sophisticated algorithms and machine learning models to process and analyze visual data captured in underwater environments. These techniques can enhance image clarity, detect and track fish movements, and provide detailed insights into behavioral patterns. The integration of computer vision in underwater research enables continuous and non-invasive monitoring of fish populations, allowing researchers to study species interactions, habitat use, and responses to environmental changes in unprecedented detail.

This paper presents a comprehensive review of the current state of computer vision techniques applied to fish behavior detection in underwater settings. A rigorous literature search strategy is adopted to identify and analyze relevant studies, focusing on methodologies that enhance the accuracy, robustness, and scalability of behavior detection systems. Key parameters such as computational efficiency and generalizability are also considered to evaluate the performance of these techniques across diverse marine environments.

The objectives of this review are to (1) provide an overview of the most effective computer vision techniques for underwater fish behavior detection, (2) identify the challenges and limitations associated with these methods, and (3) propose future research directions to advance the field. By synthesizing existing knowledge and highlighting areas for improvement, this paper aims to contribute to the development of more effective and reliable tools for studying and conserving marine life.

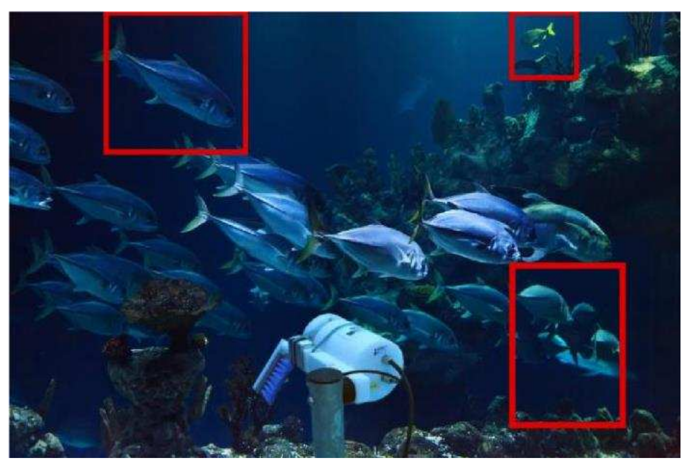

Figure 1: High level system model

II. METHODOLOGY

A. Literature Search Strategy:

To conduct a comprehensive and systematic review of computer vision techniques for fish behavior detection in underwater environments, a rigorous literature search strategy was adopted. This strategy involved several steps to ensure the inclusion of relevant and high-quality studies. These strategies are illustrated in Fig. 2 and discussed below.

1) Databases and Sources:

Multiple academic databases and digital libraries were utilized to gather relevant literature. The primary databases included:

- IEEE Xplore
- Elsevier
- Web of Science
- ScienceDirect
- Google Scholar

These databases were chosen for their extensive coverage of computer science, engineering, and marine biology research.

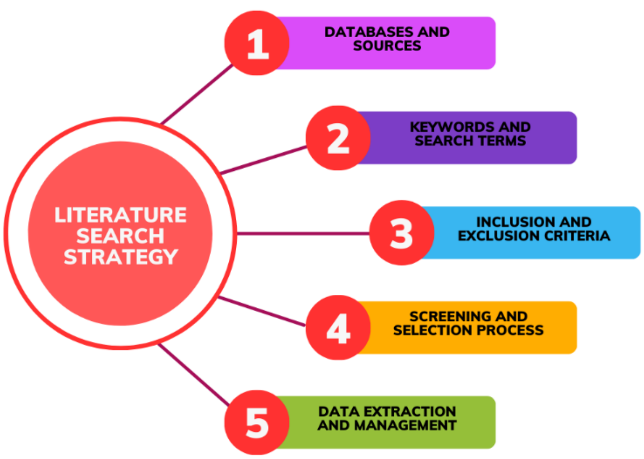

Figure 2: Literature Search Strategies.

2) Keywords and Search Terms:

A combination of keywords and search terms was employed to capture the full spectrum of relevant studies. The search terms were divided into three main categories:

- **Fish Behavior Detection:** "fish behavior," "fish tracking," "fish movement," "marine animal behavior."
- **Computer Vision Techniques:** "computer vision," "image processing," "machine learning," "deep learning," "pattern recognition."
- **Underwater Environments:** "underwater," "marine," "subsea," "aquatic."

Searches were performed using various combinations of these terms to maximize coverage. For example, searches included phrases like "fish behavior detection using computer vision" and "underwater fish tracking with machine learning."

3) Inclusion and Exclusion Criteria:

To ensure the relevance and quality of the studies, specific inclusion and exclusion criteria were applied:

Inclusion Criteria:

- Studies published in peer-reviewed journals or conference proceedings.
- Research focused on computer vision techniques applied to fish behavior detection.
- Studies conducted in underwater or marine environments.
- Publications in English.

Exclusion Criteria:

- Studies not related to fish behavior detection or computer vision.
- Research focusing on terrestrial or aerial environments.
- Non-peer-reviewed articles, such as blog posts or news articles.
- Publications in languages other than English.

4) Screening and Selection Process:

The initial search yielded many potential studies. To refine this list, a multi-stage screening process was conducted:

- **Title and Abstract Screening:** The titles and abstracts of all retrieved articles were reviewed to assess their relevance. Irrelevant studies were discarded at this stage.
- **Full-Text Review:** For the remaining studies, full texts were obtained and thoroughly reviewed. Articles that did not meet the inclusion criteria were excluded.
- **Reference List Check:** The reference lists of the selected articles were examined to identify additional relevant studies that may have been missed in the initial search.

The table 1 summarizes the study selection process that was carried out.

Table 1: Study Selection Process

Stage	Description	No of Papers	Notes on Inclusion and Exclusion
Initial Search	Total papers identified through initial search	901	
Title and Abstract Screening	Papers reviewed for relevance based on title and abstract	450	**Inclusion:** Papers related to fish behavior detection using computer vision. **Exclusion:** Papers not related to fish behavior or

			computer vision; irrelevant topics.
Full-Text Review	Papers assessed in full text for inclusion criteria	100	**Inclusion:** Papers that meet criteria after detailed review. **Exclusion:** Papers that did not meet inclusion criteria; incorrect environments or methodologies.
Reference List Check	Additional papers identified from reference lists	25	**Inclusion:** Relevant papers found in reference lists of selected papers. **Exclusion:** Papers not meeting initial criteria or duplicates.
Final Selection	Papers meeting all inclusion criteria and relevant to topic	18	**Inclusion:** Final selection of papers that met all criteria. **Exclusion:** Papers that did not meet final criteria after review.

5) Data Extraction and Management:

Key information from each selected study was extracted and organized into a structured database. The extracted data included:

- Publication details (authors, year, journal/conference).
- Research objectives and hypotheses.
- Description of the computer vision techniques used.
- Dataset characteristics (e.g., type, size, source).
- Performance metrics and results.
- Identified limitations and proposed future work.

B. Framework for Analysis

To systematically analyze and compare the computer vision techniques, a framework based on several key parameters and performance metrics was developed:

- **Accuracy and Precision:** The ability of the techniques to correctly identify and classify fish behavior.
- **Robustness:** The resilience of the techniques to variations in underwater conditions, such as changes in lighting, turbidity, and occlusions.
- **Scalability:** The capacity of the techniques to handle large datasets and their applicability to real-time analysis.
- **Computational Efficiency:** The computational resources required and the speed of processing.
- **Generalizability:** The ability of the techniques to perform well across different species and environments without extensive retraining.

Each selected study was evaluated against these criteria to determine its strengths and weaknesses. Comparative analysis was performed to identify which techniques performed best under specific conditions and to highlight areas where further improvements are needed. This systematic approach ensured a comprehensive and unbiased review of the existing literature, providing a solid foundation for the subsequent analysis and discussion sections.

III. Computer Vision Techniques in Fish Behavior DETECTION

Understanding the nuances of underwater fish behavior has traditionally been a challenging endeavor. However, with the advent of sophisticated computer vision techniques, researchers now have powerful tools at their disposal to explore and analyze marine life in unprecedented detail. In this section, we delve into the key methodologies and algorithms driving the field of underwater fish behavior detection through computer vision.

A. Image Processing for Enhanced Clarity

Image processing plays a pivotal role in enhancing the quality of underwater images and videos, which are often plagued by lighting effects and scattering. Techniques such as filtering, separating, and edge detection are employed to simplify and clarify underwater imagery (Cui et al., 2024). By removing noise and isolating objects of interest, researchers can obtain clearer insights into fish habitats, health, and evolutionary patterns (Boudhane and Nsiri, 2016). The Mean-shift algorithm stands out as a prominent technique for segmenting underwater images, enabling the identification and analysis of distinct regions within the aquatic environment.

B. Object Detection for Precision Analysis

Distinguishing fish from their background environment is a fundamental task in fish behavior detection. Object detection algorithms leverage static background models to isolate fish within a given frame, enabling precise analysis of their movements and interactions (Zheng et al., 2024) and (Spampinato et al., 2010). By subtracting background elements, researchers can focus solely on the dynamics of marine life, unraveling intricate behavioral patterns.

C. Motion Tracking for Dynamic Observations

Analyzing the motion of fish over time provides valuable insights into their behavioral patterns and ecological dynamics. Motion tracking algorithms, including optical flow techniques and Kalman filters, facilitate the monitoring of fish movement across consecutive frames (Cui et al., 2024) and (Rathi et al., 2017). By tracking individual fish or groups within a population, researchers can uncover trends, such as migration routes or social hierarchies, crucial for understanding ecosystem dynamics.

D. Harnessing the Power of Deep Learning

Deep learning approaches have revolutionized underwater fish behavior detection, offering unparalleled accuracy and scalability. Convolutional Neural Networks (CNNs) streamline the analysis process, providing robust performance even with large datasets (Boudhane and Nsiri, 2016). Models like YOLO (You Only Look Once) further enhance efficiency by simultaneously tracking multiple fish with high precision (Rathi et al., 2017) and (Burguera et al., 2024). By annotating datasets and leveraging artificial intelligence algorithms, researchers can unlock new insights into fish behavior and ecosystem health, paving the way for innovative conservation strategies.

IV. DATA ACQUISITION AND PREPROCESSING

The investigation of underwater fish behavior using computer vision technology is highly dependent on data acquisition and preprocessing. These processes are essential for collecting high-quality visual data and preparing it for analysis, allowing researchers to accurately observe and interpret fish behavior in their natural environments. Marine biologists typically determine the presence and quantities of various fish species using methods such as underwater observation and photography with human involvement, combined net casting and sonar, and, more recently, hand-held video filming. These approaches have limitations. They are invasive and therefore unable to capture normal fish behaviors, and they collect insufficient data to fully describe the observed environment (Spampinato et al., 2010).

In underwater fish behavior analysis, data sources mainly consist of visual data captured using various imaging technologies.

A. Underwater cameras

High-resolution cameras, often featuring low-light capabilities, are used to capture continuous video footage of fish in their natural habitats. These cameras can be stationary and placed on the seafloor, attached to submersibles, or mobile, carried by remotely operated vehicles and autonomous underwater vehicles (Stoner et al., 2007).

B. Stereo vision system

A stereo vision system in underwater fish behavior research employs two or more cameras to capture synchronized images from different angles. This configuration creates 3D images or videos, allowing researchers to accurately measure the size, shape, and movement of fish. In underwater environments, stereo vision systems help address challenges like light refraction and turbidity, offering detailed insights into fish behavior, interactions, and habitat use. These systems are crucial for enhancing our understanding of marine ecosystems and fish ethology (Nian, 2013).

C. Sonar imaging

Since its introduction in 1928, sonar technology has undergone significant advancements, greatly enhancing underwater fish identification and imaging. Modern sonar systems, including multi-beam and side-scan sonar, now provide high-resolution, three-dimensional images that reveal detailed structural features of fish, such as skin patterns and fin shapes, even in murky waters (Jones et al., 2001). Multi-beam sonar covers large areas with detailed resolution, while side-scan sonar excels in mapping fish habitats (David et al., 2024). Additionally, the integration of advanced signal processing and machine learning has improved automated fish classification and tracking, further advancing the field (Li et al., 2024). These modern advancements make sonar imaging a powerful tool for studying fish behavior and habitat in various underwater conditions.

After data collection, preprocessing is necessary to ensure the data is clean, consistent, and ready for analysis. Enhancing the quality of underwater images involves adjusting brightness, color and contrast balance to mitigate the effects of low light, turbidity, and color distortion typical of underwater environments. For the noise reduction process, filters are applied to eliminate noise caused by electronic interference, particles in the water or other environmental reasons. Common techniques include Gaussian blur, median filtering, and bilateral filtering. Extracting relevant frames from continuous video footage to minimize data volume and concentrate on critical moments of fish behavior. Isolating the fish from the background image to concentrate the analysis on the subjects. These include edge detection, thresholding, and CNNs techniques for semantic segmentation. And annotating the processed data to identify the different fish species and their behavior (Rauf et al., 2019).

V. ANALYSIS OF FISH BEHAVIOR

Understanding fish behavior is pivotal for various applications in marine biology, ecology, and fisheries management. The advancements in computer vision technologies have significantly enhanced our ability to monitor and analyze fish behavior in diverse underwater environments. This section explores several key application scenarios where these technologies are making a substantial impact.

A. Marine Ecology and Conservation

Marine ecologists leverage computer vision to monitor fish populations and their behaviors in natural habitats. Automated detection and tracking systems allow for continuous observation of fish without the need for invasive methods. For instance, stereo vision systems and underwater cameras are used to capture high-resolution images and videos, enabling researchers to study species interactions, habitat use, and responses to environmental changes. Such data is crucial for developing conservation strategies and managing marine protected areas effectively (Stoner et al., 2008).

B. Fisheries Management

Accurate monitoring of fish stocks is essential for sustainable fisheries management. Computer vision techniques provide a non-invasive and efficient way to estimate fish abundance and size distribution. By deploying underwater cameras and sonar imaging systems, fisheries scientists can collect data on fish populations, analyze their spatial and temporal dynamics, and make informed decisions on fishing quotas and practices. This reduces the reliance on traditional, labor-intensive methods such as net sampling and manual counting (Jones et al., 2021).

C. Behavioral Studies and Ethology

Fish ethology, the study of fish behavior, benefits greatly from the precise tracking capabilities of modern computer vision systems. Techniques like motion tracking and deep learning models enable detailed analysis of individual and group behaviors. Researchers can observe schooling patterns, feeding habits, and social interactions with high accuracy. These insights help in understanding the underlying mechanisms of fish behavior and their adaptations to different environmental conditions (Pavlov and Kasumyan, 2000).

D. Aquaculture Monitoring

In aquaculture, monitoring fish health and behavior is critical for optimizing growth conditions and preventing diseases. Computer vision systems installed in aquaculture facilities can continuously track fish movements and detect abnormal behaviors indicative of health issues. This real-time monitoring allows for early intervention and improves overall fish welfare. Additionally, automated systems reduce the need for manual inspections, thereby increasing operational efficiency (Macaulay et al., 2021).

E. Environmental Impact Assessments

Assessing the impact of human activities on marine environments is another important application of fish behavior analysis. Computer vision techniques help in monitoring how fish populations and behaviors are affected by pollution, construction, and other anthropogenic factors. By analyzing data collected from affected areas, researchers can provide evidence-based recommendations for mitigating negative impacts and promoting sustainable development practices (González-Sabbagh and Robles-Kelly, 2023).

F. Educational and Public Awareness Programs

Visualizing fish behavior through computer vision also plays a role in education and raising public awareness about marine ecosystems. High-quality video footage and interactive simulations derived from these technologies can be used in educational programs, museums, and public exhibits. This helps in fostering a deeper understanding and appreciation of marine life among the general public, thereby supporting conservation efforts (Jan et al., 2007).

VI. CHALLENGES AND FUTURE DIRECTIONS

A. Challenges

Despite the significant advancements in computer vision techniques for fish behavior detection, several challenges persist. Addressing these issues is crucial for improving the accuracy, efficiency, and applicability of these technologies in diverse underwater environments.

1. Underwater Image Quality

Underwater images often suffer from poor visibility due to factors such as low light levels, turbidity, and light refraction. These conditions result in low-contrast and noisy images, making it difficult to accurately detect and track fish. Enhancing image quality through preprocessing techniques like noise reduction, contrast adjustment, and color correction is essential but can be computationally intensive and may not always yield satisfactory results (González-Sabbagh and Robles-Kelly, 2023).

2. Environmental Variability

Underwater environments are highly dynamic, with varying lighting conditions, water clarity, and background scenes. Fish behavior detection algorithms must be robust enough to handle these variations without significant loss of accuracy. Developing adaptive algorithms that can dynamically adjust to changing environmental conditions remains a major challenge (Rauf et al., 2019).

3. Data Annotation

Training machine learning models for fish behavior detection requires large datasets of annotated images or videos. Manually annotating these datasets is time-consuming and laborintensive. Additionally, obtaining sufficient labeled data for rare or elusive species can be particularly challenging. Semisupervised and unsupervised learning approaches could help alleviate this issue, but their application in underwater environments is still in its early stages (Moniruzzaman et al., 2017).

4. Species and Behavior Generalization

Most existing computer vision models are trained on specific datasets and may not generalize well to different species or behaviors not represented in the training data. This lack of generalizability limits the applicability of these models across diverse marine ecosystems. Developing models that can perform well across various species and behaviors without extensive retraining is essential for broader application (Pavlov and Kasumyan, 2000).

5. Computational Resources

High-resolution video processing and the application of complex deep learning models require substantial computational resources. This can be a limiting factor, especially for real-time analysis and monitoring in remote or resource-constrained environments. Efficient algorithms that balance accuracy and computational load are needed to make these technologies more accessible and practical for widespread use (Macaulay et al., 2021).

B. Future Directions

To overcome these challenges and advance the field of fish behavior detection using computer vision, several promising research directions can be pursued.

1. Improved Image Enhancement Techniques

Developing more sophisticated image enhancement algorithms that can effectively handle the unique challenges of underwater imaging is crucial. Techniques that leverage artificial intelligence, such as generative adversarial networks (GANs), can be explored to improve image quality and reduce noise. These approaches could lead to significant improvements in the clarity and usability of underwater video data (Jones et al., 2021).

2. Adaptive and Robust Algorithms

Creating algorithms that can adapt to varying underwater conditions and remain robust under different environmental settings is a key area of research. This could involve the integration of environmental sensors to provide contextual data that can be used to adjust the behavior detection algorithms in real-time, improving their accuracy and reliability (González-Sabbagh and Robles-Kelly, 2023).

3. Semi-Supervised and Unsupervised Learning

To address the data annotation challenge, semi-supervised and unsupervised learning methods can be further developed and applied. These techniques can reduce the dependency on large, annotated datasets by leveraging unlabeled data to enhance model training. Active learning approaches, where the model can query the user for labels on uncertain instances, can also be beneficial (Moniruzzaman et al., 2017).

4. Transfer Learning and Model Generalization

Transfer learning, where a model trained on one dataset is finetuned on another, can be explored to improve species and behavior generalization. Additionally, creating large, diverse datasets that include multiple species and behaviors can help in developing more generalized models. Collaborative efforts across institutions to share data and resources will be instrumental in this endeavor (Pavlov and Kasumyan, 2000).

5. Edge Computing and Efficient Algorithms

Implementing edge computing solutions, where data processing is performed close to the data source (e.g., on underwater vehicles or cameras), can mitigate the need for high-bandwidth data transmission and reduce latency. Developing lightweight algorithms that can run efficiently on edge devices without compromising accuracy will be crucial for real-time applications in remote locations (Macaulay et al., 2021).

6. Multimodal Data Integration

Integrating data from multiple sources, such as sonar, environmental sensors, and visual data, can provide a more comprehensive understanding of fish behavior. Multimodal data fusion techniques can enhance the robustness and accuracy of behavior detection systems. Research into effective ways to combine and analyze these diverse data types is needed to fully realize their potential (Jones et al., 2021).

VII. CONCLUSION

This comprehensive review of computer vision techniques for detecting fish behavior in underwater environments underscores the significant advancements and ongoing challenges in this field. Despite notable progress, several challenges remain, particularly in enhancing underwater image quality, adapting to dynamic environmental conditions, and improving data annotation processes. Addressing these issues is essential for developing more accurate, efficient, and versatile behavior detection systems. Promising future directions include the development of advanced image enhancement algorithms, adaptive and robust detection algorithms, and semi-supervised learning techniques to reduce reliance on annotated datasets. Additionally, integrating edge computing and multimodal data fusion can further improve real-time analysis and provide comprehensive insights into fish behavior.

Collaborative efforts across institutions to share data and resources will be instrumental in advancing this field. By leveraging these advancements, researchers can gain deeper insights into marine ecosystems, contributing to more effective conservation strategies, sustainable fisheries management, and a better understanding of fish ethology. Ultimately, the continued evolution of computer vision technology holds great potential for transforming underwater research and supporting the preservation of marine biodiversity.

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