Underwater Fish Monitoring Through Vortex-Induced Vibration Sensing

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ABSTRACT

Underwater fish and marine animal monitoring is important in assessing biodiversity and the health of aquatic ecosystems as well as for understanding the impacts of offshore structures on those animals. Existing methods, such as acoustic sensing, tagging, flow field sensing, and optical imaging, are often energy-intensive, invasive, fragile, or dependent on lighting conditions. Inspired by the sensory mechanism of seal whiskers, we introduce an energy-efficient, non-invasive marine animal monitoring method based on vortex-induced vibration (VIV) sensing. The main intuition of our method is that as marine animals swim, they generate characteristic vortex patterns and turbulence that propagate through water. By detecting these VIV signals, our system can identify the movement of these animals. A key challenge lies in capturing these low-amplitude, rapidly dissipating vortices. To address this, we design a flexible sensor mounting structure in which the sensor is suspended by a string from a fixed base, allowing adaptive movement in response to vortex-induced flow. We validate the system in a water tank using swimming fish toys and other objects to induce vortices, achieving a classification accuracy of 96.88%, demonstrating its effectiveness and potential for monitoring underwater fish and marine animals.

INTRODUCTION

Monitoring underwater animals is essential for assessing biodiversity and ecosystem health and understanding the impacts of offshore structures on them. Tracking the populations and behaviors of endangered species such as sea turtles and sharks supports the development of effective conservation strategies [1, 2]. Marine animals also play critical roles in maintaining ecological balance, making their monitoring vital for evaluating ecosystem integrity [3]. For example, post–Deepwater Horizon oil spill monitoring of dolphins in the Gulf of Mexico reveals long-term ecological damage, which helps uncover environmental problems and informs conservation efforts [4]. Furthermore, monitoring marine animals around offshore infrastructure, such as wind farms, enhances understanding of potential ecological disturbances and supports more sustain-

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able marine spatial planning [5].

Existing underwater animal tracking methods mainly include acoustic monitoring, tagging, flow field sensing, and optical imaging, which are either energy-intensive, invasive, fragile, or light-dependent. Acoustic monitoring typically relies on active sonar, which emits acoustic signals that reflect off animals to track their movements [6–8]. However, active sonar is expensive, energy-intensive, and may harm marine life [9, 10]. Tagging involves capturing animals to attach transmitters to obtain their location or behavior data [11, 12]. However, it is invasive, impractical for large populations, and vulnerable to tag loss, failure, or limited battery life. Artificial lateral line systems monitor underwater animals by sensing water pressure and flow fields [13, 14]. However, they often rely on fragile bionic cilia or pressure-sensing pores, which are prone to damage or blockage in harsh underwater environments. Optical imaging using cameras for fish monitoring is less invasive and energy-efficient [15, 16]. However, it is restricted by turbidity, limiting its effectiveness in deep or murky waters. Therefore, a non-invasive, energy-efficient underwater fish monitoring method that works reliably in dark underwater environments is needed.

In this paper, we introduce a novel underwater fish monitoring method through fish-induced vortex vibrations. The main idea is that as fish swim, their body movements generate a Kármán vortex street that propagates through the water. By capturing and analyzing the resulting vibration patterns, we can detect fish presence.

The main research challenge is that the vortex-induced vibrations (VIV) generated by swimming fish are typically low in amplitude and decay rapidly, making them difficult to detect. The flow velocities induced by fish are on the order of centimeters per second [17], corresponding to pressure fluctuations in the millipascal (mPa) range. These weak signals are further diminished by rapid vortex dissipation due to viscous diffusion and turbulent mixing [18], making it challenging for VIV sensing.

To address this challenge, we design a flexible sensor mounting structure inspired by seal whisker dynamics, allowing the sensor to float in the water and move adaptively with vortex-induced water vibrations. The setup consists of a hook-mounted sensor box suspended by a flexible string from a fixed underwater structure. This configuration enables the sensor to track small, rapid flow displacements rather than resisting them, effectively amplifying relative motion and enhancing responsiveness to low-amplitude flow fluctuations. Additionally, we analyze the VIV patterns generated by swimming fish and construct a dynamic feature set to develop a fish recognition model.

We evaluated our method in a water tank by inducing vortices with different objects, including swimming toy fish, a box with plastic chains, and a sinking plate. The goal is to classify the source of the vortex-induced vibrations (VIVs). Our method achieved an accuracy of 96.88% in vortex source classification, validating its effectiveness and demonstrating potential for underwater animal monitoring and target recognition.

FISH-INDUCED VORTICES AND VORTEX-INDUCED VIBRATIONS

Most fish swim by undulating their bodies and oscillating the caudal fin, generating a distinctive vortex pattern in the surrounding water. During rapid maneuvers, such as turns or fast-starts, the fish first bends into a C-shape, producing a large lateral force and generating a strong vortex ring on the side opposite the bend due to intense rotational

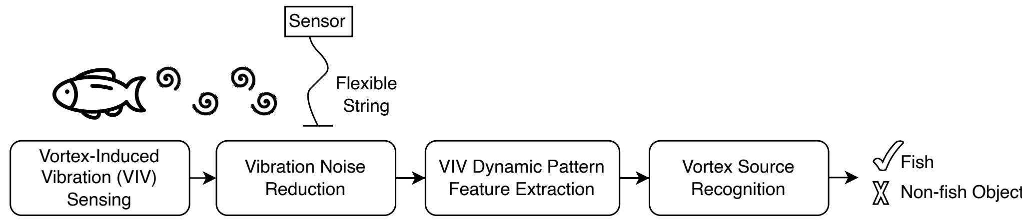

Figure 1. Fish Monitoring Method Overview

flow [19]. It then rapidly straightens, propelling itself forward. This sequence creates a complex wake composed of multiple vortices, typically dominated by a strong leading vortex ring [20]. In steady swimming, many fish species shed a series of alternating vortices from the tail, forming a reverse Kármán vortex street characterized by a jet-like flow that drives forward motion [21]. Thus, swimming fish can be detected from the distinct vortex patterns they generate. These vortex structures can also serve as indicators of swimming mode, speed, and body size.

Underwater animals can detect prey by sensing the vortices generated by swimming prey, through cues such as pressure gradients, flow velocity, acceleration, and vibrations of hair-like structures. For example, the lateral line system in fish consists of neuromasts that convert flow variations into electrical signals transmitted to the brain [22]. Cephalopods have skin mechanoreceptors that detect shear forces caused by water movement across their skin [23]. Seals and sea lions have highly sensitive whiskers capable of detecting vortex-induced vibrations or bending, while simultaneously filtering out noise from their self-movement to track prey trails that are minutes old [24]. Among these strategies, seal whiskers offer a distinct advantage in detecting fine-scale flow features and suppressing background noise, enabling the detection of prey wakes at distances up to 180 meters and as long as 35 seconds after the prey has passed, even in the absence of visual or auditory cues [25]. Inspired by this mechanism, we aim to develop a bioinspired sensing unit that vibrates in response to vortices generated by swimming fish, similar to the seal whiskers for fish monitoring.

FISH MONITORING METHOD BASED ON VORTEX-INDUCED VIBRATIONS

Our fish monitoring system detects swimming fish by capturing and analyzing vortex-induced vibration (VIV) patterns generated by their movement (see Figure. 1). First, a vibration-sensitive underwater sensing structure is developed to capture the VIV signals, which are then denoised based on prior knowledge of fish-induced vortex frequencies. We then extract dynamic features from the filtered signals and identify whether the vibration originates from fish movement.

Vortex-Induced Vibration (VIV) Sensing: To address the challenge of small amplitude and fast decaying vortices induced by swimming fish, we develop an underwater sensing structure consisting of a floating sensor box connected to the main structure (e.g., submarine or other underwater platform) via a flexible string. The flexible connection allows the sensor to vibrate in response to subtle flow disturbances, enhancing its sensitivity to tiny VIV signals.

Vibration Noise Reduction: We reduce signal noise by leveraging prior knowledge of fish-induced vortex patterns. First, we detrend the signals to eliminate low-frequency drifts and DC offsets that could obscure relevant dynamics. Previous studies have shown that seal whisker vibrations induced by fish-generated vortices occur within the 20–250 Hz range [26]. Based on this, we apply a bandpass filter to remove noise outside this effective frequency band. Finally, the signals are normalized by their standard deviation to ensure consistent amplitude scaling across samples, enhancing robustness to variations in fish movement force and distance.

VIV Dynamic Pattern Feature Extraction: To effectively distinguish swimming fish from environmental disturbances, we extract both frequency-domain and time-domain features that capture the characteristic signatures of fish-generated vortex-induced vibrations. Frequency-domain features primarily consist of Fast Fourier Transform (FFT) coefficients, which represents oscillatory patterns generated by fish, enabling differentiation from background flow [27]. Time-domain features include skewness, kurtosis, crest factor, and entropy. Skewness and kurtosis describe the asymmetry and tailedness of the signal distribution, highlighting irregularities and burstiness typical of biological motion [28]. The crest factor, defined as the ratio of peak amplitude to root-mean-square (RMS) value, captures transient, high-amplitude events characteristic of swimming. Entropy quantifies signal complexity and randomness, helping to distinguish fish-induced vibrations from steady background noise.

Given the high dimensionality of the extracted features, we reduce the feature dimensions through Partial Least Squares (PLS) regression. PLS is selected because it reduces the dimensionality of the feature space while maximizing the covariance between the feature set and the target labels [29]. Unlike unsupervised methods such as Principal Component Analysis (PCA), which only consider feature variance, PLS is supervised and explicitly identifies feature projections that are most predictive of the fish detection task. This property makes PLS well-suited for our task to identify the effective features with limited data. By projecting the original high-dimensional feature vectors into a lower-dimensional latent space, PLS improves model efficiency, reduces the risk of overfitting, and enhances classification performance.

Vortex Source Recognition: To distinguish fish-induced vortices from other sources, we develop a vortex source recognition model using logistic regression. Logistic regression is computationally efficient and effective for both binary and multiclass classification, particularly with limited data [30]. It models class probabilities as a logistic function of a linear combination of input features, making it well-suited for features mapped via PLS which outputs components that capture the maximum covariance between the labels and the features. Additionally, logistic regression is less prone to overfitting than more complex models, making it appropriate for scenarios with small sample sizes where extensive data collection is not feasible.

UNDERWATER EXPERIMENTAL EVALUATION

We evaluated our underwater marine animal monitoring method through an experiment in a water tank, capturing and classifying vortex-induced vibrations (VIVs) generated by different objects. Vortices were generated using three types of objects: (1) an

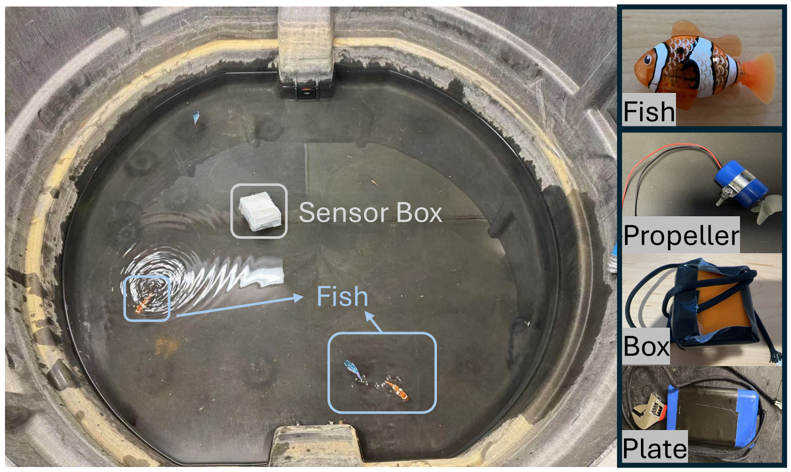

Figure 2. The Underwater Experiment Setup

autonomous toy fish, (2) a box filled with plastic chains that are manually oscillated back and forth to simulate the movement of a large inertial object, and (3) a flat sinking plate, stabilized with a metal wrench to maintain horizontal orientation, which was towed forward through the water using a line. A continuously operating electric propeller was mounted to the tank wall to simulate realistic underwater conditions, including background turbulence and ambient noise. Vibration signals were recorded using an SM-24 geophone at a 500 Hz sampling rate. For each object, 4 minutes of data were collected and segmented into 30-second samples, resulting in a total of 16 minutes of data for testing.

Our method achieved an accuracy of 96.88% for identifying fish through vortex-induced vibrations. In both binary fish vs. non-fish classification (see Figure 3(a)) and four-class vertex source identification (see Figure 3(b)), our method achieved a high overall accuracy of 96.88%. To prove the effectiveness of PLS-based feature reduction method and logistic regression-based vortex recognizing model, we compare the recognition accuracy between our methods and other baseline methods (see Figure 3(c, d)). Our method outperforms all the others, demonstrating the effectiveness of the feature dimension reduction method and the vortex source recognition model.

CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we introduce a novel method for underwater fish monitoring by detecting fish-induced vortices using vibration sensors. To enhance sensitivity to weak vortices, we develop the sensing unit with a floating sensor box connected to a fixed structure via a flexible string. We further analyze vortex-induced vibration (VIV) patterns and develop a fish recognition model based on dynamic VIV features, achieving an accuracy of 96.88% for vortex source classification in controlled water tank experiments.

In the future, we aim to design more sensitive and noise-resilient sensing units for underwater fish monitoring. In addition, we will further develop algorithms for fish tracking and species identification. We will also explore combining multiple sensors as

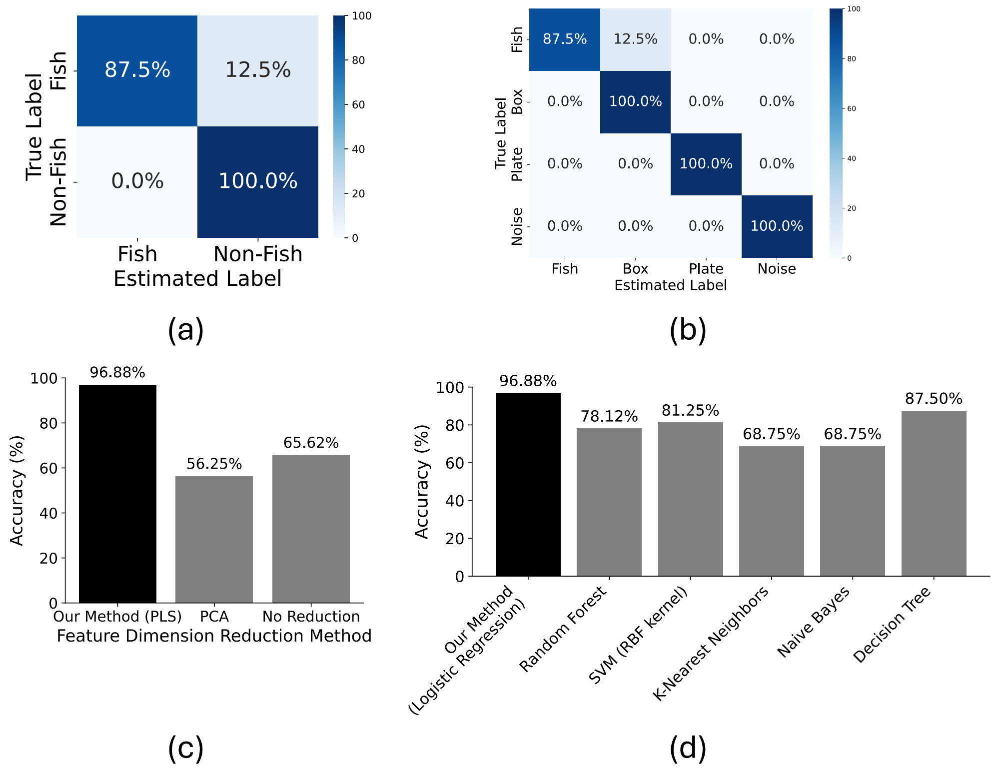

Figure 3. Underwater Experiment Results. (a) Confusion matrix for binary fish vs. non-fish classification. (b) Confusion matrix for four-class vortex source classification. (c) Accuracy comparison of our PLS-based feature dimension reduction method and other dimensionality reduction methods. (d) Accuracy comparison of our method with other classifiers.

sensor arrays to provide a more accurate and robust system.

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