Aquaculture 528 (2020) 735508

Contents lists available at ScienceDirect

Aquaculture

journal homepage: www.elsevier.com/locate/aquaculture

Review

Automatic recognition methods of fish feeding behavior in aquaculture: A review

Daoliang Li[a,b,c,d,e,*], Zhenhu Wang[a,b,c,d,e], Suyuan Wu[f], Zheng Miao[a,b,c,d,e], Ling Du[a,b,c,d,e]
Yanqing Duan[g]

[a] National Innovation Center for Digital Fishery, China Agricultural University, China
[b] Beijing Engineering and Technology Research Centre for Internet of Things in Agriculture China Agriculture University, Beijing 100083, China
[c] China-EU Center for Information and Communication Technologies in Agriculture, China Agriculture University, Beijing 100083, PR China
[d] Key Laboratory of Agricultural Information Acquisition Technology, Ministry of Agriculture, China Agriculture University, Beijing 100083, China
[e] College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China
[f] School of Foreign Languages, Renmin university of China, Beijing 100872, China
[g] Business school, University of Bedfordshire, Luton LU1 3BE, UK

ARTICLE INFO

Keywords:
Behavior recognition
Computer vision
Acoustic technology
Sensors

ABSTRACT

Feeding is a major factor that determines the production costs and water quality of aquaculture. Analysis of fish feeding behavior forms an important part of the feeding optimization. Fish feeding has generally been performed with automatic feeding machines which can lead to excessive or insufficient feeding. Recognition of fish feeding behavior can provide valuable input for optimizing feeding quantity. Due to the complexity of the environment and the uncertainty of fish behavior, the correlation and accuracy of behavior recognition are generally low. The accurate identification of fish feeding behavior till faces substantial challenges. This paper reviews the technical methods that have been used to identify fish feeding behavior in aquaculture over the past 30 years. The advantages and disadvantages of each method under different experimental conditions and applications are analyzed. Many methods are effective at evaluating and quantifying fish feeding intensity, but the recognition accuracy still needs further improvement. It is proposed by this paper that technologies such as data fusion and deep learning has great potential for improving the recognition of fish feeding behavior.

1. Introduction

In recent years, the contribution of aquaculture to the overall global fisheries has increased, from 25.7% in 2000 to 46.8% in 2016 (FAO, 2018). The continuous expansion of aquaculture has resulted in the increase of feed costs (Føre et al., 2016). To accommodate large-scale fish farming, most farmers use automatic feeding machines (Odd-Ivar Lekang, 2013). Feeding frequency and feeding quantity of feeding machines are generally set according to farmers' experience with limited flexibility according to actual fish feeding behavior (Bégout et al., 2012; Zhao et al., 2017). The use of automatic feeding machine can lead to situations of over-feeding or underfeeding (Ang and Petrell, 1998; Liu et al., 2014). The intensity and magnitude of changes in activities of fish can directly reflect fish appetite (Zhou et al., 2019). Technologies that use optical, acoustic, and other types of sensor equipment to obtain, process, and analyze images, sound, and other information of fish are used to quantify and identify fish feeding behavior. Identifying fish feeding behavior enables real-time optimal control of feed and reduces the feeding costs. (Sneddon, 2007).

The recognition of fish feeding behavior with high accuracy can effectively guide the feeding process and provide optimal feed according to degree of hunger (Alzubi et al., 2016; Føre et al., 2018). Underfeeding leads to increased aggression between individual fish for food (Huntingford et al., 2012a, 2012b). Conversely, overfeeding leads to food waste and increases the cost of feeding and the feed conversion ratio (FCR) and reduces breeding efficiency (Føre et al., 2016). Decomposition of feed deposited on the bottom produces ammonia nitrogen and harmful nitrate compounds that affect the healthy growth of fish (Xie et al., 2003; Remen et al., 2016). The development of advanced technologies, such as computer vision and artificial intelligence, has made it possible to recognize the feeding behavior of livestock and poultry in agriculture (Nasirahmadi et al., 2017). However, due to the complexity of the environment and the uncertainty of fish behavior, the correlation and accuracy of behavior recognition are generally low.

* Corresponding author at: P. O. Box 121, China Agricultural University, 17 Tsinghua East Road, Beijing 100083, China.
E-mail address: dliangl@cau.edu.cn (D. Li).

https://doi.org/10.1016/j.aquaculture.2020.735508
Received 7 May 2020; Accepted 20 May 2020
Available online 23 May 2020
0044-8486/

Accurate identification of fish feeding behavior remains a big challenge.

Over the past 30 years, extensive research has been conducted on fish behaviors, including feeding behavior, environmental stress behavior, swimming behavior, and group behavior (Jobling et al., 1995; Delcourt et al., 2009; Sadoul et al., 2014; Føre et al., 2018). This paper aims to provide a comprehensive review of the technologies and methods used for automatic recognition of fish feeding behavior in recent years. The review focuses on the direct and indirect application of computer vision technology in the recognition of fish feeding behavior and the application of active and passive acoustics to study fish behavior and spatial location. Also discussed is the auxiliary function and potential application value of other types of sensors for the recognition of fish feeding behavior. Finally, the potential applications of feeding behavior recognition technology are discussed and summarized.

2. Feeding behavior recognition methods based on computer vision

Computer vision technology has been widely used in aquaculture in recent years (Zion, 2012; Hassan and Hasan, 2016; Saberioon et al., 2017). It has been used for counting, size measurement, gender identification, quality inspection, species and population identification, and monitoring of welfare and behaviors (Zhou et al., 2018a, 2018b). The wide application of computer vision technology provides an effective means to perform real-time, automatic, and contactless research (Bégout et al., 2012). Based on the different wavelengths utilized by cameras, light can be divided into visible and infrared. Most cameras utilize visible light as the light source (Fig. 1).

2.1. Based on visible light

Computer vision technology based on visible light is used widely compared to other types of light sources. At present, studies on the identification of fish feeding behavior are mainly divided into two categories. Direct methods include the use of the measured images to obtain the shape, texture, area, dispersion, and swimming activity of the fish shoal, and other parameters (Sadoul et al., 2014). The indirect methods include assessing fish appetite by analyzing the amount of excess feed in the aquaculture water recorded by the camera.

2.1.1. Recognition of direct feeding behavior

Computer vision technology has been used to detect the presence, number, length and behavior of fish (Saberioon et al., 2017). Recent studies have shown that it also can be used to estimate the appetite of fish to achieve precision feeding (Williams et al., 2010; Cha et al., 2012; Papadakis et al., 2012, 2014; Lee et al., 2013; Al-Jubouri et al., 2017; Niu et al., 2018; Zhou et al., 2018a, 2018b). When fish displays different feeding intensities, the texture, color, shape, area, and the number of fish feeding at the same time differ (Hu et al., 2012; Jyothi et al., 2013). There are also differences in the velocity, acceleration, and angular velocity of fish, and in the degree of aggregation between fish (Cha et al., 2012; Zhao et al., 2016).

Pautsina et al. (2015) proposed a novel infrared reflection (IREF) system based on the strong absorption distance of NIR light by water. The distance of fish is estimated according to the brightness of the fish target on the image to allow for three-dimensional tracking of fish (Zhu and Weng, 2007; Pautsina et al., 2015). Compared with the general stereo vision system, this system has advantages of low hardware costs and less computation. However, the tracking accuracy is still low. Qian et al. (2016) proposed a multi-fish tracking method based on the detection of fish heads (Qian et al., 2016), which used the shape and gray features of fish head images to determine their location. The results showed that this method can determine the motion trajectory of dozens of fish in a low-density experiment. However, the accuracy of tracking group movement targets requires improvement (Marti-Puig et al., 2018). The application of structured-light (SL) sensors effectively improves the accuracy of three-dimensional tracking (98%) while reducing system costs (Saberioon and Cisar, 2016). Nevertheless, the robustness and reliability of multi-target tracking methods for groups remains a challenge in the field of computer vision (Delcourt et al., 2009; Zhao et al., 2016).

Chen et al. combined the area method and texture to study the fish feeding behavior by fish shoals. In the study, the four texture features of the inverse moment, correlation, energy, and contrast are analyzed. The results showed that the contrast and intensity of population activity of fish reached 0.8942. However, it didn't consider the interference caused by splashes and individual overlap during fish feeding. Guo et al. (2018) proposed a method to identify the feeding behavior of shoal carps. The shape and texture information of feeding images were obtained by image processing technology. Shape parameters and image entropy of fish images were calculated. BP neural network modeling was used to identify the feeding state of fish (Guo et al., 2018). The results show that the accuracy of detection can be improved by analyzing the interference of disadvantageous factors such as water surface jitter and water spray as unique texture properties. The recognition

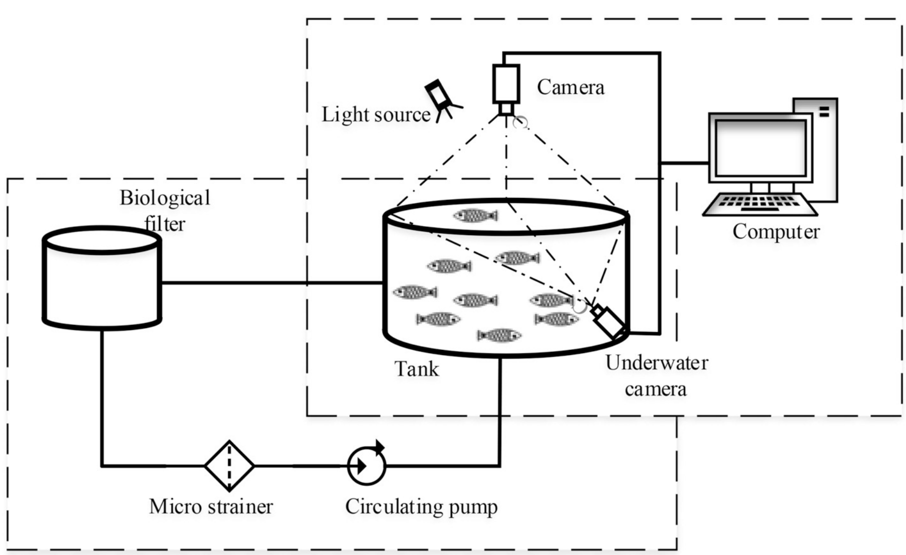

Fig. 1. Structure diagram of a fish feeding behavior recognition system based on computer vision.

accuracy reached 98.0% but the problem of overlap among individuals is still not eliminated.

Liu et al. (2014) proposed a method to measure the feeding activity of *Salmo salar,* based on the sum of the strength of different frames caused by the movement of fish. An overlap coefficient was defined to correct the calculation error caused by the overlap of fish bodies in the image (Liu et al., 2014). A computer vision-based feeding activity index (CVFAI) and manual observation feeding activity index (MOFAI) were determined and the correlation coefficient between these indexes was 0.9195. Duarte et al. (2009) proposed a method by using the subtraction of continuous frame images to identify changes in image regions caused by the movement of fish, but with a low accuracy (Duarte et al., 2009).

Zhao et al. (2016) proposed a nondestructive and effective method for quantifying feeding intensity of tilapia based on computer vision (Jiang et al., 2010; Zhao et al., 2016). With the aid of the Lucas-Kanade optical flow method and information entropy (Brox and Malik, 2011; Lucey et al., 2012; Swendsen, 2017), the feeding characteristics of fish was used to quantify the overall feeding intensity of fish. They also improved the kinetic energy model and quantified the overall feeding intensity by using the changing characteristics of the water flow field caused by the feeding behavior (Zhong et al., 2007). It revealed that interference caused by overlap between fish shoals on its quantization was limited. However, the practical application of this method needs to be further verified.

The degree of hunger is an important internal factor that affects fish appetite and feeding behavior. Ang and Petrell (1997) used cameras to monitor the feeding behavior of Japanese flounder under the state of hunger (Ang and Petrell, 1997) and the results showed that fish under this state had faster swimming speed and were more active in the surface layer (Miyazaki et al., 2000). Lee et al. (2013) developed a Sustainable Aquaculture Feed System (SAFS) that uses a developed algorithm to detect the presence of fish to analysis of fish appetite. Statistical analysis has been conducted on the fish population to evaluate fish appetite and control the feeding system (Lee et al., 2013). Although the development costs of this system are low, the detection accuracy is only 80%. Zhao et al. (2017) proposed a method to characterize the appetite of fish groups using the dispersion of fish groups (Chang et al., 2005), the interaction force, and the degree of change in the water flow field (Windsor et al., 2010; Zhao et al., 2017). The method provided good quantification and characterization across five appetite levels. However, the mismatching rate was still $2.19 \pm 0.81\%$, indicating that reliability requires further improvement.

Alzubi et al. (2016) analyzed the fish behavior by combining traditional computer vision and a support vector machine to determine whether fish were actively fed (Alzubi et al., 2016). A two-stage method has been adopted to automatically detect the amount of excessive feed on the water surface (Atoum et al., 2015). The results of the control experiment showed that the two-step method has higher accuracy than assessment of fish behavior alone. In order to further improve the classification of feeding intensity, Zhou et al. (2019) proposed a feeding-intensity evaluation system based on the LeNet5 framework combining CNN and computer vision. The system divides the feeding intensity into four levels (none, weak, medium, and strong), avoiding the errors caused by manual extraction of features in traditional machine learning methods. Compared with common research methods, the deep learning method has higher classification accuracy (> 90%) (Zhou et al., 2019).

Overall, computer vision technology is frequently used to analyze fish feeding behavior. Improvements in computer processing speed and continuous optimization of image processing algorithms increase the accuracy of recognizing fish feeding behavior (Wei et al., 2014). However, most research is still at the laboratory stage, and further studies are required for fish behavior recognition in a more complex farming environment of large-scale and intensive farming (Atoum et al., 2015).

2.1.2. Indirect feeding behavior recognition

Detection of uneaten pellets is another way of using computer vision to analyze, identify, and evaluate the feeding intensity (Foster et al., 1995; Parra et al., 2018). Cameras are used to collect images and videos of fish feeding on food pellets (Parsonage and Petrell, 2003). At the same time, images are processed and analyzed by the computer to identify pellets not eaten by fish. The pellets are then counted and other parameters of the food pellets in the image are analyzed (Liu et al., 2015). When the number of uneaten pellets in the area detected by the computer reaches a certain threshold, this indirectly suggests that the overall feeding of fish is decreasing, feedback can then be directed to the controller to reduce or stop the provision of feed (Ballester-Moltó et al., 2017).

Parsonage (2001) designed an image processing framework for Atlantic salmon cage farming, which detects and identifies fish feed pellets through upward camera observations. This framework became the basic method for detecting uneaten feed in fish farms in subsequent studies. The accuracy of detect uneaten pellets is an important index to measure system performance. Parsonage and Petrell (2003) reported a study where video segments recorded under different storage and environmental conditions were used as training sets and digital filters were used to eliminate abnormal data. This reduces the effect of misclassification of the system.

Liu et al. (2015) proposed an adaptive Otsu threshold method and a linear time component-labeling algorithm to measure the number of pellets in non-uniform illumination images to reduce the influence of uneven natural illumination on the detection of uneaten food pellets, and compared it with other Otsu algorithms (Farrahi Moghaddam and Cheriet, 2012; Liu et al., 2015). The performance of the adaptive Otsu algorithm outperformed other methods. Fish food pellets can be effectively segmented and counted based on images with uneven illumination with an error of less than 8%. Later, to address uneven illumination in underwater images, proposed a study focused on the intensity histogram of local masks based on the adaptive threshold detection algorithm for underwater images of fish food (Li et al., 2017). The adaptive threshold was calculated by EM-guided GMM histogram fitting. The central pixel of the mask could be compared with the threshold to generate the binary detection result, presenting improved detection accuracy.

The spatial and temporal distribution of food pellets in culture cages has great significance for investigating the fish feeding behavior (Skøien et al., 2016). Skoien et al. (2015) developed a pellet detector based on computer vision technology for accurate quantitative temporal and spatial distribution of food pellets in the cage (Skoien et al., 2015). An underwater camera in the device detects and counts the volume of food pellets that sink through a funnel. The top and sides of the camera are closed to prevent any impact by the fish. Additionally, an image processing algorithm is used to identify the size and speed of the subsidence material and filter any interfering matter. The device is capable of rapid detection and accurate quantification, with a detection error of 1.3%.

Atoum et al. (2015) developed an automatic feeding control system based on computer vision. The system used image processing technology to extract characteristic image data of different feeding behaviors recorded by the camera. The support vector machine classifier was used to classify different feeding behaviors to determine whether the fish were actively feeding (Atoum et al., 2015). In addition, the system was designed with a feed detector for the real-time monitoring of excessive food pellets on the surface of water. Because of these design experiments, aquaculture personnel are able to better understand the feeding behavior of fish in highly intensive aquaculture ponds and provide more reference information for accurate feeding.

In summary, the indirect identification of fish feeding behavior through the detection of food pellets with computer vision technology is currently an important application and research focus of in precision aquaculture. Acceleration in processing speeds of the detection system improved the recognition accuracy of fish feeding behavior (Li et al., 2017). However, due to the complexity of environments and the particularity of research objects (uncontrollability, fish overlap, fast moving speed, etc.) (Zion, 2012), the quality of image data is poor. There remain substantial challenges for intelligent feeding based on fish feeding behavior (Zhou et al., 2018a, 2018b).

2.2. Based on infrared imaging

Near infrared (NIR) computer vision technology is not affected by visible light intensity, and can achieve better imaging effects in a relatively dark environment (Hung et al., 2016). It is suitable for identifying fish behavior under low-light conditions (Zhou et al., 2017).

Researchers used an infrared photoelectric sensor to observe the collective behavior of eel (Mattos et al., 2016; Zhao et al., 2017), and developed an intelligent feeding control system for eel breeding (Chang et al., 2005). When the aggregation behavior is not detected, the feeding can be stopped, which can effectively reduce the waste of bait and water pollution.

In recent studies, near-infrared imaging technology is used to monitor fish feeding process and identify fish feeding behavior. One study used a near-infrared industrial camera mounted above water to collect images of fish during feeding (Zhou et al., 2017). Binary images of each fish were obtained by image processing technology. In addition, the classification method and removal of reflection frames based on support vector machine and gray gradient co-occurrence matrix are used to eliminate the influence of splash and reflection on the results. The moment method is used to calculate the center of fish mass. Delaunay triangulation subdivision was used to calculate the fish feeding behavior of flocking index (FIFFB) and quantify fish feeding behavior. The FIFFB value could accurately quantify and analyze changes in fish feeding behavior, and the linear correlation coefficient was 0.945 compared with the score in the expert manual. In recent research (Zhou et al., 2018a, 2018b), automatic feeding was achieved in combination with a fuzzy reasoning system (ANFIS) based on an adaptive network. The results showed that the feed decision-making accuracy of the ANFIS model was 98%, and the feed conversion ratio (FCR) is reduced by 10.77% compared with the feed table.

Infrared sensors and near-infrared imaging technology are more suitable for measurements in turbid water with complex light conditions compared with traditional cameras (Hung et al., 2016). Table 1 shows various schemes and the advantages and disadvantages of computer vision technology in feeding behavior recognition. It has become an important tool to improve the accurate identification of fish feeding behavior and to develop intelligent breeding equipment (Odd-Ivar Lekang, 2015). It is increasingly used to estimate biomass in aquaculture, 2D or 3D tracking (Pautsina et al., 2015), and positioning of fish stocks, and in various behavioral analyses. Further research is needed before such technology can be applied to commercial fish farms to obtain a larger sample size.

3. Feeding behavior recognition methods based on acoustic technology

The computer vision approach is user-friendly and inexpensive but has some limitations. For example, computer vision technology is generally limited to clear water. If a large number of fish are at the bottom of the cage or away from the light source, the camera system may not be able to provide an accurate picture of the fish. Although infrared light can be used in the dark, image quality may not be sufficient to monitor the movement unless appropriate infrared filters are used. These deficiencies can be overcome through the use of acoustic methods (Fig. 2) (Zhou et al., 2018a, 2018b). Methods of acquiring acoustic data can be divided into those involving passive acoustics and those involving active acoustics (Smith and Tabrett, 2013).

3.1. Based on passive acoustics

Passive acoustic recognition and monitoring of fish feeding behavior (Gannon, 2008) makes use of acceptable sounds of eating (Rodney et al., 2006; Ullman et al., 2019). More than 800 species of fish are known to produce sounds, and many studies have investigated these sounds to obtain information on their numbers, distribution, and behaviors (Juanes, 2002; Conti et al., 2006).

Long-term acoustic monitoring of fish sounds can be used to infer periodic reproduction behavior, feeding activities and changes in population abundance (Lammers et al., 2008). Tricas and Boyle (2014) recorded 85 sounds from 45 species of fish on Hawaii's coral reefs. These were associated with competition, reproduction, defense, feeding, and alertness. Most non-feeding sounds were composed of a single or a series of pulses < 100 ms long, while some parrotfish and barracuda recorded unique irregular feeding sounds with high frequency (26 kHz), an important quantitative indicator of fish feeding activity (Tricas and Boyle, 2014).

Lagardere (2000) monitored the feeding behavior of turbots and analyzed the frequency spectrum of the feeding sound. The author noted that the sounds made during the feeding process ranged from 15 to 20 dB in the frequency range 7–10 kHz, which could reflect changes in the feeding intensity of fish. Background noise is the most important factor affecting the recognition accuracy of fish feeding behavior in these studies. Mallekh and Lagardere (2003) developed a method to directly monitor the feeding activities of turbot using the sounds of fish feedings to overcome this deficiency. A usable relationship between the sound energy and the rate of feed consumption is identified (Mallekh and Lagardere, 2003). This method adopts a sound sensor (hydrophone) and a data processing system (acoustic receiver), and only selects feed sounds in the 68 kHz frequency band to reduce interference from background noise (Juanes, 2002). The results of this experiment showed that the acoustic signal measured by the acoustic detector had a linear relationship with feeding activity, indicating that the system has good application potential (Lagardere et al., 2004).

Smith and Tabrett (2013) reported that tiger shrimp can generate a pulse sound signal during feeding, which can be used to identify feeding activity (Smith and Tabrett, 2013). To support the relationship between feeding sounds and feed consumption, a strong linear correlation between tank and pond-based feeding activities ($R^2 = 0.95$ and $R^2 = 0.96$, respectively) was established. In a similar study used an acoustic control method for tilapia bait feeding, and noted that the frequency of the feeding sounds was in the range 0–6 kHz, which could be distinguished from background noise. The sound power was positively correlated with the feeding activity of fish.

The above studies support the use of feeding sounds to assess fish feeding behavior and guide accurate feeding. However, it remains necessary to measure and verify the relationship between feed consumption and intake (Zhou et al., 2018a, 2018b). In addition, the accuracy of measurements of this method should be improved to reduce the influence of environmental noise and other random noise (Mallekh and Lagardere, 2003).

3.2. Based on active acoustics

Compared with passive acoustics, more extensive research has been conducted using active acoustics for the monitoring of aquatic animal distribution, biomass estimation, fish location and tracking, and fish behavior monitoring. This method has better controllability (Xu and Zhang, 2007; Polonschii et al., 2013; Kolarevic et al., 2016). Current research can be divided into image sonar and non-image sonar.

3.2.1. Based on non-image sonar

Although fish behavioral changes can be observed directly, such methods are limited by the visibility of the water and the large volume and quantity of fish in the culture environment (Hung et al., 2016). The

Table 1
Summary of methods based on computer vision[a].

Light source	Application	Parameters	Species	Culture model	Result/accuracy	Advantage/ Disadvantage	References
Visible light	Detecting fish behaviors	Difference in frame/texture	*Cyprinus carpio specularis*;	Laboratory;	Correlation coefficient: $r^2 = 0.8942$;	Directly quantified feeding intensity, best for high	Atoum et al., 2015
			-	Tank;	Success rate:97%;	culture density, higher precision and	Guo et al., 2018
			Flatfish;	RAS;	Classification success rate: 98.51%,	accurate;	Duarte et al., 2009
			Salmo salar;	Laboratory;	Detection accuracy:90.8%;	/	Liu et al., 2014
			Tilapia;		Correlation coefficient: $r^2 = 0.9007$;	Difficult to track	Zhou et al., 2019
					Correlation coefficient: $r^2 = 0.9195$;	individual fish, accuracy is greatly affected by the	
					Classification accuracy:90%;	algorithm	
		Area/ number of fish	Carp;	Laboratory;	Accuracy: > 80%;		Lee et al., 2013
				Pond;	Reduced feed waste;		Wei et al., 2014
		Degree of dispersion/ water flow field	Nile tilapia	RAS;	Correlation coefficient: $r^2 = 0.9467$;		Zhao et al., 2017
		Speed/direction	Tilapia;	RAS;	FCR was reduced;		Ang and Petrell, 1998
			Salmo salar;	Cage;	Minimal frame loss: < 21 s/24 h;		Papadakis et al., 2012
			Sea bream;	Laboratory;			Wei et al., 2014
							Ye et al., 2016
		Image entropy	Tilapia;	RAS;	Better identification of hunger levels;		Zhao et al., 2016
		Spatial location	Nile tilapia;	Laboratory;	3D Track accuracy: 98%;		Qian et al., 2016
			-		Track > 20 fish; accuracy: 97.1%;		Saberioon and Cisar, 2016
	Feeding detection	Particle area / quantity	Salmon;	Cage;	Count error: ± 10%;	Intuitive, real time. Algorithm is simple.	Foster et al., 1995
			Seabream		Count accuracy: > 92%;	/	Skoien et al., 2015
				Marine farms;	False positive rate: < 2.7%;	Accuracy needs to be improved.	Liu et al., 2015
					Error level: 1.3%;		Li et al., 2017
Infrared	Behavior detection	Location/size/ FIFFB values	-	Pond;	Depth error: 5.3 cm	Less affected by light,	Pautsina et al., 2015
			Shrimp; *Cyprinus carpio var;*	Laboratory;	Horizontal error: 2.8 cm;	suitable for complex and cloudy light	Hung et al., 2016
			Tilapia;	RAS;	Correlation of length: 0.99;	conditions;	Kai et al., 2017
			Melanotaenia trifasciata;	Tank;	Correlation coefficient: $r^2 = 0.945$;		Zhou et al., 2017
					Decision accuracy: 98%;		Zhou et al., 2018a, 2018b
					Correlation coefficient: $r^2 > 0.98$;		

[a] In Table 1, the first column is divided into two categories according to the type of light source. The second column divides the categories into different applications. The third column further subdivides the applications based on the parameters of each research basis. After that, the fish species, culture model, results, advantages and disadvantages of each study were listed respectively.

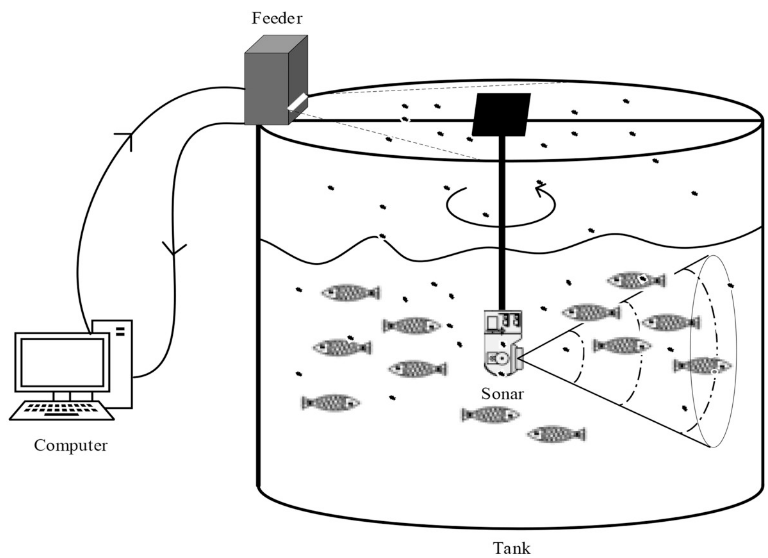

Fig. 2. Diagram showing the structure of fish feeding behavior recognition system based on acoustic technology.

application of acoustic telemetry technology may complement traditional observation techniques (Føre et al., 2017a, 2017b), providing the opportunity to monitor fish without having to interact directly with them or isolate them from other individuals. In recent years, this technology has been used widely in aquaculture to estimate biomass, locate and track fish, monitor fish behavior, and detect damage of aquaculture cages. In addition, it has great potential in the detection and identification of fish feeding behavior (Llorens et al., 2017; Føre et al., 2018).

Although the implantation of acoustic emission tags in fish may cause some injury and influence the experimental results, the development of chip integration and miniaturization enabled the method feasible for the study of fish behavior (Bégout-Anras and Lagardere, 2004; Føre et al., 2017, 2018). Bégout-Anras and Lagardere (2004) reported studies using the acoustic positioning telemetry system to study differences in the swimming behavior of labeled fish under different feeding intensities to classify feeding behavior (Bégout-Anras and Lagardere, 2004). Previous studies have shown that movement into the feeding area is a basic feature of fish feeding behavior. The feeding activity is reflected in the vertical movement pattern of the fish (Kolarevic et al., 2016). Føre et al. (2011) used two acoustic emission tags (depth and acceleration) to monitor the feeding behavior of fish. The depth tag effectively distinguishes feeding behavior and other activity patterns. During the experiment, the feeding activity was expressed in terms of fluctuations in depth patterns close to the surface with unusually strong vertical movement speeds (Føre et al., 2011). Rillahan et al. (2011) used a high-resolution ultrasonic telemetry system to continuously and accurately monitor the behavior of carp. The three-dimensional position of multiple fishes was determined. The results have important guiding significance for optimizing the mesh geometry, feeding strategy, and stocking density of carp culture (Rillahan et al., 2011). Polonschii et al. (2013) used a three-dimensional array ultrasonic transducer to monitor the dynamic position of fish swarms. The results showed that the system and associated methods can be used for remote monitoring the feeding behavior (Polonschii et al., 2013).

In addition to the direct monitoring of fish behavior, the echo integration method has been used to detect the amount of feed when the fish were in a fed state or when the feeding intensity was reduced (Steven et al., 1995; Llorens et al., 2017).

3.2.2. Based on image sonar

Acoustic imaging has more obvious advantage over computer vision in dark or turbid water. (Rakowitz et al., 2012). In recent decades, there has been great progress in the application of sonar technology in fishery acoustics, from simple analog single beam and single frequency systems to more complex digital multi-beam and multi-frequency systems (Chu, 2011). The basic principle of the acoustic sensing system is to obtain sonar images of fish feeding or uneaten food pellets by an echo sounder based on echo synthesis technology, which are analyzed by image processing (Llorens et al., 2017; Zhou et al., 2018). The use of image fusion technology based on different levels and features can effectively reduce the effect of light transmission, light interference, low contrast, blur, color attenuation, noise, and other factors that interfere with image quality during the capture process (Alavandan and Baboo, 2012; Garcia et al., 2012).

Some studies have shown that the density and spatial distribution of fish are related to their feeding desire, and the acoustic method can be used to reconstruct and analyze the number, distribution, length and activity intensity of fish (Hamitouche et al., 1998; Zhang et al., 2014; Lecornu et al., 1998; Paramo et al., 2007). Compared the two-dimensional image with the one-dimensional beam of the vertical single-beam echo sounder, the inclusion of more accurate information can better quantify the behavior, morphology, and distribution of fish stocks (Iida et al., 1996). Using sonar imaging technology based on the beam-splitting method, the three-dimensional position of fish is determined and the movement of individual or groups of fish is monitored and tracked (Rakowitz et al., 2012). Both dual-frequency recognition sonar (DIDSON) and multi-frequency digital scanning sonar produced results similar to those obtained with optical images, showing great potential for detecting fish behavior (Keefer et al., 2017). By integrating the echo intensity and time, the scattered echo energy of underwater fish is measured and used to estimate the number of fish. In addition, echo energy can also obtain by integrating the frequency of the echo spectrum density (Xu and Zhang, 2007).

The above studies on the density, quantity, spatial position, and behavior of fish were performed using sonar imaging technology. The method of processing sonar images is similar to the traditional method of processing optical images. In addition, it also includes the echo intensity, energy, and other information, which is more abundant than the information contained in the optical image. This technique is suitable for estimating the fish biomass in high-density aquaculture conditions and the three-dimensional position of fish in deep-water mass aquaculture systems. Table 2 shows the various schemes and the advantages and disadvantages of acoustic technology in feeding behavior recognition.

Table 2
Summary of methods based on acoustic technology.

Technology	Application	Species	Culture model	Result/Accuracy	Advantage/ Disadvantage	Reference
Imaging Sonar	Behaviors observation	Chinese sturgeon; Red sea bream; Bream	Cages; Laboratory; Cage	Speed (0.1–2.1 ms^{-1}); Success rate: 79%; Capture rate: 3/4;	Intuitive, easy to use; / high cost;	Xu and Zhang, 2007 Rakowitz et al., 2012 Zhang et al., 2014
Non-imaging sonar	Feeding behavior/ Feed detection	Salmon Sea bass	RAS; Cage	Clear distinction between feeding and non-feeding; $R^2 > 0.9$;	High correlation; / easily disturbed;	Føre et al., 2011 Llorens et al., 2017
Acoustic tag	Starvation grade	Salmon; Rainbow trout	Pond; Laboratory	Accuracy: 90; Average success rate: 86%;	Intuitive, accurate; / contact, damage fish;	Cubitt et al., 2008 Føre et al., 2011 Kolarevic et al., 2016
Hydrophone	Feed consumption/ Feeding-voice quantification	Turbot; Trout; Giant tiger prawn	Sea farm; Sea farm; Pond	Frequency range: 7–10 kHz; Frequency range: 4–6 kHz; Correlation coefficient: $r^2 = 0.95$	Simple and lower cost; / easily disturbed by noise	Lagardere and Mallekh, 2000 Lagardere and Mallekh et al., 2004 Smith, 2013 Lagardere et al., 2004

4. Feeding behavior recognition methods based on sensors

In addition to optical and acoustic technology, a variety of sensors based on different parameters were reported to monitor, identify, and evaluate fish feeding behavior (Rillahan et al., 2009; Andrew et al., 2002; Asaeda et al., 2005; López-Olmeda et al., 2012). Acceleration sensors and water quality parameters (dissolved oxygen, pH, and water temperature) are the widely used sensors (Fig. 3).

4.1. Based on acceleration sensor

Accelerometers have recently been used in marine biology research to study the feeding behavior of aquatic animals. The feeding behavior of most fish will lead to characteristic changes in acceleration, different from the normal movement (Horie et al., 2016). Feeding behavior can be studied in detail by measuring this characteristic change in acceleration (Tanoue et al., 2012; Parra et al., 2018).

Feeding behavior is accompanied by chewing. Researchers attached miniaturized acceleration data loggers to the mandible of the common carp to remotely identify feeding behavior (Makiguchi et al., 2012). The results showed that the frequency and amplitude of the mandible calculated by the continuous wavelet transform surge acceleration increased significantly during the feeding period compared with the non-feeding period. Although the accuracy was relatively low (89.8 ± 13.5%) and there was a high false-detection rate (25.9 ± 10.9%), this method can detect and record the feeding events of fish.

Many fish use fast-start (FS), short-term, sudden acceleration, and turning movements to complete feeding, escape, and other behaviors. Video recording and three-axis accelerometer sampling are used to observe and record the feeding shock and escape response (FS activity). Studies showed the system has a detection rate of 90% and a recognition accuracy of 80% (Broell et al., 2013). However, when the sampling frequency is low (< 10 Hz), the probability of detecting feeding and escape activities is significantly reduced. A data logger incorporating a three-axis gyroscope, a three-axis accelerometer, and a three-axis magnetometer has been used to monitor the feeding and escape behavior of Japanese cruiser fish (Noda et al., 2013). Improvements in system performance and a higher detection rate and recognition rate (84%) for FS activities (97%) were achieved. Smaller data loggers are needed to overcome hydrodynamic drag and improve recognition accuracy.

Previous studies have shown that acceleration and gyroscope data recorders carried by fish can be used to analyze and quantify the feeding behavior of various fishes (Broell et al., 2013; Noda et al., 2013). The application of acceleration sensors can also identify and classify different prey eaten by fish. Japanese scientists studied red-spotted groupers and classified their prey by implanting accelerometers

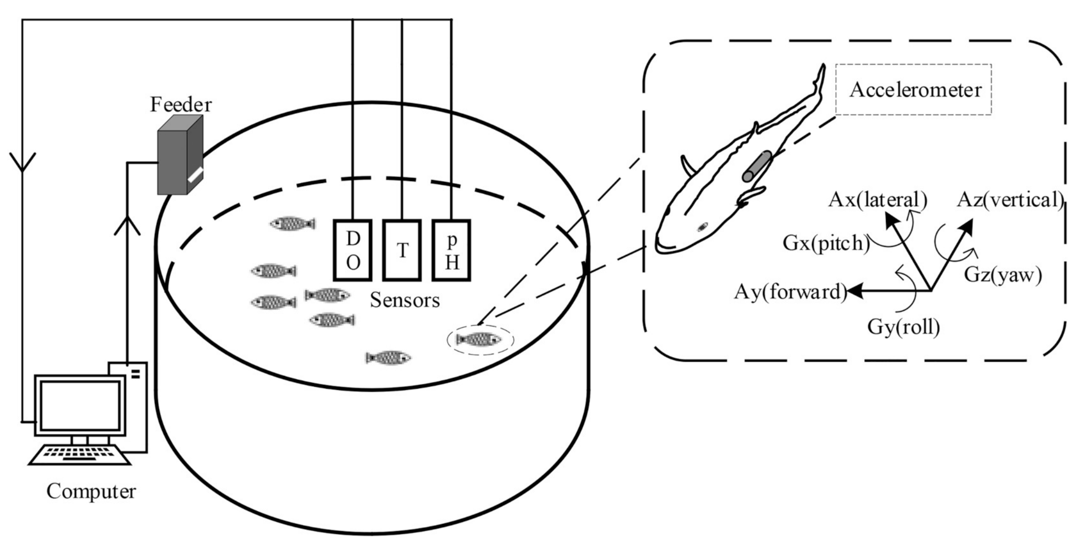

Fig. 3. Diagram showing the structure of a fish feeding behavior recognition system based on other sensors.

in the body (Horie et al., 2016). The results showed that this method is highly accurate for classifying fish (73%), shrimp (77%), crab (71%), and other prey (78%) (Horie et al., 2017). In addition, the study found that data obtained using a data logger containing gyroscopes and accelerometers has higher recognition accuracy than those obtained using accelerometers only (Noda et al., 2014). Using a novel gyroscope/acceleration data recorder that can monitor triaxial angular velocity and triaxial acceleration, Noda et al. (2014) monitored the feeding behavior of the white-streaked grouper *Epinephelus ongus* hunting different prey, and classified fish and crab prey with higher accuracy (87.5%) and a lower false detection rate (5% for crab-eating and 6.3% for fish-eating) (Noda et al., 2014). Fish feeding on the water surface will also cause fluctuations of the water surface. Subakti et al. (2017) used a sensor suspended on the water surface to monitor fish surface feeding behavior and feeding time. The results show that the use of acceleration sensors can effectively distinguish feeding behavior patterns from other behavior patterns, and this study provides important reference information for the development of intelligent feeding control systems (Subakti et al., 2017).

In summary, various kinematic parameters of fish can be determined by implanting acceleration sensors and other elements, or fixing them to the body of fish in other ways. As modern aquaculture has become increasingly focused on welfare aquaculture, this kind of invasiveness monitoring method is unlikely to be suitable for large-scale intensive aquaculture.

4.2. Based on temperature sensor and dissolved oxygen sensor

Changes in the main parameters of water quality (e.g., water temperature, dissolved oxygen concentration, pH value, and ammonia nitrogen compounds) can directly affect the appetite and food intake of fish (Xie et al., 2003; Stoner et al., 2006; Remen et al., 2016). The feeding behavior of fish can also cause change in response to the above parameters. For example, when fish eat, the concentration of local dissolved oxygen is decreased. Uneaten pellets deposit on the bottom of the water also causes changes in dissolved oxygen and ammonia nitrogen compound concentrations (Skøien et al., 2016; Li et al., 2017). Therefore, these sensors are used to monitor and quantify the feeding behavior of fish (Wang et al., 2013; Zhao et al., 2019) and develop intelligent decision-making and control systems for aquaculture.

Dissolved oxygen (DO) concentration is the main parameters affecting the appetite of fish. The change of the concentration of the DO is due to the change in the flow rate of the water caused by the fish feeding behavior. Wu et al. (2015) developed an adaptive neuro-fuzzy inference system (ANFIS) for decision making in silver perch feeding (Wu et al., 2015). The ANFIS model has an accuracy rate of 97.89% for the actual feeding behavior of fish. This demonstrates that the ANFIS model has considerable potential for success in feeding decisions in aquaculture systems. Temperature is also an important factor affecting the food intake of fish. In order to better meet fishes' food demands, Soto-Zarazúa et al. (2010) designed a feeding system using fuzzy logic control technology to consider water temperature and dissolution according to the age and weight of the fish. The oxygen condition determines the quantification of the food, which saves 29.12% of bait compared with the traditional bait feeder. The growth difference between the cultured fish is also reduced (Soto-Zarazúa et al., 2010). Taking temperature and dissolved oxygen concentration as variables, Zhao et al. (2019) conducted a similar research on the development of a feeding decision system. Compared with an artificial feeding method, there was no significant difference in fish growth ($P > .05$), whereas FCR decreased by 14.35%. In addition, the mean ammonia nitrogen concentration decreased by 22.59%, and the average turbidity increased by 5.5 cm to 28.9 cm, which reduced the eutrophication and pollution of pond water (Zhao et al., 2019).

The above-mentioned studies show that feeding control systems developed using water quality parameters, such as temperature and dissolved oxygen, and fusion technology with fish behavior parameters can indirectly reflect the degree of hunger and accurately follow the feeding needs of fish. These studies have potential implications for reducing feed waste, decreasing FCR, and reducing labor costs in aquaculture.

4.3. Based on electromyogram (EMG) transmitter

In addition to the techniques mentioned above, biotelemetry has made great progress in remote monitoring of physiological parameters (heart rate (Lucas and Priede et al., 1991), tail beat frequency, muscle activation (McFarlane et al., 2004)) of swimming fishes (Andrew et al., 2002). The researchers divided fish into fasting and satiating groups to ensure they had different levels of hunger. Ten-percent of the fish in each group were implanted with an EMG transmitter ($N = 10$; model CEMG-R11–25, Lotek Wireless, Newmarket, Ontario), which detects electro-potentials within the axial red muscle tissue when fed under different starvation states. The results showed that hungry fish in the fasting group had significantly higher levels of muscle activity during feeding than those in the satiated group (McFarlane et al., 2004). Similarly, they used the secondary classifier and SVM to identify and classify the muscle activity of fish with different hunger levels when eating. The average success rate reached 86% (Cubitt et al., 2008).

Studies have shown that these sensors have high precision for identifying hunger status and have great potential in identifying eating behavior. In addition, the fusion of different types of sensor data will provide great potential for higher accuracy of feeding behavior recognition. Table 3 shows aspects of various sensor technologies for identifying dietary behaviors, and their advantages and disadvantages.

5. Conclusion and prospect

This paper reviews and analyses the recent development of fish feeding behavior recognition (assessment of fish feeding intensity) techniques and summarizes the most important technical methods based on computer vision technology and Acoustic-based technology. Computer vision is a real-time, non-invasive, and economical technique for feeding behavior recognition. Its application in aquaculture is still limited by surface reflection and low image quality. Near-infrared imaging quality is not affected by visible light intensity and can address this limitation to some extent. Acoustic-based behavior recognition is not affected by light intensity and water turbidity. However, the accuracy of its application is still generally low and relatively expensive.

The main challenge for the future identification of fish feeding behavior may include how to obtain this information in a complex farming environment and how to improve the accuracy of real-time quantitative grading of different feeding intensity. Modern aquaculture increasingly uses a large number of sensors with different parameters. The current trend in feeding behavior research is to fuse data on advanced sensors to compensate for the lack of information from single-parameter sensors. In addition, progress in the latest classification and grading methods, such as deep learning methods, offers potentials to identify and classify fish feeding behavior. This can address the problems of poor generalization ability with the shallow neural network and insufficient ability to represent complex functions. The method can automatically extract data features, reduce the manual extraction of features, and effectively avoid the incompleteness of manually extracted features, allowing the performance in image recognition to exceed that of the traditional method.

For the foreseeable future, data fusion techniques and deep learning will be applied to the study of fish feeding behavior recognition, and intelligent feeder systems based on the identification of fish feeding behavior will also be developed and applied to modern aquaculture.

Table 3
Summary of methods based on sensors.

Technology	Application	Species	Culture model	Result/accuracy	Advantages/disadvantages	Reference(s)
Acceleration data loggers/ gyroscope	Behavior detection/ fast-start behavior	*C. carpio;* Japanese amberjacks; Great sculpin	Tank; Tank; Laboratory;	Accuracy: > 89.8%; False detection: 5.9 ± 10.9% Success rate: 84%; Accuracy: 90%;	Direct detection, high accuracy/ Contact, damage to fish body	Makiguchi et al., 2012 Noda et al., 2013 Broell et al., 2013
	Identify pray types	Red-spotted groupers; Groupers; *Epinephelus ongus*	Tank; Tank; Tank;	Success rate: 79% (shrimp-eating), 73% (fish-eating); Identification rate: 78.5%; Identification rate: 87.5%		Horie et al., 2017 Tanoue et al., 2012 Noda et al., 2014 Asaeda et al., 2005 Noda et al., 2014
DO sensor/temperature sensor	Feeding decision-making	Tilapia; Silver perch; Grass carp	Tank; RAS; Pond;	Save feed 29.12%; Accuracy: 97.89%; Accuracy: 85.39%; FCR reduced: 14.35%;	High success rate effectively reduces food waste/Susceptible to other parameters	Soto-Zarazúa et al., 2010 Wu et al., 2015 Zhao et al., 2019 Stoner et al., 2006
Electromyogram (EMG) transmitter	Feeding status/ hunger level	Trout; Rainbow trout	Tank; Tank;	Success rate: 78%; Average success rate: 85%	Directly reflects hunger levels; / Contact, damage to fish body	McFarlane et al., 2004 Cubitt et al., 2008 Carroll and Wainwright, 2006

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors would like to thank the editor and reviewers for their valuable input, time, and suggestions to improve the quality of the manuscript. This work was supported by

1. Institute of fishery machinery and instruments, Chinese Academy of Fishery Sciences

   [Grant no. 2017YFD0701702];

2. China Science and Technology Exchange Center [Grant no. 2017YFE0122100-1];
3. Guolian Aquatic Products Development Co. LTD[Grant no. 2017B010126001].

References

FAO, F. A. A. D, 2018. The State of World Fisheries and Aquaculture 2018 - Meeting the Sustainable Development Goals. http://www.fao.org/documents/card/en/c/I9540EN/.

Alavandan, J., Baboo, S.S., 2012. Performance analysis of image fusion techniques for sonar image enhancement. Int. J. Comput. Appl. 43, 28–34. https://doi.org/10.5120/6212-8861.

Al-Jubouri, Q., Al-Nuaimy, W., Al-Taee, M., Young, I., 2017. An automated vision system for measurement of zebrafish length using low-cost orthogonal web cameras. Aquac. Eng. **78**, 155–162. https://doi.org/10.1016/j.aquaeng.2017.07.003.

Alzubi, H.S., Al-Nuaimy, W., Buckley, J., Young, I., 2016. An intelligent behavior-based fish feeding system. IEEE. https://doi.org/10.1109/SSD.2016.7473754.

Andrew, J.E., Noble, C., Kadri, S., Jewell, H., Huntingford, F.A., 2002. The effect of demand feeding on swimming speed and feeding responses in Atlantic salmon Salmo salar L., gilthead sea bream Sparus aurata L. and European sea bass Dicentrarchus labrax L. in sea cages. Aquac. Res. 33, 501–507. https://doi.org/10.1046/j.1365-2109.2002.00740.x.

Ang, K.P., Petrell, R.J., 1997. Control of feed dispensation in seacages using underwater video monitoring: effects on growth and food conversion. Aquac. Eng. 16, 45–62. https://doi.org/10.1016/s0144-8609(96)01012-6.

Ang, K.P., Petrell, R.J., 1998. Pellet wastage, and subsurface and surface feeding behaviours associated with different feeding systems in sea cage farming of salmonids. Aquac. Eng. 18, 95–115. https://doi.org/10.1016/s0144-8609(98)00026-0.

Asaeda, T., Vu, T.K., Manatunge, J., 2005. Effects of flow velocity on feeding behavior and microhabitat selection of the stone Moroko Pseudorasbora parva: a trade-off between feeding and swimming costs. Trans. Am. Fish. Soc. 134, 537–547. https://doi.org/10.1577/t03-083.1.

Atoum, Y., Srivastava, S., Liu, X., 2015. Automatic feeding control for dense aquaculture fish tanks. IEEE Signal Proc. Let. 22, 1089–1093. https://doi.org/10.1109/lsp.2014.2385794.

Ballester-Moltó, M., Sanchez-Jerez, P., Cerezo-Valverde, J., Aguado-Giménez, F., 2017. Particulate waste outflow from fish-farming cages. How much is uneaten feed? Mar. Pollut. Bull. 119, 23–30. https://doi.org/10.1016/j.marpolbul.2017.03.004.

Bégout, M.L., Kadri, S., Huntingford, F., Damsgård, B., Huntingford, F., Jobling, M., et al., 2012. The Tools for studying the behaviour of farmed fish. Aquaculture and behaviors., 2012. The Tools for studying the behaviors of farmed fish. In: Huntingford, Felicity, Jobling, Malcolm, Kadri, Sunil (Eds.), Aquaculture and Behavior. Blackwell Publishing Ltd., pp. 65–86. https://doi.org/10.1002/9781444354614.

Bégout-Anras, M., Lagardere, J.P., 2004. Measuring cultured fish swimming behavior: first results on rainbow trout using acoustic telemetry in tanks. Aquaculture 240, 175–186. https://doi.org/10.1016/j.aquaculture.2004.02.019.

Broell, F., Noda, T., Wright, S., Domenici, P., Steffensen, J.F., Auclair, J.P., Taggart, C.T., 2013. Accelerometer tags: detecting and identifying activities in fish and the effect of sampling frequency. J. Exp. Biol. 216, 1522. https://doi.org/10.1242/jeb.077396.

Brox, T., Malik, J., 2011. Large displacement optical flow: descriptor matching in variational motion estimation. IEEE Trans. Pattern Anal. Mach. Intell. 33 (3), 500–513. https://doi.org/10.1109/TPAMI.2010.143.

Carroll, A.M., Wainwright, P.C., 2006. Muscle function and power output during suction feeding in largemouth bass, *Micropterus salmoides*. Comp. Biochem. Phys. A: Mol. Integr. Physiol. 143, 389–399. https://doi.org/10.1016/j.cbpa.2005.12.022.

Cha, B.J., Bae, B.S., Cho, S.K., Oh, J.K., 2012. A simple method to quantify fish behavior by forming time-lapse images. Aquac. Eng. 51, 15–20. https://doi.org/10.1016/j.aquaeng.2012.05.001.

Chang, C.M., Fang, W., Jao, R.C., Shyu, C.Z., Liao, I.C., 2005. Development of an intelligent feeding controller for indoor intensive culturing of eel. Aquac. Eng. 32, 343–353. https://doi.org/10.1016/j.aquaeng.2004.07.004.

Chu, D., 2011. Technology evolution and advances in fisheries acoustics. J. Mar. Sci. Technol. 19, 245–252.

Conti, S.G., Roux, P., Fauvel, C., Maurer, B.D., Demer, D.A., 2006. Acoustical monitoring of fish density, behavior, and growth rate in a tank. Aquaculture 251, 314–323. https://doi.org/10.1016/j.aquaculture.2005.06.018.

Cubitt, K.F., Williams, H.T., Rowsell, D., McFarlane, W.J., Gosine, R.G., Butterworth, K.G., McKinley, R.S., 2008. Development of an intelligent reasoning system to distinguish hunger states in rainbow trout (Oncorhynchus mykiss). Comput. Electron. Agric. 62, 29–34. https://doi.org/10.1016/j.compag. 2007.08.010.

Delcourt, J., Becco, C., Vandewalle, N., Poncin, P., 2009. A video multitracking system for quantification of individual behavior in a large fish shoal: advantages and limits. Behav. Res. Methods 41, 228–235. https://doi.org/10.3758/brm.41.1.228.

Duarte, S., Reig, L., Oca, J., 2009. Measurement of sole activity by digital image analysis. Aquac. Eng. 41, 22–27. https://doi.org/10.1016/j.aquaeng.2009.06.001.

Farrahi Moghaddam, R., Cheriet, M., 2012. AdOtsu: an adaptive and parameterless generalization of Otsu's method for document image binarization. Pattern Recogn. 45, 2419–2431. https://doi.org/10.1016/j.patcog.2011.12.013.

Føre, Martin, Alfredsen, J.A., Gronningsater, A., 2011. Development of two telemetry-based systems for monitoring the feeding behaviour of Atlantic salmon (Salmo salar L.) in aquaculture sea-cages. Comput. Electron. Agric. 76, 240–251. https://doi.org/10.1016/j.compag.2011.02.003.

Føre, Martin, Alver, M., Alfredsen, J.A., Marafioti, G., Senneset, G., Birkevold, J., Willumsen, F.V., Lange, G., Espmark, Å., Terjesen, B.F., 2016. Modelling growth performance and feeding behaviour of Atlantic salmon (Salmo salar L.) in commercial-size aquaculture net pens: model details and validation through full-scale experiments. Aquaculture 464, 268–278. https://doi.org/10.1016/j.aquaculture. 2016.06.045.

Føre, Martin, Frank, K., Dempster, T., Alfredsen, J.A., Høy, E., 2017a. Using acoustic telemetry to monitor the effects of crowding and delousing procedures on farmed Atlantic salmon (Salmo salar). Aquaculture 495, 757–765. https://doi.org/10.1016/j.aquaculture.2018.06.060.
Føre, Martin, Frank, K., Dempster, T., Alfredsen, J.A., Høy, E., 2017b. Biomonitoring using tagged sentinel fish and acoustic telemetry in commercial salmon aquaculture: a feasibility study. Aquac. Eng. 78, 163–172. https://doi.org/10.1016/j.aquaeng.2017.07.004.
Føre, Martin, Frank, K., Norton, T., Svendsen, E., Alfredsen, J.A., Dempster, T., Eguiraun, H., Watson, W., Stahl, A., Sunde, L.M., Schellewald, C., Skøien, K.R., Alver, M.O., Berckmans, D., 2018. Precision fish farming: a new framework to improve production in aquaculture. Biosyst. Eng. 173, 176–193. https://doi.org/10.1016/j.biosystemseng.2017.10.014.
Foster, M., Petrell, R., Ito, M.R., Ward, R., 1995. Detection and counting of uneaten food pellets in a sea cage using image analysis. Aquac. Eng. 14, 251–269. https://doi.org/10.1016/0144-8609 (94)00006-m.
Gannon, D.P., 2008. Passive acoustic techniques in fisheries science: a review and prospectus. Trans. Am. Fish. Soc. 137, 638–656. https://doi.org/10.1577/T04-142.1.
Garcia, J.A., Rodriguez-Sánchez, R., Fdez-Valdivia, J., Toet, A., 2012. Visual efficiency of image fusion methods. Int. J. Image Data Fusion 3, 39–69. https://doi.org/10.1080/19479832.2011.592859.
Guo, Q., Yang, X., Zhou, C., Li, K., Sun, C., Chen, M., 2018. Fish feeding behavior detection method based on shape and texture features. J. Shanghai Ocean Univ. 27 (2), 181–189.
Hamitouche, Chafiaa, Fracasso, Valerie, Scalabrin, Carla, 1998. Multibeam sonar image processing and three-dimensional analysis of fish schools. J. Acoust. Soc. Am. 103 (5), 2939. https://doi.org/10.1121/1.422190.
Hassan, S.G., Hasan, M., LI, D., 2016. Information fusion in aquaculture: a state-of the art review. Front. Agr. Sci. Eng. **3**, 206. Doi:10.15302/J-FASE-2016111.
Horie, J., Sasakura, T., Arai, N., Horie, J., Ina, Y., Mashino, Y., Mitamura, H., Moriya, K., Noda, T., 2016. Development of a pinger for classification of feeding behavior of fish based on axis-free acceleration data. Techno-Ocean 268–271. https://doi.org/10.1109/Techno-Ocean.2016.7890659. IEEE.
Horie, J., Mitamura, H., Ina, Y., Mashino, Y., Noda, T., Moriya, K., Arai, N., Sasakura, T., 2017. Development of a method for classifying and transmitting high-resolution feeding behavior of fish using an acceleration pinger. Anim. Biotelem. 5. https://doi.org/10.1186/s40317-017-0127-x.
Hu, J., Li, D., Duan, Q., Han, Y., Chen, G., Si, X., 2012. Fish species classification by color, texture and multi-class support vector machine using computer vision. Comput. Electron. Agric. 88, 133–140. https://doi.org/10.1016/j.compag.2012.07.008.
Hung, C., Tsao, S., Huang, K., Jang, J., Chang, H., Dobbs, F.C., 2016. A highly sensitive underwater video system for use in turbid aquaculture ponds. Sci. Rep. 6. https://doi.org/10.1038/srep31810.
Huntingford, F., Jobling, M., Kadri, S., 2012a. Conclusions: Aquaculture and Behaviour. Aquaculture and Behavior. Wiley-Blackwell. Aquaculture and Behavior. pp. 322–332. https://doi.org/10.1002/9781444 354614.
Huntingford, F., Kadri, S., Jobling, M., 2012b. Appetite and feed intake. Aquacult. Behav. 183–210. https://doi.org/10.1002/9781444354614.
Iida, K., Mukai, T., Aoki, Y., Hayakawa, T., 1996. Three-dimensional interpretation of sonar image for fisheries research. Acoust. Imag. 22, 583–588. https://doi.org/10.1007/978-1-4419-8772-3_94.
Jiang, A., Huang, X., Zhang, Z., Li, J., Zhang, Z., Hua, H., 2010. Mutual information algorithms. Mech. Syst. Signal Process. 24, 2947–2960. https://doi.org/10.1016/j.ymssp.2010.05.015.
Jobling, M., Arnesen, A.M., Baardvik, B.M., Christiansen, J.S., Jørgensen, E.H., 1995. Monitoring feeding behaviour and food intake: methods and applications. Aquac. Nutr. 1, 131–143. https://doi.org/10.1111/j.1365-2095.1995.tb00037.x.
Juanes, F., 2002. Listening to fish: an international workshop on the application of passive acoustics in fisheries. Rev. Fish Biol. Fish. 12, 105–106. https://doi.org/10.1023/A:1022698020541.
Jyothi, S., Sucharita, V., Mamatha, D.M., 2013. A survey on computer vision and image analysis based techniques in aquaculture. Digital Image Process. 5 (12).
Keefer, M.L., Caudill, C.C., Johnson, E.L., Clabough, T.S., Boggs, C.T., Johnson, P.N., Nagy, W.T., 2017. Inter-observer Bias in fish classification and enumeration using dual-frequency identification sonar (DIDSON): a Pacific lamprey case study. Northwest Sci. 91, 41–53. https://doi.org/10.3955/046.091.0106.
Kolarevic, J., Aas-Hansen, Øyvind, Espmark, Å., Baeverfjord, G., Terjesen, Bendik, Damsg, B., 2016. The use of acoustic acceleration transmitter tags for monitoring of Atlantic salmon swimming activity in recirculating aquaculture systems (RAS). Aquac. Eng. https://doi.org/10.1016/j.aquaeng.2016.03.002.
Lagardere, J.P., 2000. Feeding sounds of turbot (Scophthalmus maximus) and their potential use in the control of food supply in aquaculture I. Spectrum analysis of the feeding sounds. Aquaculture 251–258. https://doi.org/10.1016/S0044-8486(00)00375-6.
Lagardere, J.P., Mallekh, R., Mariani, A., 2004. Acoustic characteristics of two feeding modes used by brown trout (Salmo trutta), rainbow trout (Oncorhynchus mykiss) and turbot (Scophthalmus maximus). Aquaculture 240, 607–616. https://doi.org/10.1016/j.aquaculture.2004.01.033.
Lammers, M.O., Brainard, R.E., Au, W.W.L., Mooney, T.A., Wong, K.B., 2008. An ecological acoustic recorder (EAR) for long-term monitoring of biological and anthropogenic sounds on coral reefs and other marine habitats. J. Acoust. Soc. Am. **123**, 1720–1728. Doi:https://doi.org/10.1121/1.2836780.
Lecornu, L., Burdin, V., Scalabrin, C., Hamitouche, C., 1998. Fish school analysis from multibeam sonar image processing. IEEE 587–591. https://doi.org/10.1109/OCEANS.1998.725814.
Lee, J., Loo, J., Chuah, Y., Tang, P., Tan, Y., Goh, W., 2013. The use of vision in a sustainable aquaculture feeding system. Res. J. Appl. Sci. Eng. Technol. 6, 3658–3669.
Lekang, Odd-Ivar, 2013. Feeding systems. In: Lekang, Odd-Ivar (Ed.), Aquaculture Engineering. John Wiley & Sons, Ltd., New York, pp. 286–297.
Lekang, Odd-Ivar, 2015. Feeding equipment. In: Allen Davis, D. (Ed.), Feed and Feeding Practices in Aquaculture. Elsevier Ltd., Netherlands, pp. 349–368.
Li, D., Xu, L., Liu, H., 2017. Detection of uneaten fish food pellets in underwater images for aquaculture. Aquac. Eng. 78, 85–94. https://doi.org/10.1016/j.aquaeng.2017.05.001.
Liu, Z., Li, X., Fan, L., Lu, H., Liu, L., Liu, Y., 2014. Measuring feeding activity of fish in RAS using computer vision. Aquac. Eng. 60, 20–27. https://doi.org/10.1016/j.aquaeng.2014.03.005.
Liu, H., Xu, L., Li, D., 2015. Detection and recognition of uneaten fish food pellets in aquaculture using image processing. SPIE 94430G. https://doi.org/10.1117/12.2179138.
Llorens, S., Pérez-Arjona, I., Soliveres, E., Espinosa, V., 2017. Detection and target strength measurements of uneaten feed pellets with a single beam echosounder. Aquac. Eng. 78, 216–220. https://doi.org/10.1016/j.aquaeng.2016.10.008.
López-Olmeda, J.F., Noble, C., Sánchez-Vázquez, F.J., 2012. Does feeding time affect fish welfare? Fish Physiol. Biochem. 38, 143–152. https://doi.org/10.1007/s10695-011-9523-y.
Lucey, S., Navarathna, R., Ashraf, A.B., Sridharan, S., 2012. Fourier Lucas-Kanade algorithm. IEEE Pattern Anal. Mach. Intell. https://doi.org/10.1109/TPAMI.2012.220.
Makiguchi, Y., Sugie, Y., Kojima, T., Naito, Y., 2012. Detection of feeding behaviour in common carp Cyprinus carpio by using an acceleration data logger to identify mandibular movement. J. Fish Biol. 80, 2345–2356. https://doi.org/10.1111/j.1095-8649.2012.03293.x.
Mallekh, R., Lagardere, J.P., 2003. An acoustic detector of turbot feeding activity. Aquaculture 221 (1–4), 481–489. https://doi.org/10.1016/S0044-8486(03)00074-7.
Marti-Puig, P., Serra-Serra, M., Campos-Candela, A., Reig-Bolano, R., Manjabacas, A., Palmer, M., 2018. Quantitatively scoring behavior from video-recorded, long-lasting fish trajectories. Environ. Model. Softw. 106, 68–76. https://doi.org/10.1016/j.envsoft.2018.01.007.
Mattos, B.O.D., Nascimento-Filho, E.C.T., Anjos-Santos, A.D., Sánchez-Vázquez, F.J., Fortes-Silva, R., 2016. Daily self-feeding activity rhythms and dietary self-selection of pirarucu (Arapaima gigas). Aquaculture 465, 152–157. https://doi.org/10.1016/j.aquaculture.2016.09.005.
McFarlane, W.J., Cubitt, K.F., Williams, H., Rowsell, D., Moccia, R., Gosine, R., McKinley, R.S., 2004. Can feeding status and stress level be assessed by analyzing patterns of muscle activity in free swimming rainbow trout (Oncorhynchus mykiss Walbaum)? Aquaculture 239, 467–484. https://doi.org/10.1016/j.aquaculture.2004.05.039.
Miyazaki, T., Masuda, R., Furuta, S., Tsukamoto, K., 2000. Feeding behaviour of hatchery-reared juveniles of the Japanese flounder following a period of starvation. Aquaculture 190, 129–138. https://doi.org/10.1016/s0044-8486(00)00385-9.
Nasirahmadi, A., Edwards, S.A., Sturm, B., 2017. Implementation of machine vision for detecting behaviour of cattle and pigs. Livest. Sci. 202, 25–38. https://doi.org/10.1016/j.livsci.2017.05.014.
Niu, B., Li, G., Peng, F., Wu, J., Zhang, L., Li, Z., 2018. Survey of fish behavior analysis by computer vision. J. Aquac. Res. Dev. 9 (5). https://doi.org/10.4172/2155-9546.1000534.
Noda, T., Kawabata, Y., Arai, N., Mitamura, H., Watanabe, S., 2013. Monitoring escape and feeding behaviors of cruiser fish by inertial and magnetic sensors. PLoS One 8, e79392. https://doi.org/10.1371/journal.pone.0079392.
Noda, T., Kawabata, Y., Arai, N., Mitamura, H., Watanabe, S., 2014. Animal-mounted gyroscope/accelerometer/magnetometer: in situ measurement of the movement performance of fast-start behavior in fish. J. Exp. Mar. Biol. Ecol. **451**: 55–68. Doi:https://doi.org/10.1016/j.jembe.2013.10.031.
Papadakis, V.M., Papadakis, I.E., Lamprianidou, F., Glaropoulos, A., Kentouri, M., 2012. A computer-vision system and methodology for the analysis of fish behavior. Aquac. Eng. 46, 53–59. https://doi.org/10.1016/j.aquaeng.2011.11.002.
Papadakis, V.M., Glaropoulos, A., Kentouri, M., 2014. Sub-second analysis of fish behavior using a novel computer-vision system. Aquac. Eng. 62, 36–41. https://doi.org/10.1016/j.aquaeng.2014.06.003.
Paramo, J., Bertrand, S., Villalobos, H., Gerlotto, F., 2007. A three-dimensional approach to school typology using vertical scanning multibeam sonar. Fish. Res. 84, 171–179. https://doi.org/10.1016/j.fishres.2006.10.023.
Parra, L., Sendra, S., García, L., Lloret, J., 2018. Design and deployment of low-cost sensors for monitoring the water quality and fish behavior in aquaculture tanks during the feeding process. Sensors 18, 750. https://doi.org/10.3390/s18030750.
Parsonage, K.D., 2001. Detection of Fish-Food Pellets in Highly-Cluttered Underwater Images with Variable Illumination. http://hdl.handle.net/2429/13057.
Parsonage, K.D., Petrell, R.J., 2003. Accuracy of a machine-vision pellet detection system. Aquac. Eng. 29, 109–123. https://doi.org/10.1016/s0144-8609(03)00049-9.
Pautsina, A., Císař, P., Štys, D., Terjesen, B.F., Espmark, Å.M.O., 2015. Infrared reflection system for indoor 3D tracking of fish. Aquac. Eng. 69, 7–17. https://doi.org/10.1016/j.aquaeng.2015.09.002.
Polonschii, C., Bratu, D., Gheorghiu, E., 2013. Appraisal of fish behaviour based on time series of fish positions issued by a 3D array of ultrasound transducers. Aquac. Eng. 55, 37–45. https://doi.org/10.1016/j.aquaeng.2013.03.001.
Qian, Z., Wang, S.H., Cheng, X.E., Chen, Y.Q., 2016. An effective and robust method for tracking multiple fish in video image based on fish head detection. BMC Bioinforma. 17. https://doi.org/10.1186/s12859-016-1138-y.
Rakowitz, G., Tušer, M., Říha, M., Jůza, T., Balk, H., Kubečka, J., 2012. Use of high-frequency imaging sonar (DIDSON) to observe fish behaviour towards a surface trawl. Fish. Res. 123-124, 37–48. https://doi.org/10.1016/j.fishres.2011.11.018.
Remen, M., Sievers, M., Torgersen, T., Oppedal, F., 2016. The oxygen threshold for

maximal feed intake of Atlantic salmon post-smolts is highly temperature-dependent. Aquaculture 464, 582–592. https://doi.org/10.1016/j.aquaculture.2016.07.037.
Rillahan, C., Chambers, M., Howell, W.H., Watson, W.H., 2009. A self-contained system for observing and quantifying the behavior of Atlantic cod, Gadus morhua, in an offshore aquaculture cage. Aquaculture 293, 49–56. https://doi.org/10.1016/j.aquaculture.2009.04.003.
Rillahan, C., Chambers, M.D., Howell, W.H., Watson, W.H., 2011. The behavior of cod (Gadus morhua) in an offshore aquaculture net pen. Aquaculture 310, 361–368. https://doi.org/10.1016/j.aquaculture.2010.10.038.
Rountree, Rodney A., Goudey, Clifford, Luczkovich, Joseph J., Mann, David Allen, 2006. Listening to fish:applications of passive acoustics to fisheries science. J. Acoust. Soc. Am. 30, 433–446. https://doi.org/10.1121/1.4786172.
Saberioon, M.M., Cisar, P., 2016. Automated multiple fish tracking in three-dimension using a structured light sensor. Comput. Electron. Agric. 121, 215–221. https://doi.org/10.1016/j.compag.2015.12.014.
Saberioon, M., Gholizadeh, A., Cisar, P., Pautsina, A., Urban, J., 2017. Application of machine vision systems in aquaculture with emphasis on fish: state-of-the-art and key issues. Rev. Aquac. 9, 369–387. https://doi.org/10.1111/raq.12143.
Sadoul, B., Evouna Mengues, P., Friggens, N.C., Prunet, P., Colson, V., 2014. A new method for measuring group behaviours of fish shoals from recorded videos taken in near aquaculture conditions. Aquaculture 430, 179–187. https://doi.org/10.1016/j.aquaculture.2014.04.008.
Skoien, K.R., Alver, M.O., Alfredsen, J.A., 2015. A computer vision approach for detection and quantification of feed particles in marine fish farms. IEEE International Conference on Image Processing, IEEE. https://doi.org/10.1109/ICIP.2014.7025330.
Skøien, K.R., Alver, M.O., Zolich, A.P., Alfredsen, J.A., 2016. Feed spreaders in sea cage aquaculture –motion characterization and measurement of spatial pellet distribution using an unmanned aerial vehicle. Comput. Electron. Agric. 129, 27–36. https://doi.org/10.1016/j.compag.2016.08.020.
Smith, D.V., Tabrett, S., 2013. The use of passive acoustics to measure feed consumption by Penaeus monodon (giant tiger prawn) in cultured systems. Aquac. Eng. 57, 38–47. https://doi.org/10.1016/j.aquaeng.2013.06.003.
Sneddon, L.U., 2007. Fish behaviour and welfare. Appl. Anim. Behav. Sci. I 104, 173–175. https://doi.org/10.1016/j.applanim.2006.09.006.
Soto-Zarazúa, G.M., Rico-García, E., Ocampo, R., Guevara-González, R.G., Herrera-Ruiz, G., 2010. Fuzzy-logic-based feeder system for intensive tilapia production (Oreochromis niloticus). Aquac. Int. 18, 379–391. https://doi.org/10.1007/s10499-009-9251-9.
Stoner, A.W., Ottmar, M.L., Hurst, T.P., 2006. Temperature affects activity and feeding motivation in Pacific halibut: implications for bait-dependent fishing. Fish. Res. 81, 202–209. https://doi.org/10.1016/j.fishres.2006.07.005.
Subakti, A., Khotimah, Z.F., Darozat, F.M., 2017. Preliminary study of acceleration based sensor to record nile tilapia (Oreochromis niloticus) feeding behavior at water surface. J. Phys. Conf. Ser. 795, 12060. https://doi.org/10.1088/1742-6596/795/1/012060.
Swendsen, R., 2017. Thermodynamics, statistical mechanics and entropy. ENTROPY-SWITZ 19, 603.
Tanoue, H., Komatsu, T., Tsujino, T., Suzuki, I., Watanabe, M., Goto, H., Miyazaki, N., 2012. Feeding events of Japanese lates Lates japonicus detected by a high-speed video camera and three-axis micro-acceleration data-logger. Fish. Sci. 78, 533–538.
Tricas, T.C., Boyle, K.S., 2014. Acoustic behaviors in Hawaiian coral reef fish communities. Mar. Ecol. Prog. Ser. 511, 1–16. https://doi.org/10.3354/meps10930.
Ullman, C., Rhodes, M.A., Allen Davis, D., 2019. Feed management and the use of automatic feeders in the pond production of Pacific white shrimp Litopenaeus vannamei. Aquaculture 498, 44–49. https://doi.org/10.1016/j.aquaculture.2018.08.040.
Wang, Y.L., Mai, C.S., Chen, Z.L., Song, Q., Chen, Z.H., Wu, X.L., 2013. Research of intelligent control system for fish-farming. Appl. Mech. Mater. 303–306, 1200–1203. https://doi.org/10.4028/www.scientific.net/AMM.303-306.1200.
Wei, Y.Y., Zheng, D., Hu, L.Y., Zhan, J.M., 2014. Research on intelligent bait casting method based on machine vision technology. Adv. Mater. Res. 1073-1076, 1871-1874. Doi: https://doi.org/10.4028/www.scientific.net/AMR.1073-1076.1871.
Williams, K., Rooper, C.N., Towler, R., 2010. Use of stereo camera systems for assessment of rockfish abundance in untrawlable areas and for recording Pollock behavior during midwater trawls. Fish. B-noaa. 108, 352.
Windsor, S.P., Norris, S.E., Cameron, S.M., Mallinson, G.D., Montgomery, J.C., 2010. The flow fields involved in hydrodynamic imaging by blind Mexican cave fish (Astyanax fasciatus). Part I: open water and heading towards a wall. J. Exp. Biol. 213, 3819–3831. https://doi.org/10.1242/jeb.040741.
Wu, T., Huang, Y., Chen, J., 2015. Development of an adaptive neural-based fuzzy inference system for feeding decision-making assessment in silver perch (Bidyanus bidyanus) culture. Aquac. Eng. 66, 41–51. https://doi.org/10.1016/j.aquaeng.2015.02.001.
Xie, S., Zhang, L., Wang, D., 2003. Effects of several organic acids on the feeding behavior of Tilapia nilotica. J. Appl. Ichthyol. 19, 255–257. https://doi.org/10.1046/j.1439-0426.2003.00451.x.
Xu, X., Zhang, X., 2007. A remote acoustic monitoring system for offshore aquaculture fish cage. IEEE 86–90. https://doi.org/10.1109/MMVIP.2007.4430721.
Zhang, H., Wei, Q., Kang, M., 2014. Measurement of swimming pattern and body length of cultured Chinese sturgeon by use of imaging sonar. Aquaculture 434, 184–187. https://doi.org/10.1016/j.aquaculture.2014.08.024.
Zhao, Jian, Gu, Zhaobin, Shi, Mingming, Lu, Huanda, Li, Jianping, Shen, Mingwei, 2016. Spatial behavioral characteristics and statistics-based kinetic energy modeling in special behaviors detection of a shoal of fish in a recirculating aquaculture system. Comput. Electron. Agric. 127, 271–280. https://doi.org/10.1016/j.compag.2016.06.025.
Zhao, J., Bao, W.J., Zhang, F.D., Ye, Z.Y., Liu, Y., Shen, M.W., Zhu, S.M., 2017. Assessing appetite of the swimming fish based on spontaneous collective behaviors in a recirculating aquaculture system. Aquac. Eng. 78, 196–204. https://doi.org/10.1016/j.aquaeng.2017.07.008.
Zhao, S., Ding, W., Zhao, S., Gu, J., 2019. Adaptive neural fuzzy inference system for feeding decision-making of grass carp (Ctenopharyngodon idellus) in outdoor intensive culturing ponds. Aquaculture 498, 28–36. https://doi.org/10.1016/j.aquaculture.2018.07.068.
Zhong, Z., Ye, W., Wang, S., Yang, M., Xu, Y., 2007. Crowd energy and feature analysis. IEEE 144–150. https://doi.org/10.1109/ICITECHNOLOGY.2007.4290448.
Zhou, C., Zhang, B., Lin, K., Xu, D., Chen, C., Yang, X., Sun, C., 2017. Near-infrared imaging to quantify the feeding behavior of fish in aquaculture. Comput. Electron. Agric. 135, 233–241. https://doi.org/10.1016/j.compag.2017.02.013.
Zhou, C., Lin, K., Xu, D., Chen, L., Guo, Q., Sun, C., Yang, X., 2018a. Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture. Comput. Electron. Agric. 146, 114–124. https://doi.org/10.1016/j.compag.2018.02.006.
Zhou, C., Xu, D., Lin, K., Sun, C., Yang, X., 2018b. Intelligent feeding control methods in aquaculture with an emphasis on fish: a review. Rev. Aquac. 10, 975–993. https://doi.org/10.1111/raq.12218.
Zhou, C., Xu, D., Chen, L., Zhang, S., Sun, C., Yang, X., Wang, Y., 2019. Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision. Aquaculture 507, 457–465. https://doi.org/10.1016/j.aquaculture.2019.04.056.
Zhu, L., Weng, W., 2007. Catadioptric stereo-vision system for the real-time monitoring of 3D behavior in aquatic animals. Physiol. Behav. 91, 106-119. Doi:https://doi.org/10.1016/j.physbeh.2007.01.023.
Zion, B., 2012. The use of computer vision technologies in aquaculture -a review. Comput. Electron. Agric. 88, 125–132. https://doi.org/10.1016/j.compag.2012.07.010.