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Monitoring methods of feeding behaviour to answer key questions in penaeid shrimp feeding

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Abstract

The penaeid shrimp farming industry is a fast-growing sector which continues to suffer from significant feeding inefficiencies. Shrimp are slow to feed on pellets, with consumption dependent on a wide range of environmental and physiological parameters. Feed management on farms remains mainly based on feeding trays which can be difficult to observe and often result in overfeeding. While our understanding of shrimp feeding behaviour is beginning to improve under laboratory conditions, much less is known about shrimp behaviour in production ponds. Consequently, there is a growing interest within the industry to improve observations of shrimp feeding behaviour *in situ*, although this can be difficult due to high water turbidity and the benthic nature of shrimp. This review identifies key questions that remain unanswered in relation to shrimp feeding behaviour under commercial aquaculture conditions, and considers how they could be addressed using state-of-the-art applications based on three technologies commonly used in other areas of aquaculture. The use of passive acoustics, computer vision and telemetry are highlighted, alongside their potential to help farmers achieve better feeding efficiencies and sustainability as well as to help understand shrimp feeding behaviour in relation to various biotic and abiotic parameters.

Key words: computer vision, feeding behaviour, passive acoustics, precision aquaculture, shrimp farming, telemetry.

Introduction

Overview of shrimp feeding behaviour

The production of shrimp in aquaculture is growing rapidly with a reported output of 6 million tons in 2018, representing a five-fold increase since 2000 (FIGIS 2018). Penaeid shrimps are the dominant farmed species, with the Pacific white shrimp (*Litopenaeus vannamei* Boone) accounting for more than 80% of overall output (FIGIS 2018). However, despite this production volume, shrimp farming is prone to significant inefficiencies with regards to feeding, which can comprise up to half of total production costs (Silva *et al*. 2012; Engle *et al*. 2017). Shrimp can be slow to feed on pellets (Gadient & Schai 1994), and feeding behaviour can vary greatly depending on shrimp physiological condition and environmental factors (Bardera *et al*. 2018). This often results in feed losses for farmers leading to increases in the feed conversion ratio (FCR), degradation of chemical and microbiological water quality, higher nutrient discharge rates into the environment (Smith *et al*.

This article is a Sena De Silva paper.
The Sena De Silva paper is an honorific title dedicated to the memory of Professor Sena De Silva, who was the founding editor of *Reviews in Aquaculture* and a globally renowned aquaculture scholar, pioneer and advocate. The title is awarded to high quality articles that excel in one, or more, of the following qualities: i) Novelty and originality; ii) Likelihood of direct positive impacts for the aquaculture sector, with keen focus on any of, or all three: environmental sustainability, economic viability, and social responsibility iii) Overall quality of scientific reasonings coupled with real-world applicability.

2002; Li *et al.* 2017; Jescovitch *et al.* 2018; Ullman *et al.* 2019a) and increases in water exchange requirements (Davis *et al.* 2006). Feed management is, therefore, a priority for the industry in both an economic and environmental context. As a result, there has been an increased focus on understanding feeding habits of shrimp (e.g. Pontes *et al.* 2006; Costa *et al.* 2016; Bardera *et al.* 2019, 2020a). There is also a general consensus that closer monitoring of behaviour in aquaculture plays an important role in enhancing animal welfare through the early detection of abnormal behavioural patterns related to stressful events or diseases (as reviewed in Saberioon *et al.* 2017).

Shrimp have limited storage capacities in their digestive system and therefore continuously eat small quantities of feed (Reis *et al.* 2020). However, in ponds and tanks, food pellets are subjected to nutrient leaching in the water, and this has been associated with a growth reduction in *L. vannamei* in time frames longer than 30 min (Ullman *et al.* 2019b). Shrimp, therefore, have to find the feed quickly (Ullman *et al.* 2019b; Reis *et al.* 2020). As omnivorous (Dall *et al.* 1990) and benthic feeders (Kumlu *et al.* 2001), shrimp rely mostly on chemical cues to locate food at the bottom of ponds (Hindley 1975) which are detected using a wide array of chemoreceptors located over the body, such as on the antennules, legs and mouthparts (Derby & Sorensen 2008). The subsequent behavioural responses of shrimp to chemical stimuli can then be split into four categories, namely, antennule flicking, probing movements from the pereiopods, locomotion and movements from the mouthparts (Lee & Meyers 1996).

A detailed description of the different factors influencing shrimp feeding behaviour was recently reviewed by Bardera *et al.* (2018) who considered three major categories as important, namely, individual level, environmental and water quality effects (Bardera *et al.* 2018). At an individual level, the same authors have shown a significant influence of feed-deprivation, moult status (Bardera *et al.* 2019) and sex (Bardera *et al.* 2020a) on the feeding behaviour of *L. vannamei*. The influence of the environment on shrimp behaviour has been demonstrated with increases in stocking density (from 50 to 100 individuals m^{-2}) resulting in reduced searching and feeding behaviours (Costa *et al.* 2016). Photoperiod has also been shown to have a significant effect; however, the direction in which light availability drives feeding seems strongly species dependent (e.g. Nakamura & Echavarria 1989; Pontes *et al.* 2006; Silva *et al.* 2012). Furthermore, in *L. vannamei*, the most farmed shrimp species, it is still unclear whether animals have a preference for the dark or the light phase for feeding (e.g. Pontes *et al.* 2006; Santos *et al.* 2016). With strong effects on crustacean physiology, water quality parameters also have an impact on shrimp feeding behaviour with known effects of temperature (Bórquez-Lopez *et al.* 2018), salinity (Rosas *et al.* 2001), dissolved oxygen (Zhang *et al.* 2006; Bórquez-Lopez *et al.* 2018), pH (De la Haye *et al.* 2011) and nitrogenous wastes (Frías-Espericueta *et al.* 2000) on crustacean behaviour. Little is known about the precise effects of changes in the water parameters previously mentioned, both at individual and group levels. It is not known, for example, to what extent high ammonia concentrations affect feeding behaviour (Bardera *et al.* 2018). Water quality parameters should be kept optimal and within the safety limits (see Carbajal-Hernández *et al.* 2012 for a review of recommendations); however, this can often be a complex process on farms with restrictions on clean water availability.

The need to upscale behavioural observations

Although understanding of individual-level and environmental effects on shrimp behaviour continues to improve (e.g. Costa *et al.* 2016; Bardera *et al.* 2019, 2020a), no direct observations have yet been published on shrimp behaviour in aquaculture ponds, where the variability of environmental parameters (e.g. stocking density, light availability) and water quality (e.g. variations in pH, dissolved oxygen, temperature, visibility) can be far more extreme than in laboratory studies. Recent work on shrimp behaviour conducted indoors reported optimal water quality values with stable temperature close to 26°C and dissolved oxygen concentrations higher than 5 mg L^{-1} (Costa *et al.* 2016; Bardera *et al.* 2020a). Environmental conditions on outdoor farming facilities are often much harder to control, being directly subjected to climatic variations as well as weather events (e.g. rainfalls, high heat events). For example, large fluctuations in dissolved oxygen and pH between day and night are common in shrimp ponds (e.g. Jescovitch *et al.* 2018; Reis *et al.* 2020), where populations of phytoplankton can bloom and crash several times during a production cycle. It is also not known how the previously mentioned small-scale observations translate to large groups of several hundreds of thousands of individuals where size variability can also be much higher. Furthermore, the design of laboratory studies can also obscure other important effects such as arena or pond size, resulting in unequal access to feed.

A broad range of techniques are currently available to monitor activity of aquatic animals; however, observing shrimp feeding behaviour *in situ* can present considerable challenges due to conditions in aquaculture ponds and the benthic feeding behaviour of shrimp making direct surface observations difficult (Reis *et al.* 2020). For example, camera-based techniques require adaption as shrimp are commonly raised in highly turbid waters with poor light conditions (Smith & Tabrett 2013; Hung *et al.* 2016; Huang *et al.* 2018). Tracking using telemetry techniques is often

Table 1 Key questions for understanding shrimp feeding behaviour in ponds and how they might be addressed using state-of-the-art techniques

	Key questions	Potential tools to answer key questions	Current or potential limitations with technology
Feed operations	When to feed and in what amounts? Where to feed? Should feed be provided at fixed locations or at changing sites during the production cycle?	Passive acoustics linked to automatic feeders can provide local and instantaneous feed demand estimates (Smith & Tabrett 2013)	Noise artefacts in the pond (e.g. aerators and rain; Smith & Shahriar 2013) Investment cost for the farmer (Jescovitch *et al*. 2018; Ullman *et al*. 2019a)
	Does dietary nutrition (i.e. nutrient density) affect feeding behaviour? How do pond conditions and farming protocols influence feeding activity? Can daily patterns in feeding be observed?	Image segmentation techniques (thresholding) can be applied to footage from the pond bottom to detect the amount of feed remaining (Li *et al*. 2017)	Water turbidity (resulting in low contrast) and non-uniform illumination are major constraints (Li *et al*. 2017)
Observing and interpreting behaviours	How does swarming behaviour relate to feeding regimes and environmental conditions?	Deep-learning algorithms for object detection can be used to detect shrimp either in real-time or on playback footage. Two or even three dimension coordinates of shrimp passing by can be produced from footage	Software needs to be trained with previous footage taken from the pond of interest. High turbidity resulting in low contrast and poor light availability at the bottom can considerably limit the visual range
	What are shrimp reactions towards feeders in relation to feeding events and how does this influence local densities?	Echo sounders can also be used to detect concentrations of shrimp around feeders	Shrimp lack a swim bladder and often lay on the pond bottom making them difficult to detect
Movement around feeders	Does the innate homing behaviour seen in many other crustacean species exist within penaeid shrimp ponds? Are movement patterns or eventual homing behaviour affected when artificial shelters are provided? Are large movements of shrimp from non-fed towards fed areas seen when feed is provided? Is there a hierarchy among individuals in access to fed areas?	Telemetry (i.e. PIT-tags) combined with underwater antenna systems set at strategic locations in ponds can provide answers over large-scale movement patterns	PIT-tags represent contamination on a farm if not removed before harvest High cost of PIT-tag reader (>USD$ 2000) The technique is intrusive and requires trapping and manipulating a potential large number of individuals

not appropriate due to the regular moulting of crustaceans during which external tags can be lost (Freire & González-Gurriarán 1998; Haddaway *et al.* 2011). In addition, the small size of shrimp can make the use of large tags impossible (Wolcott 1995). Therefore, monitoring of feeding activity on shrimp farms has traditionally relied on the use of feeding trays, a labour-intensive method, that can be subjective and provide inaccurate feed demand estimates (Smith & Shahriar 2013; Smith & Tabrett 2013; Ullman *et al.* 2017; Reis *et al.* 2020). This short review, therefore, aims to identify the key questions surrounding shrimp feeding behaviour under commercial conditions and how they may be addressed by state-of-the art applications of tools commonly used for marine ecology and fish farming. Current limitations of these technologies are highlighted in the hope of stimulating multidisciplinary studies that will provide farmers and researchers with improved observations of shrimp feeding behaviours in ponds.

Novel applications of monitoring tools in a commercial context: from traditional feed management towards precision shrimp farming

Various aspects of feeding in penaeid shrimp farming now need to be further investigated to help farmers increase feeding efficiency. Table 1 summarizes these key research questions and the tools which could be used to provide answers. Three major topics have been identified in regards to the future of feed management for shrimp, namely:

(1) How and where feed should be most efficiently provided

(2) The observation and interpretation of feeding behaviours

(3) The tracking and visualization of animal movements around feeders

To date, most *in situ* research in aquaculture has focused on salmon farming (e.g. Føre *et al.* 2011; Pinkiewicz *et al.* 2011; Kolarevic *et al.* 2016), and it is likely that the shrimp farming industry could benefit from methods originally developed for fish aquaculture. Acoustics, computer vision and telemetry are currently the three main approaches being used and developed for studies on feeding behaviour in fish aquaculture (Zion 2012; Føre *et al.* 2017; Saberioon *et al.* 2017; Zhou *et al.* 2018a). Underwater passive acoustics have previously been widely utilized for remote observation of marine mammals (Ford & Fisher 1978; Cummings & Holliday 1985), and new applications have recently appeared in commercial shrimp farming to monitor feeding activity at a population level. Computer vision systems constitute a new field of study in shrimp aquaculture, but are already used in fish farming to monitor feeding activity from swimming and grouping behaviours (e.g. Zhou *et al.* 2017). Telemetry (i.e. measuring from a distance, Wolcott 1995) is currently used in aquatic research for decapods but applications for use in commercial shrimp, small in size and moulting at a high frequency, still need to be developed. However, passive internal tags, not previously used on shrimp with the purpose of monitoring behaviour, could be used in research ponds to provide new information on movements of large numbers of individuals around feeding areas. The joint application of these tools for better monitoring of feeding behaviour links with the broader concept of precision aquaculture, defined by Føre *et al.* (2017) as the application of control-engineering principles to enhance monitoring and control of biological processes on aquatic farms. The following sections describe how recent or potential application of these tools could be useful for this purpose.

Passive acoustic monitoring

Passive acoustic monitoring (PAM) is the recording and exploitation of sounds using passive acoustic sensors such as hydrophones (Gibb *et al.* 2019). Widely used in the remote observation of marine mammals (Ford & Fisher 1978; Cummings & Holliday 1985), PAM has had a more recent application in modern shrimp farming through the control of feed dispersal in ponds (see Smith & Shahriar 2013; Smith & Tabrett 2013; Jescovitch *et al.* 2018; Silva *et al.* 2019; Ullman *et al.* 2019a; Reis *et al.* 2020). The technology uses a hydrophone to detect the ‘clicking’ sounds or ‘feeding signatures’ produced by penaeid shrimp when they interact with feed (Hunt *et al.* 1992), with distinctive spectral features exploited by an algorithm to automatically detect the number of signatures recorded at a given time (Smith & Shahriar 2013; Smith & Tabrett 2013). Smith and Tabrett (2013) identified the resonant frequency band as discriminative of feeding signatures, which is itself characterized by the peak, low cutoff, high cutoff frequencies and the bandwidth. However, Peixoto *et al.* (2020a) selected sound duration, minimum and maximum frequencies, peak frequency and maximum energy as variables to characterize feeding signatures.

In this way, the acoustic characterization of penaeid shrimp feeding behaviour has been documented for the white shrimp (*Penaeus setiferus* Linnaeus) (Berk *et al.* 1996), the black tiger prawn (*Penaeus monodon* Fabricius) (Smith & Tabrett 2013) and more recently for *Litopenaeus vannamei* (Silva *et al.* 2019; Peixoto *et al.* 2020a,b). The main findings of these studies are summarized in Table 2. In aquaculture ponds, the number of recorded feeding signatures can be used as a proxy of feeding activity, as it has been found to strongly correlate with pellet consumption (Smith & Tabrett 2013). Therefore, a change in the number of signatures during successive feed distribution events can indicate variation in feeding activity (Smith & Shahriar 2013), signalling that an adjustment of the feed ration is

Table 2 Overview of studies on the use of passive acoustic monitoring for smart feed management in shrimp farming

	Species	Major findings	References
Preliminary studies	*Penaeus monodon*	Spectral characteristics of feeding signatures can be used in ponds to detect feeding activity	Smith and Tabrett (2013)
		Pellet consumption rate strongly correlated with the average production of feeding signatures in ponds (R^2 of 0.95 and 0.96)	
	L. vannamei	*Litopenaeus vannamei* is acoustically active, and the sounds it generates can be used as an indication of feeding activity in captivity	Silva *et al*. (2019)
		Acoustic variables were not influenced by shrimp size	
		Click rate combined with the energy generated at peak frequency can represent an indicator of the quantity of feed consumed	Peixoto *et al*. (2020a,b)
		Diet texture was closely related to the acoustic intensity produced by *L. vannamei* while feeding	
		Acoustic parameters of clicks were not affected by the diet length	
		Doubling the length of pellets resulted in doubling the number of clicks emitted by shrimp per pellet	
		Feed consumption significantly correlated with the feeding acoustic energy emitted by shrimp (*P*-values between 0.003 and 0.007 depending on diet lengths)	
Assessments in ponds against traditional feeding strategies	*L. vannamei*	Acoustic feeding resulted in significantly higher average body weight at harvest compared with manual and time-setting feeding (8.6 and 7.58 g increases, respectively)	Napaumpaiporn *et al*. (2013)
		A 46% increase in average body weight at harvest after 16 weeks compared with shrimp hand fed twice daily was found	Ullman *et al*. (2019a)
		A 25% increase in average body weight at harvest compared with shrimp fed with timer feeders 6 times a day was observed	
		Ponds with acoustic feeders presented the highest ammonia and nitrite concentrations of all treatments	Jescovitch *et al*. (2018)
		The acoustic feeding treatment resulted in larger shrimp compared with different standard feeding protocols (between 3.49 and 6.24 g increase in final individual weight)	Reis *et al*. (2020)

required. PAM can also allow detection of individuals in the area surrounding a sensor. As a result, the system can provide measurement of the density of individuals within an area (e.g. Butler *et al*. 2017) and even an estimation of their position if binaural technologies are used in combination with techniques based on time of arrival (Stevenson *et al*. 2015). However, PAM does not allow for tracking of individuals across time or for the unique identification of each detected individual (Zenone *et al*. 2019).

There are existing challenges in the application of this technology as the soundscape of a shrimp pond is often polluted by loud background noises from machines such as paddlewheel aerators, air diffusers, pumps (Smith & Shahriar 2013; Ullman *et al*. 2019a; Peixoto *et al*. 2020a) but also from rain, wind and even vehicles (Smith & Shahriar 2013). Spectral characteristics of feeding signatures can also overlap with those of background noises (Smith & Shahriar 2013). To overcome this challenge, Smith and Shahriar (2013) developed and described a context-aware sound classifier to improve the identification accuracy of feeding events from interference in ponds. By applying a filter on pond acoustic recordings, which models background noise from aerators, the authors were able to extract potential feeding signature candidates on which spectral subtraction was then applied. Distinctive spectral features (see Smith & Tabrett 2013) were then extracted from those candidates which could be classified either as feeding signatures or interference noise using a Gaussian mixture model. A Context-Aware Dynamic Bayesian Network (CADBN) was then applied to take into account the time of feed distribution events in the pond to increase classification accuracy of feeding signatures (Smith & Shahriar 2013). Peixoto *et al*. (2020a) also argued that acoustically effective feed should be used in ponds with such feeders to improve the detection accuracy of feeding events. Recordings with shrimp feeding on dry extruded diets showed higher sound intensity than pelleted feed, the consumption of extruded diets, therefore, being more likely to be detected from recordings (Peixoto *et al*. 2020a). To further increase detection success of feeding signatures, feed should also be consumed quickly after distribution since soaked feed loses its hardness and increases its water content, resulting in a decrease in the

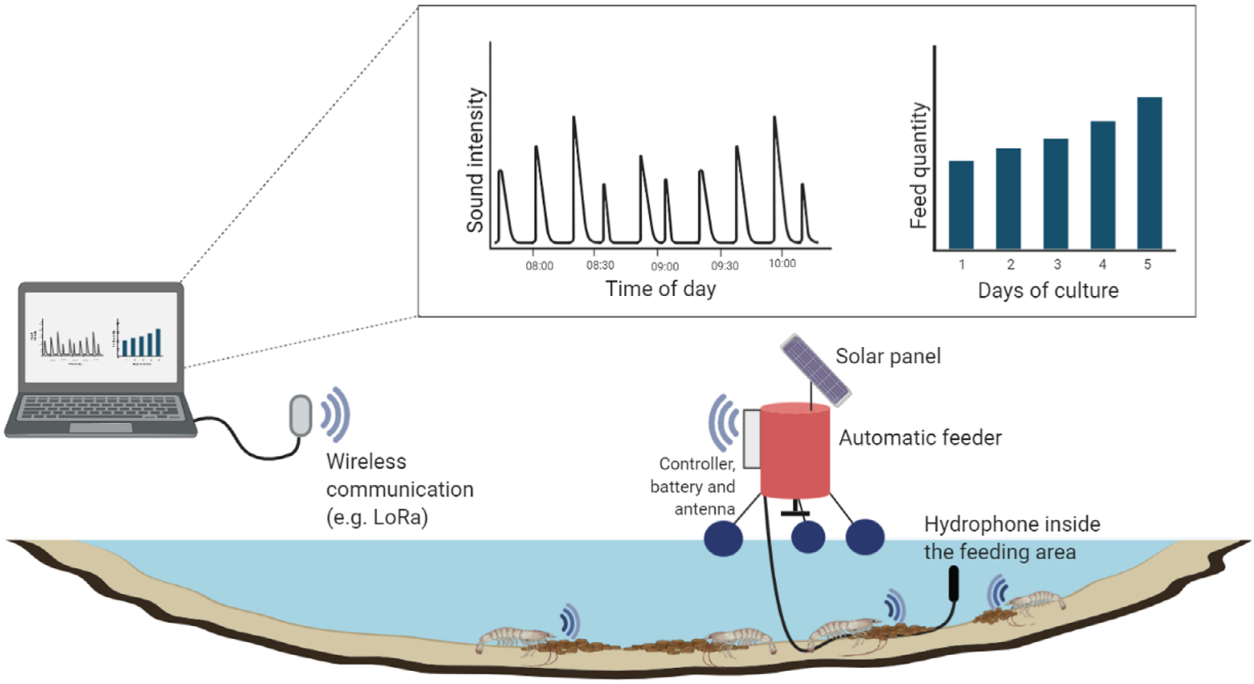

Figure 1 Representation of an acoustic feeding system. The hydrophone records the pond soundscape and sends signals to the controller located either on the feeder or on the shore. The controller then assesses the relative feeding activity and automatically adjusts the feeding ration. Acoustic and feeding data are sent to a computer at the farm's office at regular intervals. Created with BioRender.com.

maximum energy of sounds associated with feeding (Peixoto *et al.* 2020a).

Acoustic automatic feeders (e.g. Eruvaka Technologies Pvt. Ltd., Vijayawada, India) rely on passive acoustic principles for feed distribution in ponds and are currently in operation in areas that are major producers of penaeid shrimp, such as Ecuador and Southeast Asia (Fig. 1). Such systems represent an alternative to traditional feeding protocols that are based on the use of feeding trays, and have a range of benefits (Ullman *et al.* 2019a). Acoustic feeders help ensure feed is distributed at times when shrimp are the most likely to consume it (Jescovitch *et al.* 2018) and therefore aid in reduction of feed wastage (Ullman *et al.* 2019a). The advantages of acoustic feeders over automatic-timed feeders or hand-feeding have recently been documented for *P. monodon* and *L. vannamei*, providing a better yield per hectare at similar stocking densities (Napaumpaiporn *et al.* 2013; Jescovitch *et al.* 2018; Ullman *et al.* 2019a; Table 2). Therefore, by sending real-time indications of feeding activity, acoustic feeders provide farmers with vital information on when to feed and in what amounts feed should be applied in ponds (Table 1; Smith & Tabrett 2013). If several automatic feeders with different hydrophones are used concurrently in a single pond, they could even provide information on the important locations for shrimp feeding (as suggested by Smith & Tabrett 2013). For researchers, passive acoustics can represent a valuable tool towards a better understanding of potential circadian rhythms regulating feeding activity in farmed shrimp at a large scale (Table 1), which has only been researched in laboratory conditions so far (Pontes *et al.* 2006; Santos *et al.* 2016). Peixoto *et al.* (2020b) also recently used passive acoustic monitoring in an innovative way by evaluating the effect of different diet lengths on the feeding behaviour of *L. vannamei* through the use of hydrophones. The authors found that small pellets were consumed faster than large ones, although final consumption was similar among diet lengths. Feed consumption was also significantly correlated with the acoustic energy of clicking sounds, which paves the way for the use of passive acoustic monitoring to provide direct estimations of feed consumption (Peixoto *et al.* 2020b).

Computer vision and artificial intelligence

The application of computer vision can aid in understanding shrimp feeding behaviours and management practices, an area which has received considerable interest over recent years in fish farming (see Zion 2012; Føre *et al.* 2017; Saberioon *et al.* 2017; Niu *et al.* 2018; Zhou *et al.* 2018a). For example, a feeding decision system for tilapia solely based on real-time monitoring of behaviour (i.e. food snatching strength and group flocking level) was recently

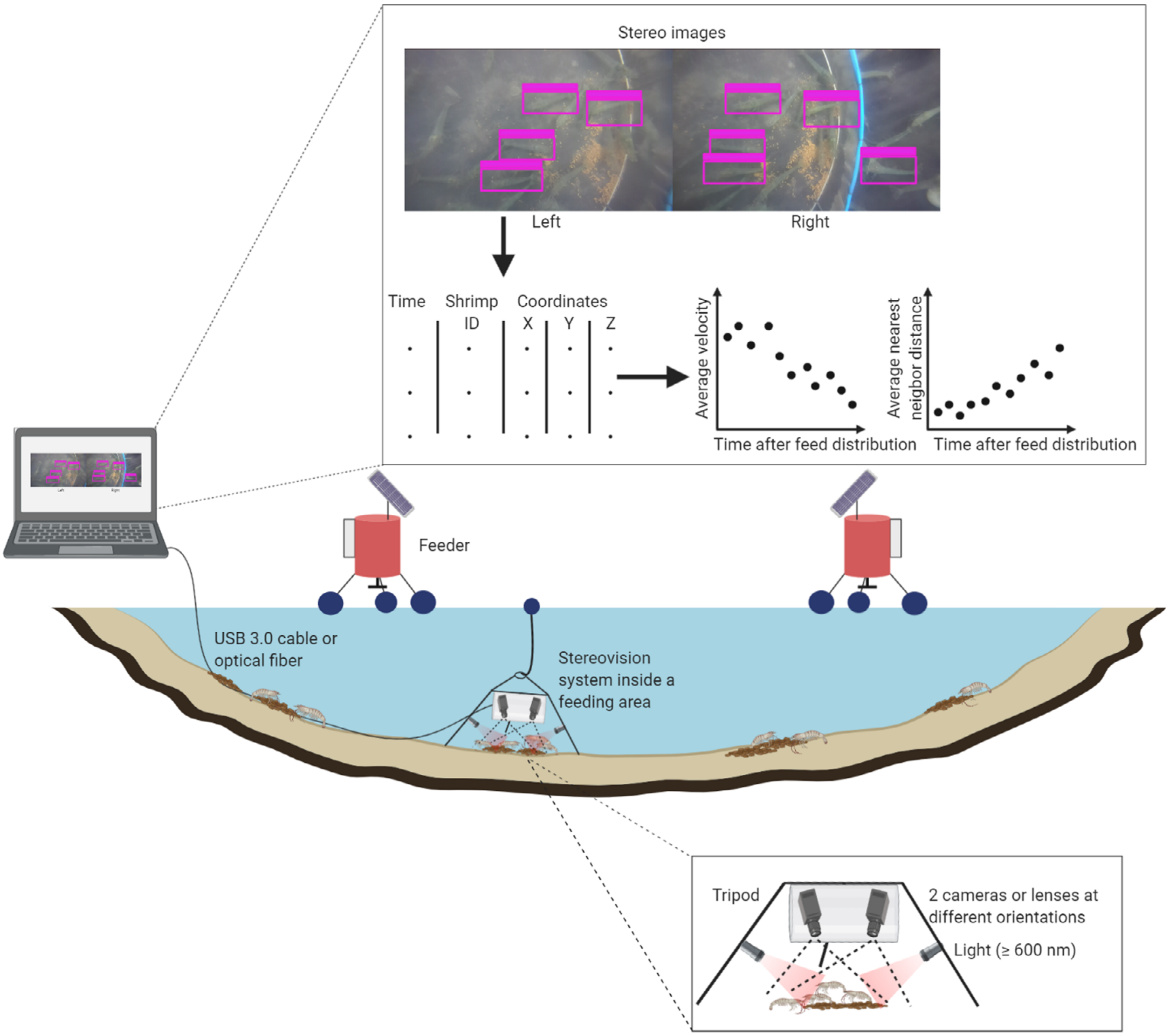

Figure 2 Representation of a computer vision system to monitor shrimp behaviour. The stereo camera provides two views of the scene, enabling its 3D mapping. Object-detection algorithms are then applied on the frames to spot the shrimp, from which 3D coordinates are computed. Coordinates enable the calculation of various metrics such as orientation, velocity and nearest neighbour distances which can be linked to feed distribution events. Created with BioRender.com.

described by Zhou *et al*. (2018b) who reported a 10.77% decrease in FCR compared with a traditional feed management protocol based on fish biomass. To date, literature on computer vision in shrimp farming is scarce; however, a number of innovative technologies, such as deep-learning algorithms and pixel segmentation techniques (i.e. image thresholding), have been trialled in shrimp ponds for feed and disease management purposes (e.g. Huang *et al*. 2018; Chirdchoo & Cheunta 2019).

A major constraint associated with underwater video recordings is the degradation of image quality, due to light attenuation by water as a result of light absorption and scattering at depth and under high turbidity (Schettini & Corchs 2010). Depending on farming protocols, computer vision could be reasonably applied or on the contrary, simply represent an unrealistic solution. For example, Jescovitch *et al*. (2018), in outdoor pond trials with shrimp stocked at a density of 17.2 individuals m^{-2}, reported average turbidity values between 7 and 10 NTU (Nephelometric Turbidity Unit), which could potentially allow for the use of image acquisition systems. However, in systems based on bioflocs, for example, no footage could realistically be recorded given the very high turbidity values associated with those protocols (Samocha *et al*. (2007) reported up to

77.9 NTU in bioflocs shrimp tanks). Polarization techniques can be used to de-scatter the image (as reviewed in Jonsson *et al.* 2009; Lu *et al.* 2017a), and near-infrared (NIR) technologies can be applied to counter light attenuation underwater (Lucas & Baras 2000; Mueller *et al.* 2006; Lu *et al.* 2017a). Decapod crustaceans lack sensitivity of NIR wavelengths (Johnson *et al.* 2002; Weiss *et al.* 2006); thus, such technologies can be easily implemented without disruption to behaviour. Software-based approaches also exist for underwater image enhancement, using defogging (dark channel prior algorithms; Chao & Wang 2010; He *et al.* 2011) and contrast enhancement techniques (histogram equalization algorithms; as reviewed in Lu *et al.* 2017b).

Computer vision is efficient in monitoring a number of aspects of feeding behaviour in penaeid shrimp in real-time. Deep-learning algorithms based on neural networks such as YOLO (You Only Look Once, Redmon *et al.* 2016) have already been used for the automatic recognition of underwater animals (e.g. Li *et al.* 2016; Pedersen *et al.* 2019; Mahmood *et al.* 2020) and have good detection accuracy with potential application in an industry-context. For example, Huang *et al.* (2018) recently presented a prototype of a real-time underwater surveillance system for shrimp ponds and tanks. This apparatus included an underwater camera, an image enhancement algorithm for image haze removal and the use of YOLO to detect shrimp present inside the camera field. Object-detection algorithms can also provide coordinates of detected individuals from underwater footage. This can include detection in three dimensions if stereovision is employed (i.e. the joint use of two cameras providing different angles of the same scene, e.g. Stereolabs Inc., San Francisco, CA, USA) which can provide key metrics such as distance between individuals and speed (Fig. 2). As an alternative to deep-learning algorithms, which require large training data sets, Osterloff *et al.* (2016) proposed an approach based on a random forest algorithm to map shrimp abundance over time on a deep-sea coral reef from frames recorded with a fixed underwater observatory. The software was trained with only 80 annotated frames containing mostly *Pandalus* spp. (Leach) shrimp species and enabled the accurate comparison of shrimp abundance between frames and across different locations on the frames.

Object-detection algorithms could provide researchers with key observations on both shrimp behaviour and their movement around feeders. For example, how shrimp densities vary close to feeding stations in relation to feed distribution events has not been the topic of any published work to date, and underwater footage analysed with such software could be useful to obtain the number of observable individuals through time at given locations next to feeders. Recent work from Cao *et al.* (2020) also demonstrated the potential of object detection to achieve better spatial feeding accuracy inside Chinese mitten crab ponds (*Eriocheir sinensis* H. Milne-Edwards). The authors developed a real-time object detector (Faster MSSDLite) to detect live crabs in aquaculture ponds and overcome the challenge of crabs' irregular shapes and the underwater environment (Cao *et al.* 2020). The algorithm is based on SSD (Single Shot MultiBox Detector, Liu *et al.* 2016), a deep convolutional neural network similar to YOLO. However, it was found to be faster and more accurate than YOLOv3, with detection speed reaching 74.07 frames per second and an average precision of 99.01%. This computer vision system can be mounted on an automatic feeding boat along with a GPS (Global Positioning System) device to map crab density across the pond and therefore automatically determine the feeding needs at various locations (Cao *et al.* 2020).

Footage from echo sounders could complement video observations, as performed for fish by Terayama *et al.* (2019) where poor quality night-time footage and high-resolution sonar images were translated into realistic day-time images of fish. More research is, however, needed in order to link sonar images to density in shrimp, which, to our knowledge, has not yet been published. In addition, the use of echo sounders will possibly have a significant impact on the behaviour of shrimp through the emission of sound at audible frequencies. Nevertheless, there has been some recent interest shown by several companies in the development of sonar technologies to monitor the shrimp biomass in ponds (e.g. Marine Instruments, Spain (Holmyard 2018) and Minnowtech, USA (Wright 2019)). Shrimp reactions towards feeders also remain largely unknown, and thus, data on their orientation and velocity around main feeding areas could help understand the patterns through which local concentrations in animals might change around feeders. It is also unknown whether shrimp exhibit anticipatory behaviour as observed in Atlantic salmon (*Salmo salar* Linnaeus) when feeders start spreading pellets onto the surface (Oppedal *et al.* 2011). Large swarms (or troops) of shrimp were previously reported from scuba observations in ponds (McNeil 2001) which computer vision, and particularly stereovision, could help investigate (Table 1). Observations on the shape of swarms, size distribution, movements and triggers of such formations are yet to be published in penaeid shrimp under commercial conditions.

Another way computer vision can aid in monitoring of feeding behaviours and activity indirectly is to automatically assess the amount of feed remaining at a particular location, such as on a feeding tray. Several papers recently described such systems in fish and shrimp ponds (e.g. Li *et al.* 2017; Huang *et al.* 2018; Chirdchoo & Cheunta 2019), which in return could lead to a decrease in feeding costs. In addition to the use of YOLO to detect shrimp, Huang *et al.*

(2018) presented a program based on neural networks to separate feed from non-feed pixels, thereby automatically assessing the surface area of the feeding tray covered by feed through time. Similarly, Chirdchoo and Cheunta (2019) successfully developed and trialled a cheap software to automatically detect feed pellets remaining on shrimp feeding trays through the use of a segmentation program which separates pixels based on the colour of feed samples. However, turbidity and uneven illumination are still major constraints for the use of segmentation algorithms for feed detection in ponds (Li *et al.* 2017). For farmers, those algorithms based on segmentation techniques using real-time footage could help inform when feeding should be stopped if a large amount of feed is still detected at the bottom, sometime after the initial distribution (Table 1).

Telemetry

Telemetry has become an important tool for monitoring behaviour of animals in aquaculture, and has been applied successfully in salmon farming (e.g. Føre *et al.* 2011, 2017). In fish cages, acoustic transmitters implanted in animals are used to send signals to receivers (i.e. hydrophones) (Wolcott 1995; Thorstad *et al.* 2013), and can provide for example information on swimming depth when used in combination with pressure sensors (e.g. Føre *et al.* 2011) or activity when jointly used with accelerometers (e.g. Kolarevic *et al.* 2016).

Due to tag size, there can be limitations for the application of telemetry in certain species such as shrimp, however, the use of smaller passive tags (i.e. those without a battery) can overcome this. In shrimp, this technique may only be suitable using small tags, such as passive integrated transponder tags (PIT-tags). PIT-tags are made of a small glass tube in which an integrated circuit chip, an antenna coil and a capacitor are inserted (Roussel *et al.* 2000). When passing by a reader which creates an electromagnetic field, the PIT-tag retransmits a unique code enabling individual identification of the animal (Lucas & Baras 2000; Håstein *et al.* 2001). Only a small number of studies have inserted PIT-tags inside small crustaceans such as shrimp (Caceci *et al.* 1999; Foote *et al.* 2018) with a focus on the use of PIT-tags for breeding programs. Implantation of tags can have implications for the health of the animal and may also alter behaviour. Caceci *et al.* (1999) implanted PIT-tags in the tail of small (6.9 g on average) giant freshwater prawns (*Macrobrachium rosenbergii* de Man) and did not report any increase in mortality for tagged individuals compared with the control group. However, the authors did not assess the behavioural impact of PIT-tagging. Similarly, Foote *et al.* (2018) recently implanted PIT-tags in *P. monodon* individuals but did not specify the size of the smallest tagged individuals. They did not find any differences in mortality rates compared with the control group, but again, the study did not assess the impact of tagging on behaviour. Indications of size limit for the use of PIT-tags can, however, be found in Black *et al.* (2010) who implanted PIT-tags in slender crayfish (*Orconectes compressus* Faxon) individuals. The likelihood of mortality induced by tagging was shown to be a function of carapace length, with smaller individuals less likely to survive after tagging than larger ones. The authors advised against tagging crayfish smaller than 22 mm in carapace length (Black *et al.* 2010), which would roughly correspond to a wet body mass of 7.2 g for penaeid shrimp according to the morphometric relationships provided by Franco *et al.* (2006).

As PIT-tags have been used successfully in small crustaceans, studies using these devices are likely to become more frequent for the monitoring of shrimp feeding behaviour, in particular, individual movements at and around feeding stations (Table 1). For example, in the wild, monitoring movement in mud crabs (*Scylla serrata* Forskal) in an estuarine lagoon in south-eastern Australia using telemetry and an automatic reading gate revealed general seaward movements of adults as a result of intraspecific aggression (Alberts-Hubatsch 2015). The joint use of two gates close to each other enables the acquisition of both speed and direction of the detected individuals (e.g. Meynecke *et al.* 2008; Alberts-Hubatsch 2015; Fig. 3). Other antenna designs exist such as flat-bed antennas (as used in Armstrong *et al.* 1996 and Lucas *et al.* 1999) which consist of a coil inserted inside a flat board which can be installed at the bottom of a pond and has the potential of detecting benthic animals such as shrimp (Armstrong *et al.* 1996). However, control measures should be implemented prior to or during the experiment since various factors can have an effect on detection success and lead to data misinterpretation (Payne *et al.* 2010). PIT-tag antennas could be jointly used with cameras (see Armstrong *et al.* 1996) to assess the effect of shrimp density close to the antenna, sludge accumulation at the bottom of ponds or variations in salinity on the detection rate of tags from the receivers.

In aquaculture facilities, telemetry for behavioural studies has mostly been carried out using a few tagged individuals in cages, tanks or ponds which can commonly contain thousands of individuals (e.g. Bauer & Schlott 2006; Rillahan *et al.* 2009; Føre *et al.* 2011; Jurajda *et al.* 2016; Kolarevic *et al.* 2016). For instance, Jurajda *et al.* (2016) tagged 23 common carp (*Cyprinus carpio* Linnaeus) with radio tags and released them in a 130 ha aquaculture pond to study their feeding activity and habitat utilization. Føre *et al.* (2011) used depth and activity transmitters in 18 Atlantic salmon to study feeding activity in a cage containing 8000 individuals. However, while the authors highlighted the potential applications of these devices for feed management strategies in cages, they did not provide guidance on the percentage of the population which should be tagged to get

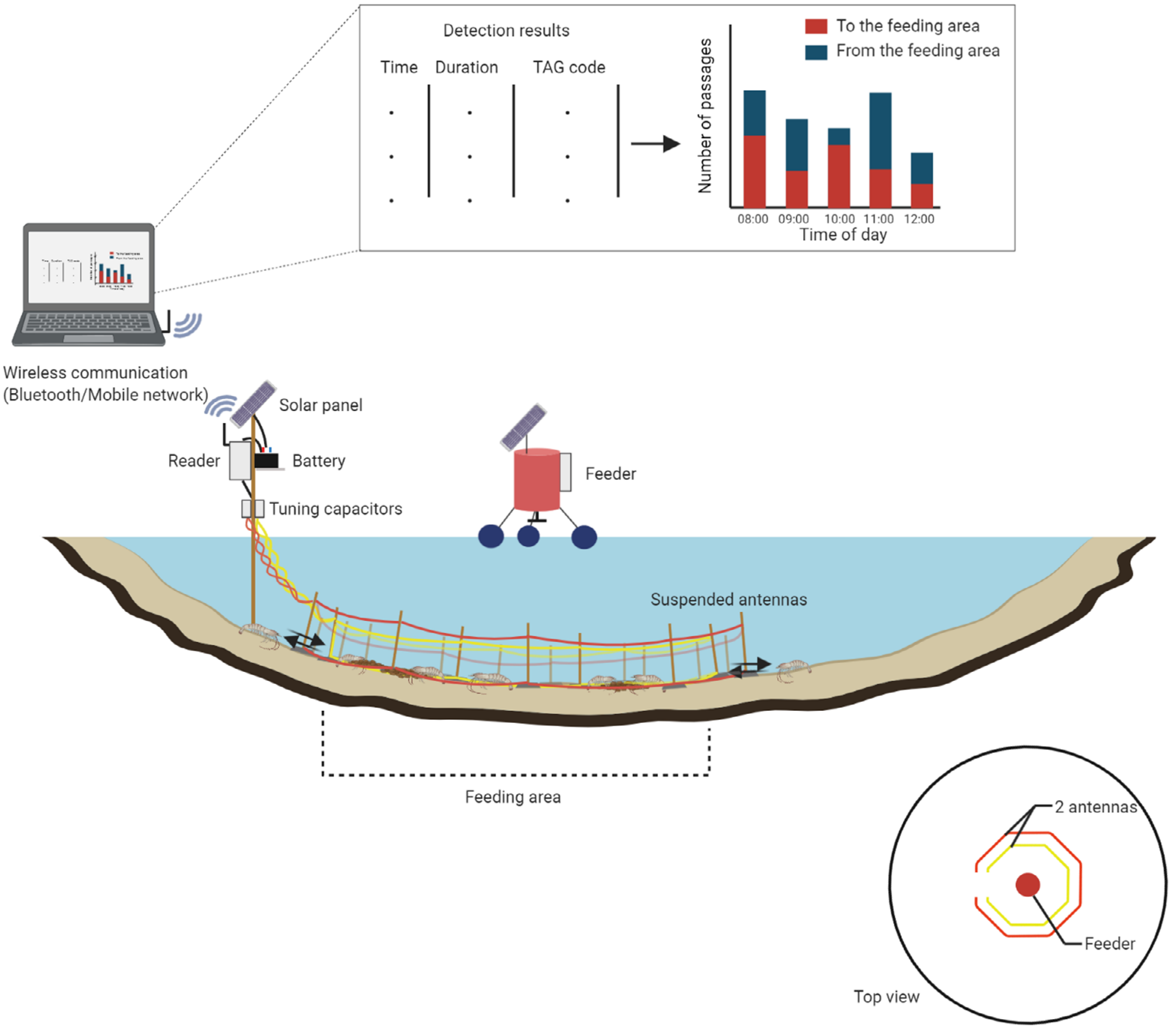

Figure 3 Representation of a telemetry system to monitor shrimp movements in ponds. Two antennas are used side by side in order to provide both speed and orientation of the tagged individuals that enter and leave the area covered by the feeder. The reader sends detection reports to a nearby computer, from which graphs on the number and directions of passages through time can be drawn. Created with BioRender.com.

an accurate overview of group behaviour. In experimental shrimp ponds, the proportion of the population that should be tagged needs to be carefully assessed but the low cost of each tag compared with data-loggers, acoustic and radio transmitters allows for a considerable number of individuals to be monitored (Thorstad *et al.* 2013; Meynecke *et al.* 2015). PIT-tags also represent a serious hazard for consumers, which undoubtedly will limit their use to a research context in experimental farms where they could help visualize movement patterns inside the pond and towards feeders (Table 1). For example, it is still unknown if the major commercial species of shrimp exhibit homing behaviours in ponds like other decapods do in the wild (Vannini & Cannicci 1995; Moland *et al.* 2011). This potentially could give valuable information on how to position feeders in ponds and in relation to one another. Furthermore, it is worth noting that only a fraction of the pond is fed, irrespective of the feeding strategy. Therefore, there is also a need to better understand what happens within the non-fed areas of the pond in terms of shrimp densities and movements with questions such as: Do some shrimp actively avoid feeding areas and, if so, is such a behaviour related to some kind of hierarchy linked to size or sex? Such knowledge could be provided by telemetry techniques and aid in understanding necessary management actions that are required to reduce variability in sizes at harvest for commercial farms. For example, in salmon (*Salmo salar*) aquaculture cages, Kadri *et al.* (1996) found that in order to prevent just a few individuals keeping others away from food pellets, feed should be randomly distributed across space and time.

Combining monitoring of environmental conditions and behaviour to improve shrimp welfare and feed management

Future work on shrimp welfare and feed management will be able to focus on monitoring feeding behaviour and environmental parameters at the same time through real-time online tracking of water quality from sensors in ponds. The ultimate goal of this approach will be to predict feed intake from environmental changes and various stressors, such as variations in water quality, and adjust feeding accordingly. Conversely, this approach could also have strong potential to spot early problems associated with water quality and disease outbreaks before they become severe (Saberioon *et al.* 2017; Yang *et al.* 2020). To that end, a number of wireless sensors for water quality monitoring already exist on the market and are currently in use on shrimp farms (e.g. Reis *et al.* 2020; Orozco-Lugo *et al.* 2020). Some sensors are even mounted on drones (unmanned surface vehicles) supplied with GPS systems which allow for the mapping of water quality over large pond surfaces (e.g. Cao *et al.* 2018). They can provide farmers with real-time data on water quality (Reis *et al.* 2020) and give warning signals on smartphones when readings exceed or go below predefined limits (e.g. Eruvaka Technologies). Communication technologies include (but are not limited to) ZigBee, Bluetooth and LoRaWAN (see Hu *et al.* 2020 for a review). Some systems available on the market can also control aeration depending on dissolved oxygen readings and automatically stop feeding when oxygen values go below preset limits (e.g. AQ1 Systems, Tasmania, Australia).

In fish aquaculture, changes in animal movements and social behaviour in shoals have already been the focus of research effort since they can reflect changes in environmental parameters and therefore be used to predict water quality (e.g. Israeli & Kimmel 1996; Serra-Toro *et al.* 2010; Cook *et al.* 2014; Pautsina *et al.* 2015). However, it is unclear how this kind of approach could translate to shrimp ponds. Computer vision and sonar technologies could play a role through the analysis of nearest neighbour distances (Murphy *et al.* 2019), velocity (Bardera *et al.* 2020b) and surface-seeking behaviour (Zhang *et al.* 2006). For example, increased activity with short but frequent random swimming movements was observed under hypoxic conditions in *L. vannamei* (Zhang *et al.* 2006). When hypoxia was severe (under 50% oxygen saturation value), lower activity and slower swimming speeds were reported, and shrimp exhibited a clear surface-seeking behaviour (Zhang *et al.* 2006). Passive acoustics could also be used since they provide information on feeding activity (Smith & Tabrett 2013). Historic data on relative feeding activity and environmental parameters could be jointly analysed in order to spot or predict disease outbreaks and water quality issues from abnormal shrimp acoustic behaviour.

Other existing feeding approaches can be entirely based on water quality parameters. In fish farming, Zhao *et al.* (2019) developed an Adaptive Neural Fuzzy Inference System (ANFIS) to adjust feeding rations of grass carp (*Ctenopharyngodon idellus* Cuvier & Valenciennes) based exclusively on temperature and dissolved oxygen values. ANFIS is based on a neural network structure which has to be trained first with a data set comprising dissolved oxygen, temperature and corresponding feeding rate values (i.e. feed consumption divided by fish biomass) obtained in controlled conditions to establish the relationship between input (i.e. water quality parameters) and output data (i.e. feeding rate; Zhao *et al.* 2019). Feeding rate was considered here as the optimal feeding level. After initial training and its application at a large scale in a pond, the authors found a reduction of 14.35% in the FCR and more than 22% in ammonia-nitrogen concentrations in the pond fed with the ANFIS protocol compared with a standard feeding protocol based on a timer feeder. A similar but simpler approach was tried for shrimp farming with the application of fuzzy logic as a basis for an intelligent feeding strategy for *L. vannamei* in tanks (Bórquez-Lopez *et al.* 2018). Temperature and dissolved oxygen values were also the only water quality parameters taken into account to control feeding rate. Dissolved oxygen was found to be the parameter that most influenced feed consumption. Results also showed that shrimp fed with the fuzzy logic protocol had an FCR 35% lower than the control based on feeding table strategies.

Conclusion

The shrimp farming sector continues to suffer from feeding inefficiencies which remain an obstacle towards its development and improved sustainability. Shrimp feeding behaviour is complex and our understanding of it is still in its infancy. Traditional techniques involving feeding trays and feed tables are still commonly used, however, can be limited in their reliability and subjectivity. For the farmer, the use of close monitoring tools has already been associated with better economic returns and a return of investment as a result of improved yields (Napaumpaiporn *et al.* 2013; Jescovitch *et al.* 2018; Ullman *et al.* 2019a; Reis *et al.* 2020), and it is now hoped that the industry will broadly adopt smarter feeding management techniques as has been done in salmon farming. For the researcher, the application of technological tools described here could develop new paths towards a better understanding of shrimp behaviour in relation to feeding operations.

Passive acoustics represent the most promising technology so far, being already widely used on shrimp farms around the world. It has been proven to produce reliable and instantaneous feed demand estimates (Smith & Tabrett 2013; Silva *et al.* 2019; Peixoto *et al.* 2020b) and its adoption results in improvements in feed management (Napaumpaiporn *et al.* 2013; Jescovitch *et al.* 2018; Ullman *et al.* 2019a; Reis *et al.* 2020). Since passive acoustics have already been developed for the shrimp farming industry, research efforts should focus on this technology and go beyond the assessment of feeding activity by developing feed consumption estimates, i.e. predicting the quantity of feed actually consumed from acoustic metrics (as suggested in Smith & Shahriar 2013; Smith & Tabrett 2013 and more recently in Peixoto *et al.* 2020b). This new approach would not only be directly beneficial to farmers, but also for researchers over the long-term since it will enable them to run feed consumption trials that used to be only possible in laboratory studies (i.e. in small indoor tanks were feed leftovers can be recovered) at the scale of a commercial pond (Peixoto *et al.* 2020b). This would help answer key questions surrounding the influence of environmental parameters on feed consumption in real pond conditions through the joint analysis of historic data from acoustic recordings and water quality sensors.

Computer vision can also represent a suitable tool for researchers willing to upscale observations to ponds when visibility allows it. This observation technique has the potential to provide behavioural indicators for the estimation of feed intake. Feature variables (as defined by Norton & Berckmans 2017) which are considered the most relevant behavioural metrics to accurately quantify feeding activity will have to be extracted from animal bio-responses either through combination with passive acoustic monitoring (which gives a proxy of feeding activity, Smith & Tabrett 2013), or from preliminary laboratory trials in which feed intake can properly be monitored. Long-term monitoring of behaviour along with water quality can also provide early warning information related to welfare (e.g. Israeli & Kimmel 1996 and Pautsina *et al.* 2015). Computer vision systems can provide insight into group movements in relation to feeding areas and therefore represent a valuable addition to passive acoustics. Although recent advances in machine learning can overcome a number of challenges related to water conditions, reliable routine assessment of feeding behaviour from underwater observations for farmers seems far from being achieved, with no complete system being available on the market for shrimp farmers as yet.

Finally, although is it only applicable in experimental ponds, telemetry techniques represent an interesting approach to better understand movements and space utilization at a large scale, regardless of visibility. PIT-tag telemetry is already well established and could be easily applied in the near future to provide insights on how feed could be better applied in time and space to provide access to feed to a larger proportion of individuals.

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