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Observing fish interactions with marine energy turbines using acoustic cameras

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Abstract

Marine current energy converters such as tidal and riverine turbines have the potential to provide reliable, clean power. The risk of collision of fishes with marine energy turbines is not yet well understood, in part due to the challenges associated with observing fish at turbine sites. Turbidity and light availability can limit the effectiveness of optical sensors like video cameras, motivating the use of acoustic cameras for this task. However, challenges persist in collecting and interpreting data acquired from acoustic cameras. Given the limited number of turbine deployments to date, it is prudent to draw on the application of acoustic cameras to monitor fish in other scenarios. This article synthesizes their use for other fisheries applications to inform best practices and set realistic expectations for the results of acoustic camera monitoring at turbine sites. We discuss six key tasks performed with acoustic cameras: detecting objects, identifying objects as fish, counting fish, measuring fish, classifying fish taxonomically and analysing fish behavior. Specific challenges to monitoring fish at turbine sites are discussed. This article is intended to serve as a reference for researchers, regulators and marine energy developers on effective use of acoustic cameras to monitor fish at turbine sites. The studies detailed in this article provide evidence that, in some scenarios, acoustic cameras can be used to inform the risk of fish collision with marine energy turbines but doing so requires careful study design and data processing.

KEYWORDS
acoustic cameras, collision risk, current energy converters, imaging sonar, marine energy, tidal turbines

1 | INTRODUCTION

Because of their ability to operate without illumination or water clarity, acoustic cameras are increasingly popular tools for imaging marine animals and objects in the water column at ranges on the order of tens of metres (Colbo et al., 2014). Recently, they have been used for fisheries research to monitor fish presence and behaviour in a variety of habitats, including at marine energy sites. Marine current energy turbines convert the energy in water currents (i.e. tidal, riverine or ocean currents) to electricity.

An illustration of various types of current energy turbines can be found in Copping et al., 2021. Collision of fishes with moving components of current energy turbines (hereafter referred to as turbines) has been identified by researchers and regulators as a potential risk associated with this form of renewable energy development (Copping & Hemery, 2020).

Quantification of collision risk requires an understanding of the number of fish that encounter a turbine (i.e. encounter rate), the behaviour of fish around a turbine and the likelihood of collision occurring if a fish does pass through the swept area of the turbine. The encounter rate is related to the abundance of fish in the area where the turbine is deployed. Relevant behaviours include avoidance or attraction (i.e. do fish avoid the turbine area or are they attracted to it?) as well as fine-scale evasion behaviours around turbine blades. Ultimately, this information can be used to predict whether there may be individual or population-level impacts on fish species. To date, data to address these questions are limited due to the challenges associated with monitoring fishes at turbine sites (Sparling et al., 2020).

Acoustic cameras have been identified as well suited to collect data to inform collision risk at sites where optical cameras have limited capabilities (Matzner et al., 2017; Polagye et al., 2014). However, while they can provide valuable data, there are limitations to what information about individuals, schools and shoals can be observed with acoustic cameras. When compared with video cameras, the imagery is low resolution and does not represent colour, so identification and classification of each detected object is based on its size, shape or behaviour. Further, background noise or acoustic artefacts can obscure object detection. Despite these limitations, acoustic cameras are the only sensor to date capable of directly observing fish interactions with turbines in turbid or dark waters and have been applied to study fish interactions with turbines in several studies. While these studies have provided some preliminary information about collision risk, results have been limited by challenges associated with noise from entrained air (e.g. Amaral et al., 2015) or debris (e.g. Staines et al., 2022) and interpretation and processing of collected data (Viehman & Zydlewski, 2015). However, acoustic cameras have been used more broadly to monitor fish for other applications, including ecological assessment of fish behaviours (e.g. Langkau et al., 2016; Magowan et al., 2012; Rand & Fukushima, 2014) and hydroelectric dam monitoring (e.g. Grote et al., 2014; Lenihan et al., 2019; Piper et al., 2018).

In this review, we describe the capabilities and limitations of acoustic cameras to inform researchers, regulators and marine energy developers about how and when they may be used most effectively to observe fish interactions with turbines and to identify areas for future research. To do this, first, we provide a contextual overview of acoustic camera operation. Then, we draw on literature from the broader fisheries research community to provide a synopsis of how acoustic cameras are used to monitor fish and how these capabilities can be applied to understanding the risk of collision between fish and a turbine. Finally, we identify challenges or considerations specific to marine energy turbine sites.

2 | ACOUSTIC CAMERA FUNDAMENTALS

Multibeam sonars were initially developed in the 1960s for seafloor characterization, but more recently have been applied to imaging animals, objects and physical processes in the water column (Colbo et al., 2014). Correspondingly, in the last two decades, high-frequency (i.e. high-resolution) multibeam sonars, referred to here as acoustic cameras, have been designed for water column imaging over ranges less than a metre to tens of metres. In this section, we provide relevant background about the operating principles of acoustic cameras, which we define as multibeam sonars with operating frequencies above 500 kHz.

The fundamental principles of all active acoustic sonars are the same. A transducer transmits an acoustic pulse at a specified frequency or spanning a specified frequency range. After pulse transmission, the acoustic wave travels through the water column and scatters off targets and boundaries, and some of these signals return to the receiver (i.e. backscatter). Backscattered returns are received, digitized and typically processed onboard the instrument in near-real time. A simplified version of the sonar equation describes this process:

$$EL = SL - 2TL + TS,$$

where EL is echo level (received level), SL is source level (magnitude of the transmitted pulse), TL is transmission loss due to spreading and attenuation (the factor of two accounts for spreading and loss in both directions) and TS is target strength, or the backscattering from individual targets in the pulse's path. All values are in decibels. For acoustic cameras (and all multibeam sonars), multiple transducers are combined into an array, referred to as a beam array. Using the known direction of transmission of each beam relative to the array, received signals from all transducers in the beam array are combined to form a composite image. While the sonar equation is important for understanding the transmission and reflection of sound underwater, especially for calibrated fisheries echosounders (Korneliussen, 2018), in most acoustic camera applications, sensors are uncalibrated and backscatter values are relative. This means that acoustic cameras are not typically used to quantitatively assess scattering like fisheries echosounders.

The backscattering from a fish (i.e. backscattering cross section or TS) depends on the physical characteristics of the fish and the transmitted acoustic frequency. Backscatter from an object increases with the ratio of the sound speed and density of the object to that of the surrounding water. Therefore, in fishes that have gas-filled swimbladders, these high impedance anatomical features contribute 90%–95% of the scattering, and, at the relatively low frequencies used by most fisheries echosounders, scattering from the rest of the fish body is often considered negligible (Foote, 1980). Conversely, at the relatively high frequencies used by acoustic cameras, the body of the fish contributes more significantly to the scattering and, under some conditions, the shape and morphology of the fish may be detected (Chu et al., 2015). This is an important capability of acoustic cameras for monitoring fishes—imaging the body of the fish allows users to monitor fine-scale movements and measure size, therefore improving classification capabilities. However, as discussed in subsequent sections, acoustic camera data interpretation is complex, and capabilities vary depending on the site, sensor configuration and size and species of fishes being monitored.

Generally, acoustic camera data are recorded as beamformed images, though, in some cases, raw data may be accessed. In this work, we define the cross-beam direction in the beamformed image as the direction moving across the beam array, perpendicular to transmission and the along-beam direction as the direction moving along the beam array, parallel to transmission (often referred to as range with single beam sonars). These directions are depicted in Figure 1. Image resolution in the cross-beam direction is limited by the spacing and width of the individual beams and their ping rate, while resolution in the along-beam direction is limited by the characteristics of the transmitted pulse (frequency, pulse duration). In practice, beamformed images are frequently exported as Cartesian images (i.e. in .mp4 video or .jpg image file), requiring transformation of data from polar to Cartesian coordinates, which may affect image resolution. Because Cartesian images are typically viewed and processed in a similar manner to imagery from optical cameras, each point in the image is commonly referred to as a 'pixel'.

A variety of acoustic cameras are commercially available and differ in how they transmit, receive, beamform and display acoustic returns (Thompson, 2003), which, in turn, results in differences in their capabilities for monitoring fish. Brief overviews of the operational

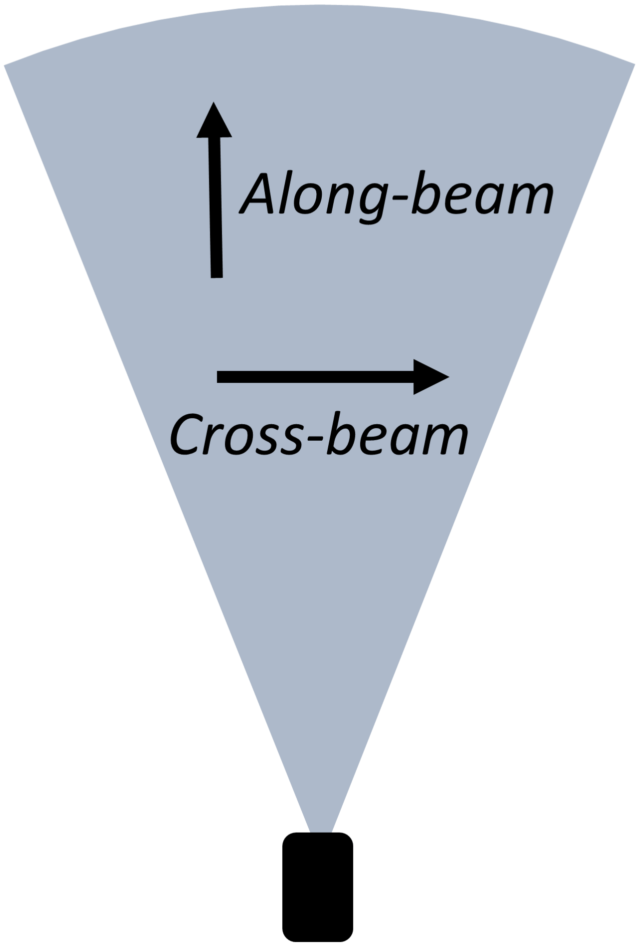

FIGURE 1 Graphic depiction of along-beam and cross-beam directions.

details of two distinct acoustic cameras are provided in the following paragraphs to illustrate the concepts presented in this section and highlight the differences between two commonly used technologies. We note that this does not represent a comprehensive list of all commercially available acoustic camera systems.

Teledyne BlueView acoustic cameras use a blazed array of transducers (Thompson et al., 2001) to form multiple subsectors, each with 22.5° horizontal fields of view (FOVs). These subsectors are stitched together to form 45°, 90° or 130° beam array configurations. Frequency modulated pulse transmissions have a wide frequency range. For instance, the BlueView M900 ranges from 600 to 1200 kHz with the centre frequency at 900 kHz for each subsector. Frequency and beamwidth change within a sector to facilitate fast ping rates without interference: each transducer array forms a directional beam for a specific frequency, for example, at 1200 kHz the beam points towards −22.5° from the centre of the FOV and at 600 kHz it points towards −45° from the centre of the FOV. Returned signals are processed in the frequency domain and a discrete Fourier transform is used to extract the frequency-steered directional signal response relative to the array angle. This information is then processed to produce an image that can be viewed in real time or recorded for later processing (pers. comm. Tyler Whitaker, Teledyne Technologies).

In contrast, Sound Metrics Corporation (SMC) acoustic cameras (the Adaptive Resolution Imaging Sonar [ARIS] and the Dual-frequency IDentification Sonar [DIDSON]) conduct beamforming with an acoustic lens, which reduces the width of individual beams in the array, increasing both the cross-range resolution and the dynamic range of the image at the cost of a relatively narrow horizontal FOV (Belcher et al., 2001, 2002). Rather than transmitting from all beams simultaneously, subsets of equally spaced beams transmit sequentially, which removes most sidelobe returns because adjacent beams are not simultaneously operational. SMC sensors operate at high frequencies (700–3000 kHz), which provides increased cross-beam resolution at the expense of decreased maximum range (pers. comm. Bill Hanot, Sound Metrics Corporation). Because their high-resolution imagery is suitable for imaging smaller targets like fish, SMC sensors are the acoustic camera most frequently used in the studies discussed in this review.

3 | CAPABILITIES OF ACOUSTIC CAMERAS FOR MONITORING FISH AROUND TURBINES

Acoustic cameras are used for six distinct tasks for monitoring fish, presented here in increasing level of analytical complexity and effort:

- detecting objects,
- identifying objects as fish,
- counting fish,
- estimating fish length,
- classifying fish taxonomically and
- analysing fish behaviour.

In the following sections, we summarize the pertinence of each of these tasks for assessing the risk of fish collision with turbines and describe the capabilities and limitations of acoustic cameras for performing each task. Finally, we provide an overview of the data processing techniques and software used for analysis.

3.1 | Detecting objects

Any acoustic camera-based assessment of fish initially requires detection and identification of imaged fishes. Many studies do not explicitly discuss object detection prior to identification of an object as a fish, but confidence in this step is essential and should not be overlooked. The successful detection of an ensonified object is related to its backscatter, sometimes referred to as the brightness of that object. If an object's backscatter is less than or near the background noise level, then its detection will be difficult or impossible. The background noise level is a combination of volume and boundary reverberation. Volume reverberation is backscatter from entrained air or particles, such as sediment, in the water column, while boundary reverberation is backscatter from the bottom of a waterbody (i.e. seafloor), the water surface or infrastructure like the frame holding a tidal turbine (Viehman & Zydlewski, 2015). Volume reverberation levels may vary with the operating frequency of an acoustic camera depending on the size of entrained air and particles (e.g. Polagye et al., 2020). In addition to background noise levels, the detectability of an object depends on its range from the transducers; an object becomes more difficult to resolve with increasing distance from the sensor because of beam spreading (i.e. decreasing cross-beam resolution), attenuation of the transmitted sound, and increasing volume reverberation.

Even when an object can be detected above background noise, it may intermittently 'disappear' as its orientation and position change. Tušer et al. (2014) demonstrated this in a controlled tank experiment: Fish that were otherwise detectable by an SMC DIDSON were not detectable when they were oriented directly head-on or tail-on. Similarly, a fish that moves in a sporadic manner may be difficult or impossible to detect in some positions. For example, as an eel swims (anguilliform), it scatters more sound when it is convex towards the acoustic camera than when it is concave (Mueller et al., 2010). Fish may also be temporarily undetectable when they move between the acoustic camera and a hard surface and are obscured by boundary reverberation.

An object must register in multiple pixels to be detectable above sensor background noise, and the probability of detection increases with the number of pixels that the object is registered in (Handegard & Williams, 2008). When an object scatters more sound than the background noise, it 'lights up' as many pixels as it scatters sound in. If part of an object, like the end of a fish's tail or tip of its head, is partially ensonified in a pixel and scatters enough sound, it lights up that entire pixel (Burwen et al., 2010). The smallest detectable target varies between acoustic cameras: the size of pixels is related to the resolution of the acoustic camera, which is driven by operating frequency, the number of beams and transducer design. An object also typically must be detected in multiple frames to be detected by a human reviewer or computer-driven methods. Tracking a target through the beam array yields confidence that it represents an object, rather than a spurious detection of noise.

Challenges associated with target detection can sometimes be mitigated through adjustment of software-configurable settings and/or the physical positioning of the acoustic camera. Some acoustic cameras allow the user to select between multiple operating frequencies. Generally speaking, higher operating frequencies provide both increased along-beam and cross-beam resolution due to shorter wavelengths and narrower beam widths respectively. However, the trade-off for higher operating frequencies is a decrease in overall detection range. Other user-configurable settings, such as the pulse width or source level, may decrease background noise levels, though settings available to users vary between instruments and manufacturers. High background noise levels due to volume reverberation can be difficult to mitigate. Moving the acoustic camera to a location with less entrained air or sediment will help, but is not always possible when the area of interest is a specific location (i.e. near a turbine installation). Similarly, boundary reverberation may be avoided by proper aiming of the acoustic camera to avoid boundaries such as the water surface, seafloor or underwater structures. Unfortunately, boundary reverberation challenges may be unavoidable when monitoring for fish collision with a turbine because of the requirement to directly observe fish interactions with the turbine structure.

3.2 | Identifying objects

If an object is detected (referred to then as a target), the next stage of processing is to identify whether it is a target of interest (e.g. fish or not a fish). In most cases, this involves the separation of fish from debris, entrained air or other sources of background noise. In ideal circumstances, the shape of a target can make identification straightforward. However, the smaller a target is, the fewer pixels it is made up of and the less the target's shape is observable. Background noise may also obscure distinctive aspects of a fish's shape (i.e. fins). Target movement can aid in human and computer-driven identification. While debris and entrained air move passively, many animals have a component of acceleration to their movements, making them stand out from the rest of the targets moving through the beam array. Co-temporal measurements of water velocity (e.g. from an Acoustic Doppler Current Profiler [ADCP]) can be used to determine the velocity of passive particles to aid in target identification. The velocity of detected targets can be compared to the velocity of passive targets to determine whether they differ.

The chance of accurate identification increases with the number of frames in which the target is observed, because there is an increased probability that the shape or movement will be observed as the orientation of the target changes relative to the beam array, and the motion of the target can be observed for a longer duration. This means that a faster frame rate may improve identification capabilities. Additionally, the number of frames in which a target is detected is inversely related to the velocity of the target. This is important for turbine sites where water velocities typically exceed 1 m/s (Polagye & Thomson, 2013). Further, because beamforming does not occur simultaneously in the beam array in most acoustic camera designs, movement of a target during the generation of an image can create motion artefacts. This may appear in the form of 'broken' targets (Staines et al., 2022) or rigid targets like sticks that may appear to move like eels (EPRI, 2017).

3.3 | Counting fish

Counting fish (i.e. abundance estimation) for management purposes is a long-standing objective in the field of fisheries (Hilborn & Walters, 1992). It is of particular importance when studying the risk of fish collision with a turbine because the rate of encounter and probability of collision are likely driven by the number of fish present. Fish counting is especially challenging in shallow, turbid environments or near infrastructure such as tidal or in-river turbines where the use of traditional approaches, such as trawls or optical cameras, are not effective. Acoustic cameras can address this gap and extend counting abilities to formerly unobservable scenarios (Lankowicz et al., 2020), but accurate interpretation of data requires accounting for several limitations and sources of error.

Counting fishes near turbines to inform determinations of collision risk is a relatively new application for acoustic cameras. Previously, acoustic cameras have been used to count fishes in a variety of scenarios, such as entering hydropower turbine draft tubes (Braga et al., 2022) or in an aquaculture net pen (Han et al., 2009), and a variety of counting techniques have been used that provide absolute (e.g. Ogburn et al., 2017) or relative (e.g. Becker & Suthers, 2014) abundance estimates. While the specific methodology for fish counting may vary between scenarios, several general factors should be considered in any fish counting application.

First, attempts to count fishes with acoustic cameras can be challenging when there is a high density of fish and they are entering and exiting the beam array in quick succession (Braga et al., 2022). In this scenario, fish can be double counted, missed or, when counting is performed by a human reviewer, the analyst may struggle to maintain consistency through frames (Holmes et al., 2006). Furthermore, when a school or shoal of fish is in the beam array through multiple frames, changes in the orientation, range and relative position of individual fish can complicate counting as fish disappear and reappear from view (see Supplementary Materials, '2 Fish School Video' from Staines et al., 2020 for an example of this). Milling behaviour is when a fish maintains position in or repeatedly moves into and out of the beam array (Eggleston et al., 2020). Like high fish density, milling complicates fish counting: the same fish may be counted multiple times because it is not possible to determine whether the same fish is re-entering the frame. This may be adjusted for using a co-temporal count from a different sensor (e.g. optical camera) or physical capture.

As discussed under Section 3.1, the ability to detect objects and identify them as targets of interest is affected by background noise. Similarly, boundary and volume reverberation can reduce accuracy when counting fishes. Braga et al. (2022) observed this phenomenon in a turbine draft tube at a hydroelectric dam; when fish passed over the concrete floor, their brightness resembled that of the concrete surface. Viehman and Zydlewski (2015) and Staines et al. (2022) found that entrained air and scattering from hard surfaces affected counting capabilities around turbines, even after focusing and attempting to aim the beam array to minimize background noise.

3.4 | Estimating fish length

Broadly, estimations of fish length are used to inform fisheries management through determination of size and age distributions of the population (Hilborn & Walters, 1992). At turbine sites, this may inform monitoring requirements or the determination of acceptable collision risk levels. Additionally, the risk of collision of a fish with a turbine blade is assumed to be higher for larger fish (Hammar et al., 2015), and fish length distributions can serve as inputs to probability- and physics-based models that estimate the probability of encounter or collision (Buenau et al., 2022). Acoustic cameras offer one approach to collecting these data, but their limitations should be considered relative to both study design and data interpretation.

A variety of approaches have been used to assess the accuracy of fish length estimates derived using acoustic cameras. These range from the use of synthetic fish-shaped targets (Cook et al., 2019) to the tethering of fish of known lengths in the beam array (Burwen et al., 2010). Generally, these assessments have found that length estimates from acoustic cameras fall within 5%–20% of the true length (Cook et al., 2019). Several factors have been found to affect accuracy, including the range from the acoustic camera, angular position within the beam array, orientation of the fish and species. We briefly discuss each of these factors below. Factors related to the position of the fish in the beam are illustrated in Figure 2.

Several studies have found that the range of a fish from an acoustic camera does not statistically affect the accuracy of the associated length estimates (Burwen et al., 2010; Daroux et al., 2019; Gurney et al., 2014; Hightower et al., 2013). This observation is counterintuitive: cross-beam resolution decreases with range due to beam spreading, so a decrease in accuracy with range would be expected. It is possible that beam spreading has a relatively small effect when compared to other sources of error such as fish movement and background noise. However, in some scenarios, length estimates may be less accurate for fish at short ranges from the acoustic camera: Cook et al. (2019) found that, between the 1.5 and 3 m range, the length estimate accuracy using an SMC ARIS decreased with range to the sensor, and they attributed this to acoustic cross-talk resulting in overestimates. Acoustic cross-talk occurs when backscatter from a strong scatterer is received in the sidelobes of adjacent beams (Sung et al., 2018).

The angular position of a fish within the beam array (i.e. the beams in which it is detected) can affect the accuracy of length estimates. Tušer et al. (2014) found that estimates of fish length using an SMC DIDSON were slightly overestimated when fish were detected towards the centre of the beam array and were underestimated when they were detected towards the edges. The authors attribute this to lower beam intensity towards the edge of the array.

The orientation of a fish relative to the acoustic camera also plays a role in the accuracy of length estimates. Generally speaking, the most accurate length estimates are obtained when the fish is oriented perpendicular to the beam array (i.e. broadside) and the area of the fish ensonified is maximized (Burwen et al., 2010; Zhang et al., 2014). However, broadside ensonification of the fish can also result in acoustic cross-talk that can blur the edges of the fish that causes the fish to appear elongated (Cook et al., 2019). The orientation of the acoustic camera in the water column should also be considered—length estimation may be more accurate and straightforward from a horizontally oriented acoustic camera that ensonifies the side of the fish compared to a vertically oriented acoustic camera that ensonifies the top or bottom of the fish (i.e. a downward-looking, vessel-mounted acoustic camera; Kerschbaumer et al., 2020).

The accuracy of length estimations has been shown to vary between species due to differences in the swimming mode and/or the body morphology of the fish (Cook et al., 2019; Hightower et al., 2013). The speed of the fish may also play a role if it is moving through the image so quickly that it moves significantly during the time it takes to create an image. In this case, cross-talk may occur that can 'blur' the edges of the fish, making it appear to be longer (Burwen et al., 2010). The time that it takes SMC ARIS to 'create an image' (acquire sample data) is primarily a function of end range as all

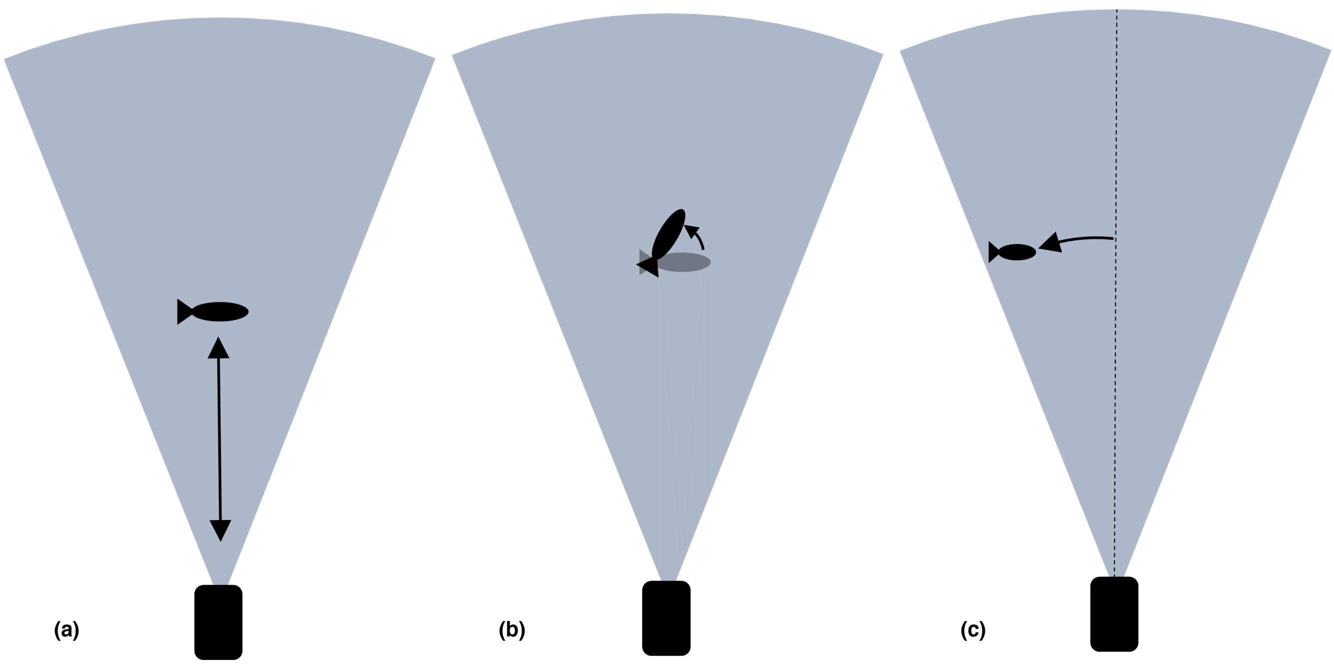

FIGURE 2 Graphic depictions of (a) the range (along-beam direction) of a fish from the sonar, (b) the orientation of the fish in the beam array and (c) the angular position of the fish in the beam array.

beam forming is done through the acoustic lens in real time. The time required for image rendering on the acquisition computer is an order of magnitude faster than for data acquisition. Sensor manufacturers can provide guidance on calculation of image generation time for a particular acoustic camera.

The accuracy of length estimates from acoustic cameras has been compared to alternative non-invasive sensing techniques. Cook et al. (2019) compared length estimates obtained using an SMC ARIS acoustic camera to those made using a stereo optical camera system and found that while the optical camera system was, on average, an order of magnitude more accurate, it was limited by its relatively short range and the requirement for illumination. Lin et al. (2016) compared length estimates from an SMC DIDSON acoustic camera to those derived by applying target strength/fish length relationships to data from a 200 kHz fisheries echosounder and found that the DIDSON was more accurate, largely because of the dependence of echosounder-derived length estimates on accurate target strength/fish length relationships.

3.5 | Classifying fish taxonomically

Taxonomic classification of fish species is important when assessing collision risk when it is desirable to quantify the impacts on certain species of regulatory interest (i.e. threatened, endangered or commercially important). The ability to perform taxonomic classification of fishes identified in acoustic camera data depends on the species present, background noise levels, the orientation of the fish and the distance of the fish from the acoustic camera. Further, accurate classification typically requires a priori knowledge of the species present in the habitat being monitored, either from concurrent physical sampling, optical cameras or historical data. Even for expert reviewers, classification of fishes in acoustic camera data is challenging and limited, and results may differ between reviewers (Jones et al., 2021).

Classification is only possible when the fish species present have large size differences relative to the length measurement error (Burwen et al., 2010; Stott & Miner, 2022) or when a species is morphologically distinct from other species present. For example, multiple studies have classified eels in acoustic camera data with high confidence because of their distinctive shape and swimming mode (e.g. Lenihan et al., 2019; Magowan et al., 2012; Mueller et al., 2008). In some cases, other morphological features such as caudal fins may be discernible at close ranges, but the ability to discern these features varies with fish orientation (Jones et al., 2021) or the proximity of the fish to other features in the environment (i.e. boundary reverberation) (Parsons et al., 2017). Generally speaking, distinctive features that may aid in taxonomic classification are more easily discernible for larger fish (Jones et al., 2021; Staines et al., 2020).

In many cases, fish behavior (i.e. swimming speed or location in the water column) may provide more information to support taxonomic classification than individual images (Jones et al., 2021). This stands in contrast with taxonomic classification of fishes in optical camera imagery, where classification can often be performed based on a single image. Several studies have proposed the use of tail beat frequency as a quantitative behavioural metric that may aid in classification (e.g. Able et al., 2014; Egg et al., 2017; Helminen et al., 2020; Kang, 2011; Mueller et al., 2010; Parsons et al., 2017). Helminen et al. (2021) and Mueller et al. (2010) demonstrated the potential of this approach and successfully calculated tail beat frequencies from data collected using an ARIS and DIDSON respectively. However, the utility of this technique is likely to change between sites because fish may alter their behaviour in different environments (Helminen et al., 2021) and background noise levels will affect the ability to discern tail beats (Mueller et al., 2010).

Finally, the 'acoustic shadow' may offer further insight into the morphology of a fish. Acoustic shadows are a relatively low-intensity region behind a target resulting from reflection and attenuation of the beam, and are only visible in some scenarios that depend on the range and orientation of the target. Langkau et al. (2012) investigated the utility of the acoustic shadow in a series of tank tests with both synthetic fish-shaped targets and live fish and found that the acoustic shadow showed detailed morphology of synthetic targets, and, while noise and artefacts from acoustic cross-talk reduced the accuracy of the method for classifying live fish, in many cases, acoustic shadows could still be intuitively identified by a human observer. Acoustic shadows have also been shown to aid in discrimination between species of fish in data collected in the field (e.g. Able et al., 2014; Artero et al., 2021; Jones et al., 2021). While acoustic shadows may aid in classification in some scenarios, they can also pose a challenge for detection if acoustic shadows of larger fish mask detections of smaller fish (Magowan et al., 2012).

3.6 | Analysing fish behavior

Acoustic camera imagery is often of high enough quality to provide users with the ability to define and describe the small-scale behaviour of fishes within the beam array. As discussed in the previous section, fish behaviour can aid in taxonomic classification. However, further discussion of fish behaviour in this section describes their movements in relationship to their environment and not for classification. Specifically, the behaviours described in this section are chosen to inform the ability to use an acoustic camera to observe detailed movements associated with fish interactions with a turbine (e.g. evasion, avoidance and collision).

3.6.1 | Spawning

The spawning behaviour of fishes is specific to species and is made up of small-scale movements that are often sex-specific. While the spawning behaviour of fish does not directly inform the determination of collision risk with turbines, the ability to identify specific fine-scale behaviours with acoustic cameras is evidence that fish interactions with turbines may also be observable. Tiffan and Rondorf (2005) successfully observed and characterized chum salmon (*Oncorhynchus* *keta*) spawning behaviour at night using an SMC DIDSON. Behaviours included defensive chasing away of smaller fish by both sexes as well as nest digging and covering behaviour by females as evidenced by imaged sediment plumes and substrate movement. The release of gametes during spawning was not observable. Allis shad (*Alosa alosa*) are broadcast spawners, so, unlike chum salmon that build nests, they release gametes in the pelagic water column. Langkau et al. (2016) successfully observed Allis shad spawning behaviour using an SMC DIDSON with fish pairs and sometimes triplets of fish circling as part of the known spawning behaviour of this species. Successful spawning events terminated with the release of gametes that could be seen as a cloud in the DIDSON images, followed by individuals separating and swimming away from each other.

3.6.2 | Predator/prey

The interactions between fishes and their predators are important to understand when managing populations or communities, especially when anthropomorphic influences can lead to variations in predation levels (Murphy et al., 2021). Further, ecological modelling techniques used to study interactions between prey and predators have been applied to predict the risk of the collision of fish and turbines (Buenau et al., 2022). Avoidance and evasion behaviours associated with fish eluding predators can also be used to describe fish responses to the presence of moving turbine blades (Sparling et al., 2020), and acoustic camera observations of these behaviours are informative for collision risk assessments. Smith et al. (2021) observed fish behaviour in front of a floating surface collector (FSC) on the North Fork dam of the Clackamas River using an SMC ARIS. The authors showed that the direction of travel of most prey-sized targets was away from the FSC when predator-sized targets were present and towards it when predators were absent. In a separate study, using an SMC DIDSON, Cheng et al. (2022) directly observed predator/prey interactions between bull trout (*Salvelinus confluentus*) and outmigrating sockeye salmon (*Oncorhynchus nerka*) smolts downstream of a salmon counting fence. Murphy et al. (2021) demonstrated that an SMC ARIS can observe fish *avoidance* behaviour (i.e. changes in travel direction), while Cheng et al. (2022) provided evidence that the SMC DIDSON observed distinct fish *evasion* behaviour when encountering predators.

3.6.3 | Attraction/repulsion

Fishes may be attracted or repelled by external stimuli such as visual cues or water velocity rheotaxis, and the associated behaviours are important for managing fish populations or communities that are affected by anthropogenic influences. Understanding how fishes respond to the presence of a turbine is critical when assessing collision risk. While some fish species or life stages may be attracted to turbines because lower flow speeds in the turbine wake provide a place for resting or foraging, others may be repelled due to blade movement visual cues, generator noise or closer range stimuli like the hydrodynamics in the upstream nearfield of the turbine.

Several studies have analysed fish attraction or repulsion to anthropogenic structures using acoustic cameras. Schmidt et al. (2018) combined measurements from an SMC DIDSON and an ARIS with flow velocity measurements to determine fish hydrodynamic preferences upstream of a dam trash rack. Similarly, Viehman and Zydlewski (2015) employed downward-looking SMC DIDSON acoustic cameras to characterize fish behaviour around a tidal turbine tested from a moored barge. Behaviour was classified into seven categories that included 'avoiding' and 'remaining in wake'—both of which are examples of repulsion and attraction behaviour. Fish behaviour in front of a towed trawl net was observed by Rakowitz et al. (2012) using an SMC DIDSON and 11 categories of avoidance were documented that included moving away from, under and over the trawl.

4 | DATA PROCESSING

Extensive processing is required to extract the information about fish discussed in the previous sections from acoustic camera data. Data processing may be manual, semi-automated or automated. Here, we define *manual processing* as frame-by-frame human review of acoustic camera imagery; *semi-automated processing* as any processing that includes at least one step that removes human involvement and is done automatically; and *automated processing* as end-to-end approaches that input raw data and output final metrics with minimal human oversight (i.e. requires tuning of parameters).

Analysis of fish in acoustic camera data is most commonly performed manually by a human observer using software provided by the instrument manufacturer (Able et al., 2014). Most acoustic camera manufacturers provide software with manual tuning options to optimize the visualization of objects of interest. Tuning may include applying thresholds or filters to remove background noise, performing background subtraction to remove backscatter of non-moving objects (e.g. river bottom) or correcting for transmission loss to account for spreading and absorption. Manual data processing typically consists of watching image frames in sequence like a movie, with the playback speed adjusted depending on the number and speed of objects in the frame. After an object is detected, the observer may determine whether it is a fish (i.e. identification), measure its length, attempt species classification or note its behaviour. Identification is typically performed by reviewing the target in successive image frames to determine its shape and movement. When a fish is detected in multiple frames, observers selectively choose the best detection(s) for analysis and measurement. Some software packages have built-in tools for annotation, which can output data to a log file for further analysis (i.e. counting of fish or generation of fish length distributions). Frame-by-frame manual review may be performed with an echogram, which can reduce processing time. In this representation of acoustic camera data, each image frame is compressed to a vertical line that contains the maximum sonar return for all beams displayed for each range sample. The result is similar to the echograms used to visualize fisheries echosounder data: the vertical axis represents range, and the horizontal axis represents time. Fish passing through the beam array create a track in the echogram that is often detectable during manual review.

A key consideration when interpreting the results of manual processing is observer bias. Several studies have analysed the effect of observer bias on fish counts (Keefer et al., 2017; Petreman et al., 2014), length estimation (Daroux et al., 2019; Helminen et al., 2020; Lagarde et al., 2020) and classification (Able et al., 2014; Holmes et al., 2006; Jones et al., 2021; Magowan et al., 2012). While differences between observers were not always found to be statistically significant, they highlight the subjectivity inherent to manual processing. Notably, Daroux et al. (2019) compared results between experienced and inexperienced operators and found that experienced operators produced more accurate length estimates. While this is an unsurprising result, it indicates that training is necessary for effective review of acoustic camera data and that review may not easily be crowdsourced, an approach that has been taken for the review of optical camera data sets (e.g. for camera traps [Hsing et al., 2018]). Because of observer bias, the best way to obtain consistent results across a data set is to use a single observer. When this is not possible because of the volume of data or time constraints, observer bias may be mitigated by having all observers review a subset of data and comparing results.

A different type of bias may be caused by the subsampling of data. Frequently, it is not feasible to analyse the entire data set and data are subsampled, requiring the assumption that the observed data are representative of the entire data set. While this approach has been shown to provide accurate estimates of fish passage (Lilja et al., 2008; Petreman et al., 2014), it is likely to miss some events of interest (e.g. turbine blade strike) if the goal of the research may be to detect a particular rare event (Cotter et al., 2017; Matzner et al., 2016).

While manual processing remains the most common approach to analysing fish in acoustic camera data, several studies have implemented semi-automated or automated processing to standardize and accelerate analysis. Semi-automated processing pipelines for fish detection, identification, counting and length estimation have been implemented using manufacturer-provided software (Martignac et al., 2015) or using commercially available software such as Echoview (https://echoview.com; Boswell et al., 2008; Kang, 2011) and Sonar5-Pro (Martignac et al., 2021), and automated pipelines have been implemented in custom software (Kupilik & Petersen, 2014). These pipelines automate the detection and, in some cases, tracking of targets and automatic extraction of information (i.e. length) about the targets. However, it is important to benchmark automated analyses against manual processing. Comparisons of Echoview-generated fish length estimates and manual measurements have found that manual measurements were more accurate (Helminen et al., 2020; Hightower et al., 2013), which can generally be attributed to the fact that human reviewers can more easily select the 'best' detection(s) of a fish to measure and exclude those detections where the fish is not fully elongated, the image is affected by acoustic cross-talk, or the fish is not entirely ensonified.

Development of automated or semi-automated approaches for target classification is an active area of research. While there are no standardized approaches, several recent studies have applied machine learning to the classification of fishes in acoustic camera data. Stott and Miner (2022) trained a classification and regression tree for classification of four fish species using human-extracted features, including the mode of swimming (amiiform or other), width of the head and width of the body. This approach was shown to be 100% effective when applied to data collected in a test tank, but in situ accuracy was not assessed. Kandimalla et al. (2022) applied a neural network-based algorithm to simultaneously detect and classify eight species of fish in a publicly available labelled data set of DIDSON imagery collected at a single riverine site containing between 100 and 2000 detections of each labelled species. Overall, this approach achieved a mean average precision (mAP) of 0.73, but results varied between species.

Semi-automated or automated analysis of fish behaviour is less common because of the inherently qualitative nature of behaviour analysis. The methods that do exist typically rely on effective target tracking. For example, Williamson et al. (2021) implemented automated tracking of targets between subsequent frames (with human quality control) and calculated metrics based on the position of the target to quantitatively describe behaviour, including the direction that the target was moving relative to the flow and its tortuosity, a measure of the number of twists and turns in a target's path. Comparison of these metrics between a tidal turbine test site and an undisturbed site provided insight into the behaviour of marine animals around a tidal turbine mounting structure.

5 | DISCUSSION

Imagery is an intuitive medium: It conveys information that is readily interpretable by scientists, regulators and stakeholders. It is no wonder that when presented with a turbine site in turbid water where fish collision is seen as a risk, acoustic cameras are frequently the tool of choice for monitoring because they can provide human-interpretable imagery in conditions where optical cameras are not viable. However, unlike video from optical cameras, acoustic camera imagery contains image artefacts, perspective shifts and other phenomena that require experience and expertise to interpret. In the following sections, we describe challenges to using acoustic cameras to monitor fish at turbine sites and identify key considerations necessary to use them most effectively.

5.1 | Challenges

While acoustic cameras offer advantages over alternative technologies for fish monitoring, several key challenges persist, many of which are exacerbated in the high-energy conditions that are characteristic of the habitats where turbines are deployed. First, the detection, identification and classification capabilities of acoustic cameras vary significantly between sites. At some sites, where there is little debris in the water column and the species present are morphologically distinct or only one species is present, taxonomic classification of most detected fish may be possible; at other sites, where the fish species present have similar morphologies, the detection, identification and counting of fish may be straightforward, but classification may not be possible; and at other sites, where entrained air and debris obscure detection, it may not be possible to detect and identify fish at all. The latter is characteristic of many current energy sites. For example, at a riverine energy site, fish could not be distinguished from woody debris (i.e. twigs and sticks) because the fast-moving currents precluded observation of any fish movement (Staines et al., 2022). Similarly, entrained air from waves or turbulence can complicate data analysis because the acoustic scattering from bubbles (i.e. volume reverberation) may obscure all or part of the acoustic camera FOV, precluding detection of any targets of interest. This has been observed at multiple tidal energy sites (Cotter & Polagye, 2020; Viehman & Zydlewski, 2015).

An additional challenge for analysis of acoustic camera data is discerning targets that are near other objects in the FOV, such as the seabed, rocks or dock pilings. For some applications, it may be possible to position the acoustic camera to avoid these objects, but at turbine sites, acoustic camera placement is often dictated by the position of the turbine being monitored. This can be particularly challenging for moving objects such as turbine blades. Not only does this movement preclude the use of standard background subtraction approaches, but moving parts can produce backscatter artefacts in other parts of the image due to acoustic cross-talk or, in the case of SMC acoustic cameras, motion artefacts over the course of the generation of a composite image.

An acoustic camera can only resolve the along-beam (range) and across-beam dimensions, not the elevation (long-axis of beam array) of a target in the beam. If objects are located at the same range, in the same beams, but at different elevations (assuming the long-axis of beam array is vertical), they cannot be separated (Belcher et al., 2002). This is illustrated in Figure 3, in which the two white fish are at the same range and are ensonified by the same beams in the beam array, but are at different elevations. In this scenario, it is not possible to discern both white fish, so the acoustic camera will display a single target. If a human reviewer was aware that two fish were present because they were identified and tracked in previous frames, the reviewer would still not be able to determine the distance between the fish or whether they physically interacted with each other. This limitation is particularly relevant when trying to determine whether a fish comes in contact with a turbine blade and is made even more complex by the constant motion of the blade itself. However, in some cases, sudden changes in fish orientation or trajectory may indicate collision (e.g. Courtney et al., 2022; Staines et al., 2022).

Another challenge in interpreting acoustic camera data is beam aliasing that can occur when a previous transmission (ping) returning from a distant object or from multi-path reflections arrives at the acoustic camera at the same time as the current ping. These returns cannot be distinguished, which can lead to objects appearing at the wrong range, an object or boundary appearing at multiple locations in the image ('reflections'), or 'dark beams' in the image. When imaging a moving object, like a turbine, these challenges can be exacerbated because they may change dynamically with turbine rotation. This, as well as several of the other sources of noise previously discussed in this work, can be observed in Video S1.

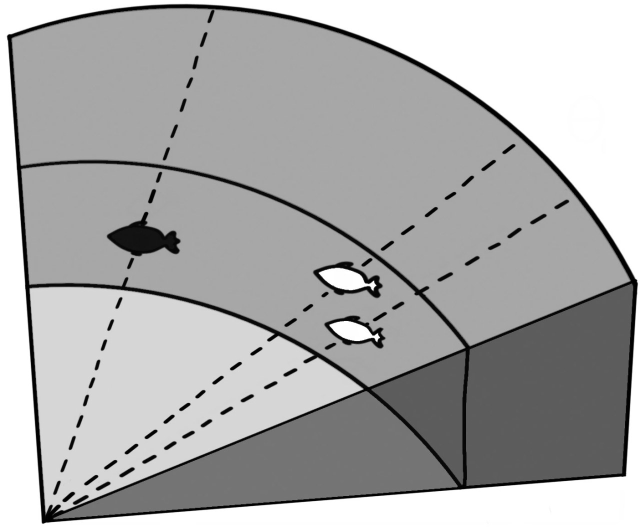

FIGURE 3 Graphic depiction of the detection of multiple fish at the same range in an acoustic camera beam array. The two white fish are at the same range and are ensonified by the same beams in the beam array but are at different elevations in the beams. The black fish is at the same range as the white fish, but is ensonified by different beams.

Analysis of acoustic camera data often relies on expert manual review, which is time intensive and costly (labour effort). These constraints can limit the volume of data that may be processed and the repeatability of results. This is a challenge for all applications, but is particularly relevant for the monitoring of turbines where events of interest (i.e. collision or near-miss events between a fish and a turbine) rarely occur (Sparling et al., 2020). Observation of such events requires analysis of large volumes of data, because subsampling is likely to miss rare events. To address this, several automated or semi-automated approaches have been developed, but are generally not as accurate as manual processing. This does not mean that it is not possible for automated processing to be as accurate as human review, but rather that this is a key area of development required to facilitate effective acoustic camera-based monitoring of fish interactions around turbines. Automated processing also addresses the lack of repeatability associated with human annotation of data. However, because any automated processing approach requires training or validation with human-annotated data, it can still reflect human biases. Challenges facing the advancement of automated processing tools include the requirement for time- and cost-intensive data annotation to train and validate machine learning algorithms and the uncertainty associated with even expert annotations. The latter can, in some cases, be addressed through data collection from multiple sensors; for example, a publicly available data set collected in the Ocqueoc River in Michigan, USA, used co-spatial optical camera data for taxonomic classification before identifying the same targets in acoustic camera data (McCann et al., 2018).

5.2 | Considerations for deploying acoustic cameras at turbine sites

Most studies discussed in this review use SMC acoustic cameras (ARIS or DIDSON) because of their relatively high resolution and ability to suppress artefacts due to the use of an acoustic lens. However, several considerations should be weighed before selecting and deploying an acoustic camera for environmental monitoring at a turbine site. Sensor selection will be informed by the fish species of interest, the range over which monitoring is necessary and the level of information desired (e.g. identification or classification). In a scenario where only the fine-scale behaviour of fish around a turbine is of interest, and it is possible to deploy an acoustic camera close to the turbine, an acoustic camera with relatively short range and high resolution (high frequency) is desirable. Conversely, if the monitoring objective is to count fish passing a turbine in a wide river, and fine-scale interactions are not the objective, a longer range, lower resolution (low-frequency) acoustic camera would be more appropriate. The orientation and positioning of the acoustic camera can be as important as the selection of the sensor itself and will often involve a trade-off between minimizing sources of noise and imaging the area of interest. Because it is not possible to resolve the elevation of a fish in the beam array, the ability to discern collisions with a turbine blade is likely to be limited to only some portions of the swept area of the turbine rotor. In some cases, this may be addressed through the use of multiple acoustic cameras that can 'see' the turbine from different angles. However, use of multiple acoustic cameras would increase the cost of monitoring and fusion of multiple data streams would increase the complexity of data analysis. Finally, it is important to consider interference with other acoustic sensors used at the site (e.g. ADCPs, echosounders and hydrophones), because active acoustic transmissions may interfere with each other or produce sound at frequencies of interest for passive acoustic monitoring.

6 | CONCLUSIONS

In dark or turbid water, acoustic cameras are the only sensor that can directly observe fish-turbine interactions. The extensive use of acoustic cameras for fisheries applications described in this review provides evidence that acoustic cameras can be used to characterize fishes in a variety of scenarios. Further, the limited number of studies that have applied acoustic cameras at turbine sites show that, while challenges persist, acoustic cameras can observe fish–turbine interactions. In some cases, challenges can be mitigated through optimized positioning of the acoustic camera, careful selection of parameters and rigorous data processing, but capabilities will vary between sites. The limited number of deployments of acoustic cameras around turbines precludes the development of generalized approaches to sensor deployment and data processing. Nevertheless, targeted studies to address the specific challenges associated with observing fish-turbine interactions could lead to the development of standards for data collection and advance the development of automatic processing tools. Standardization will promote the transferability of data and results, allowing for meaningful comparisons between marine energy turbine sites.

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DATA AVAILABILITY STATEMENT

No new data are associated with this publication.

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SUPPORTING INFORMATION

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