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Nonintrusive methods for biomass estimation in aquaculture with emphasis on fish: a review

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Abstract

Fish biomass estimation is one of the most common and important practices in aquaculture. The regular acquisition of fish biomass information has been identified as an urgent need for managers to optimize daily feeding, control stocking densities and ultimately determine the optimal time for harvesting. However, it is difficult to estimate fish biomass without human intervention because fishes are sensitive and move freely in an environment where visibility, lighting and stability are uncontrollable. Until now, fish biomass estimation has been mostly based on manual sampling, which is usually invasive, time-consuming and laborious. Therefore, it is imperative and highly desirable to develop a noninvasive, rapid and cost-effective means. Machine vision, acoustics, environmental DNA and resistivity counter provide the possibility of developing nonintrusive, faster and cheaper methods for *in situ* estimation of fish biomass. This article summarizes the development of these nonintrusive methods for fish biomass estimation over the past three decades and presents their basic concepts and principles. The strengths and weaknesses of each method are analysed and future research directions are also presented. Studies show that the applications of information technology such as advanced sensors and communication technologies have great significance to accelerate the development of new means and techniques for more effective biomass estimation. However, the accuracy and intelligence still need to be improved to meet intensive aquaculture requirements. Through close cooperation between fisheries experts and engineers, the precision and the level of intelligence for fish biomass estimation will be further improved based on the above methods.

Key words: acoustics, aquaculture, fish biomass estimation, environmental DNA, machine vision, resistivity counter.

Introduction

Fish as a vital source of nutritious protein, make up of human diet all around the world (FAO, 2018). Fish farming has become one of the fastest growing sectors of food production in recent years (Olsen & Hasan, 2012). In intensive fish farming, the reliable estimation of fish biomass is very important for aquaculture industries. Fish biomass is derived from the total number of fish counted in a specific area of water multiplied by the average weight of fish sampled (Harvey *et al.* 2003), which can be used to predict daily intake demand to avoid under- or overfeeding (Alver *et al.* 2005). Fish biomass data can help aquaculture industries ensure the optimum use of the capital invested in facilities and control water quality affected by overfeeding (Lopes *et al.* 2017). Quantitative estimation of fish biomass forms basis of scientific fishery management and conservation strategies for sustainable fish production (Davison *et al.* 2015; Lorenzen *et al.* 2016; Saberioon & Cisar 2018). Therefore, there is an urgent need for farmers to estimate fish biomass accurately.

The most common biomass estimation procedures are that the average weight of fish in ponds or cages can be obtained by periodic sampling (Chan *et al.* 1998) and the number of existing fish is usually calculated by the discrepancy between the number of fish initially sown and countable dead fish (Rodríguez-Sánchez *et al.*, 2018). Therefore, fish biomass can be estimated by multiplying the average weight by this number (Costa *et al.* 2006). However, manual sampling can cause physical damage or great stress to fish, affecting its welfare and growth (Ashley 2007). In addition, manual sampling is also usually time-consuming, laborious and has an inherent inaccuracy of 15–25% (Klontz & Kaiser 1993), giving rise to an issue of how to obtain fish weight by noninvasive ways. Furthermore, the number of individuals can be obtained under normal conditions, but the number of losses cannot be quantified in the case of extensive deaths, theft or predators. The daily feed intake recorded can be also converted to fish biomass using expected feed conversion ratio (FCR) (Aunsmo *et al.* 2013), which may not be accurate enough. Therefore, using noninvasive, rapid and economically feasible methods for fish biomass estimation is necessary to meet intensive fishery farming requirements.

With the development of new information technologies, researchers and practitioners in aquaculture communities have explored various methods to quantify fish biomass in cages or ponds without manual intervention. The number and types of these methods including machine vision (Hsieh *et al.* 2011; Zion 2012; Shortis *et al.* 2016; Andradi-Brown *et al.* 2016; Saberioon *et al.* 2017; Boldt *et al.* 2018; Wilson *et al.* 2018), acoustics (Rooper *et al.* 2010; Martignac *et al.* 2015; Giorli *et al.* 2018), environmental DNA (Doi *et al.* 2017; Mizumoto *et al.* 2018) and resistivity counter (Sheppard & Bednarski 2015) have been developed rapidly over the past three decades. These methods as a fast, noninvasive, objective and repeatable alternative provide possibility for remotely monitoring fish biomass in aquaculture.

Literature reviews show that there are limited research and development on fish biomass estimation. There is no systematic analysis on various noninvasive methods for fish biomass estimation. Therefore, the objective of this article is to summarize the development of various noninvasive methods that have been used for mass measurement, counting or direct fish biomass estimation over the past three decades, including machine vision, acoustics, environmental DNA and resistivity counter, and their basic concepts and principles are presented. In addition, the advantages and disadvantages of each method are also discussed and summarized. Moreover, the paper discusses and presents the future research directions on developing new methods and techniques to estimate noninvasively fish biomass. Finally, we present a conclusion of these noninvasive methods. This review can help researchers to understand the current development of nonintrusive methods for biomass estimation and provide valuable guidance for how to assess fish biomass, which can help make a significant breakthrough of intensive precision fish farming.

Machine vision-based methods

The application of machine vision instead of human eyes for object recognition has been increased considerably (Shortis 2015). As a noninvasive, objective and repeatable tool, it has been widely employed in aquaculture for size measurement (Naiberg *et al.* 1993; Torisawa & Kadota 2011), mass estimation (Hufschmied *et al.* 2011), species and stock identification (Storbeck & Daan 2001; Zion *et al.* 2007; Spampinato *et al.* 2010; Fouad *et al.* 2013; Shafait *et al.* 2016; Atienza-Vanacloig *et al.* 2016; Siddiqui *et al.* 2017), gender identification (Zion *et al.* 2008), quality assessment (Brosnan & Sun 2004; Dowlati *et al.* 2012), grading (Zhang *et al.* 2014a), behaviour monitoring (Duarte *et al.* 2009; Zhou *et al.* 2017) and counting (Rosen *et al.* 2013; Assis *et al.* 2013; Shortis *et al.* 2016). Fish mass and number are closely related to fish biomass. Therefore, machine vision provides an effective means for monitoring fish biomass remotely under different scenarios. According to light wavelength range, the study of machine vision for fish biomass estimation is mainly focused on different types of light sources including visible light and infrared light.

Machine vision based on visible light

The monocular camera or stereovision system based on visible light offers image information at the pixel level, and then, quantitative information can be extracted and analysed from digital images for object recognition, which has ability to improve the quality of human vision by electrically perceiving and understanding of an image. A typical machine vision system often consists of image acquisition, image processing and statistical analysis procedures (Sun 2016), as shown in Figure 1. As a noninvasive and cost-effective method, it has been widely used in aquaculture over the past two decades (Beddow *et al.* 1996; Hockaday *et al.* 2000; Serna & Ollero 2001; Martinez-de Dios *et al.*, 2003), and three of its major applications are fish mass measurement, counting and direct fish biomass estimation.

Fish mass measurement

Fish size (i.e. length, area, width and perimeter) is a vitally important parameter during different growth stages. Machine vision provides an automatic and effective approach for measuring size, which makes it possible to determine fish mass by size. Until now, weighting is the

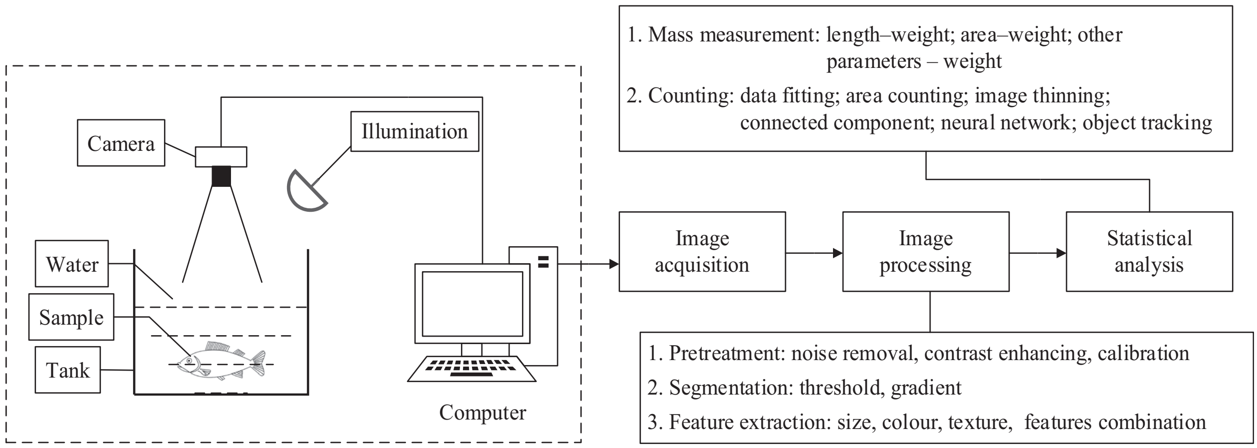

Figure 1 The machine vision system based on visible light for fish biomass evaluation

most common way to estimate fish mass, making it time-consuming, costly, laborious, invasive and resulting poor consistency (Shafry *et al.* 2012; Romero 2015). Therefore, automatic and noninvasive methods for mass measurement are of significant interest to fish farming industry (Viazzi *et al.* 2015). The machine vision has been applied extensively to investigate the relationship between fish size and mass (Petrell *et al.* 1997; Tillett *et al.* 2000; Hong *et al.*, 2014), and the most common models are shown as follows, where W denotes the fish weight, x and x_i represent fish size parameters, a, b and b_i are model parameters. The study of fish size is mainly focused on length, area and other parameters by monocular camera or stereovision system.

$$\text{Polynomial:} \quad W = a + \sum_{i=1}^{n} b_i x_i \tag{1}$$

$$\text{Linear:} \quad W = a + bx \tag{2}$$

$$\text{Power curve:} \quad W = a \cdot x^b \tag{3}$$

Fish length usually equals the length of the line that connects the head tip to the tail tip, which can be measured by linear or nonlinear methods in 2D or 3D (Hao *et al.* 2015). The relationships between fish length (L) and weight (W) have been studied by scholars in recent decades (Froese 1998; Aguirre *et al.*, 2008; Nieto-Navarro *et al.* 2010; Datta *et al.* 2013), and the most representative mathematical equation with L and W is the power model: $W = a \cdot L^{\mathrm{b}}$ (Fulton 1904). Due to simple algorithm, 2D machine vision systems have obvious advantages in obtaining fish mass by the length of fish lateral image (De Verdal *et al.* 2014; Viazzi *et al.* 2015). Some scholars have utilized monocular camera systems only to estimate fish length (Dunbrack 2006; Hsieh *et al.* 2011; Shortis *et al.* 2013; Trobbiani & Venerus 2015; Williams *et al.* 2016). Fish length was extracted from binary images on conveyor belt (White *et al.* 2006; Jeong *et al.* 2013). For curved fish body, Huang *et al.* (2016) adopted fish morphological midline to measure length in chute with mean absolute error of 1.49%. A third-order regression curve approximated to rainbow trout (*Oncorhynchus mykiss*) silhouette was also proposed to estimate curved fish length (Miranda & Romero 2017). Recently, Al-Jubouri *et al.* (2017) designed a dual synchronized orthogonal webcam system to estimate zebrafish length with average error about 1%. In addition, 3D stereovision systems can provide simultaneous views from different positions, which has also been applied for mass estimation of free-swimming fishes (Chan *et al.* 1998; Harvey *et al.* 2001; Martinez-de Dios *et al.*, 2003). And they have been also used to only measure length of free-swimming salmon (*Salmo salar*) (Tillett *et al.* 2000), northern bluefin tuna (*Thunnus thynnus thynnus; Linnaeus*, 1758) (Costa *et al.* 2006; Costa *et al.* 2009) and other fish species (Torisawa & Kadota 2011; Lin *et al.* 2016a). Muñoz-Benavent *et al.* (2017) used stereovision system with deformable model of ventral silhouette proposed by Atienza-Vanacloig *et al.* (2016) to estimate length of bluefin tuna (*Thunnus Thynnus*). However, stereovision system requires many complex algorithms to find the same point for fish length measurement (Pérez García *et al.* 2018). And Rizzo *et al.* (2017) utilized a paired-laser photogrammetric to measure length of small free-swimming benthic fishes with high accuracy. This method has simple calculation, but image optimization is needed to reduce influences of water turbidity and depth.

The relationship between fish area and weight has been reported in numerous studies (Gümüş & Balaban 2010; Zhang *et al.* 2011). Generally, the fish area is computed directly by converting the number of its pixels to cm^2 (Balaban *et al.* 2010b), which can be used to approximatively predict fish weight. For example, Poxton and Goldsworthy (1987) utilized a digital camera to monitor turbot growth based on the weight–area logarithmic relationship. Subsequently, the relationship between fish mass and area from side view also has been studied (Zion *et al.* 1999; Liang & Chiou 2009). And the silhouette area from top-view images was used to predict free-swimming sturgeon mass (Hufschmied *et al.* 2011). The area of fish image is usually uncertain due to the tail fins of fish, and some scholars have considered the effect of this factor on mass (Balaban *et al.* 2010a; Balaban *et al.* 2010b) and proved that removals of tail fins did not improve accuracy. Additionally, De Verdal *et al.* (2014) performed machine vision to estimate the weight of sea bass larvae by lateral area without fins, showing that the model based on area did not perform well, but it is a relatively simple method. In contrast, the model based on area from fish side view without removal of tail fins performed well to predict Jade perch (*Scortum barcoo*) mass (Viazzi *et al.* 2015). These above-mentioned studies show that using fish area can effectively predict its mass, but the accuracy still need to be improved to meet other fish species.

Some researchers have also attempted to extract other parameters, such as height, perimeter and other features (Lines *et al.* 2001). A camera with structured light was used to predict dead flatfish weight by 3D projected volume (Storbeck & Daan 1991), but shadowy regions below objects caused volume errors. To address this issue, several 2D and 3D features extracted from 3D laser vision image were used to predict weight of whole herring (Mathiassen *et al.* 2011). In addition, Beddow *et al.* (1996) adopted stereo camera to predict the weight of Atlantic salmon (*Salmon salar* L.) based on multiple parameters extracted from images with an error of (-0.1 ± 9.0)%. Different subsets of 13 shapes available from top and side views were used to predict fish weight with Support Vector Machine (SVM) (Odone *et al.* 1998; Odone *et al.* 2001). Costa *et al.* (2013) developed partial least squares model based on external shape from fish lateral images to estimate weight of cultured sea bass (*Dicentrarchus labrax*). Unlike Costa *et al.* (2006) and De Verdal *et al.* (2014) adopted 5 shapes extracted from the lateral images of European seabass larvae without fins to estimate its weight. And Viazzi *et al.* (2015) adopted view area, length and height from fish lateral images without tail fins to estimate free-swimming Jade perch (*Scortum barcoo*) mass. Although using more feature variables can improve the accuracy of mass measurement, these models make less robust and prone to errors.

In summary, all the above studies show that fish size is closely related to mass. However, the body of free-swimming fish might be not straight, which makes it inaccurate for length measurement (Huang *et al.* 2016). Therefore, it is necessary to develop bend models for free-swimming fish. Fish segmentation is usually affected by poor image quality, and the advanced algorithms such as deep learning could be developed to overcome this challenge. As the tail fins of fish can directly affect its area (Balaban *et al.* 2010b), effective software for removals of fins tail needs to be developed for more accurate area measurement of fish. Furthermore, image spatial resolution drops sharply as the fish swim away from cameras (Gokturk *et al.* 2004). A device for holding fish underwater could be an effective method for preventing motion variations. Finally, there is no a general model for mass estimation of each species, the optimal model should be individually developed for each species. The detailed information of the aforementioned studies for fish mass measurement is listed in Table 1.

Fish counting

Fish number at various growth stages can be vitally important for farmers in aquaculture, because it can enable the scientific and reasonable preparation of containers for density control and development of a marketing schedule. The general counting methods are hand counting for big fish and weighting counting for fry (Chatain *et al.* 1996). These methods not only are usually time-consuming and laborious but also can cause the stress to fish. According to the review described by Zion (2012), the monocular camera or stereovision system has been widely applied to count fishes by various algorithms.

Back propagation (BP) neural has been proposed to count fish from images (Newbury *et al.* 1995); however, there are some limitations such as artificial fish, no movement and backgrounds without noise in the training sets. To resolve the overlap problem, Zheng and Zhang (2010) presented a fuzzy artificial neural network to efficiently obtain fish counts from picture, which could handle different sized fish and fish overlap. Least Square (LS)-SVM and a BP neural network were used to count overlap fish fry from images (Fan & Liu 2013). The aforementioned studies show that calculation operations are based on nonlinear mathematics theory, which is time-consuming due to extensive computations. In order to simplify complex counting process, the relationship between number of pixels and number of fish was used to count fish fry with relatively simple background (Zhu 2009). The area information of the blobs that marks fish position was used to count fish fry in mostly uniform size (Toh *et al.* 2009). Likewise, Labuguen *et al.* (2012) and Wang *et al.* (2016) used area information of the contours compared with median area to count fish, but water level had to remain shallow to avoid overlap. In addition, Wang *et al.* (2015) adopted a curve evolution method to count turbot fish fry. Inspired by Cheng *et al.* (2014), Li *et al.* (2016) proposed

Table 1 The detailed information for fish mass measurement

Size	Work condition	Machine vision systems		Fish species	Related to weight	Results or accuracy	References
		Camera	Illumination				
Length	Polystyrene board	2D	Fluorescence	*S. barcoo*	YES	$R^2 = 0.96$	Viazzi *et al.* (2015)
	Light table	2D	Natural light	*Dicentrarchus labrax*	YES	$R^2 = 0.930$	De Verdal *et al.* (2014)
	Sea cages	3D	Natural light	—	YES	Error ≤5%	Martinez-de Dios *et al.* (2003)
	Bottom of the chamber	2D	Fluorescent	*Mugil cephalus, Cyprinus carpio, Oreochromis sp.*	NO	$R^2 = 0.950, 0.997, 0.993$	Zion *et al.* (1999)
	Conveyor belt	2D	Artificial lighting	*Solea vulgaris. et al*	NO	1.2 mm standard deviation	White *et al.* (2006)
	Conveyor belt	2D	LED	*flatfish*	NO	Coefficient of variation 0.1%	Jeong *et al.* (2013)
	Chute	2D	Natural light	—	NO	Error = 1.49%	Huang *et al.* (2016)
	Channel	2D	Artificial lighting	*Oncorhynchus mykiss*	NO	Error = 1.413 cm	Miranda and Romero (2017)
	Tank	2D	Natural light	*Zebrafish*	NO	Error = 1%	Al-Jubouri *et al.* (2017)
	Tank	3D	Natural light	*Salmo salar*	NO	Error = 5%	Tillett *et al.* (2000)
	Cage	3D	Natural light	*Thunnus thynnus, Linnaeus, 1758*	NO	Error ≤13%	Costa *et al.* (2009)
	Cage	3D	Natural light	*Thunnus orientalis*	NO	Error ≤5%	Torisawa and Kadota (2011)
		3D	Natural light	—	NO	Error = 5.1%	Lin *et al.* (2016a)
	Cage	3D	Natural light	*Thunnus Thynnus*	NO	$R^2 = 0.962$	Muñoz-Benavent *et al.* (2017)
Area	Bottom of the chamber	2D	Fluorescent	*Mugil cephalus, Cyprinus carpio, Oreochromis sp.*	YES	$R^2 = 0.954, 0.986, 0.986$	Zion *et al.* (1999)
	Board	2D	—	*Taiwan tilapia*	YES	$R^2 = 0.9303$	Liang and Chiou (2009)
	Box	2D	Fluorescent	*Alaskan Salmon*	YES	$R^2 = 0.987$	Balaban *et al.* (2010b)
	Box	2D	Fluorescent	*T. chalcogramma*	YES	$R^2 = 0.99$	Balaban *et al.* (2010a)
	Channel	2D	LED	*sturgeons*	YES	Error = 5.5%	Hufschmied *et al.* (2011)
	Plastic sheet	2D	Natural light	*Dicentrarchus labrax*	YES	$R^2 = 0.963$	De Verdal *et al.* (2014)
	Polystyrene board	2D	Fluorescence	*S. barcoo*	YES	$R^2 = 0.99$	Viazzi *et al.* (2015)
Others	Tank	3D	Natural light	*Salmon salar* L.	YES	Error = (−0.1±9.0)%	Beddow *et al.* (1996)
	Channel	3D	Artificial lighting	—	YES	Error = 3%	Odone *et al.* (2001)
	—	2D	Natural light	*Dicentrarchus labrax*	YES	$R^2 = 0.9772$	Costa *et al.* (2013)
	Light table	2D	Natural light	*Dicentrarchus labrax*	YES	$R^2 = 0.980$	De Verdal *et al.* (2014)
	Polystyrene board	2D	Fluorescence	*S. barcoo*	YES	$R^2 = 0.99$	Viazzi *et al.* (2015)

binarization normed gradients to locate fish from underwater videos and to count them. The endpoints of extracted skeleton based on thinning method were proposed to efficiently count free-swimming fish (Le & Xu 2017), which could resolve fish overlap. However, the underwater environment is usually more complex and fish density is high. The method may not be accurate. For motion background, Fabic *et al.* (2013) proposed blob counting based on connected component labelling to count fishes from underwater video sequences. Recently, Hernández-Ontiveros *et al.* (2018) used properties (area and perimeter) of the connected component to count ornamental fish, which is low cost and easy to handle.

In addition, research attentions have focused on object tracking (Chuang *et al.* 2016; Rodriguez *et al.* 2017; Wang *et al.* 2017), such as deep learning (Xu & Cheng 2017), particle filter (Erikson & Mario 2005), Kalman filter (Sharif *et al.* 2016; Feijó *et al.,* 2018) and the well-known idTracker (Pérez-Escudero *et al.* 2014). For multiple free-swimming fish counting, the trajectory tracking algorithm provides an efficient and reliable way to avoid repeated counting of individual fish in multiple frames (Walther *et al.* 2004; Butail & Paley 2010). For instance, Erikson and Mario (2005) utilized machine vision systems to track and count fishes with Bayesian filtering technique in a controlled environment. The proposed method can operate under severe environmental changes and handle problems such as occlusions. Unlike Erikson, Spampinato *et al.* (2008) and Hossain *et al.* (2016) proposed CamShift algorithm to track and count fishes from underwater videos in unconstrained environments. Inspired by Spampinato *et al.* (2008) and Fier *et al.* (2014) adopted a heuristic blob-tracking algorithm to count fish in their natural habitat. Additionally, Pérez-Escudero *et al.* (2014) utilized a video-tracking software called idTracker to keep the correct identity of each zebrafish during the whole video. Chuang *et al.* (2014) performed trawl-based underwater camera system to track multiple fish by reliable feature-based object matching method.

In summary, machine vision technology provides a non-invasive, repeatable and objective tool for free-swimming fish counting (Denney *et al.* 2017). However, the above-mentioned studies have disadvantages. For instance, a single camera is not adequate to capture the entire area for fish number. Therefore, multiple camera systems are required to integrate images at different positions to provide comprehensive perspective using image synthesis. In addition, there are still some challenges such as fish overlap, poor light, turbidity, bubbles and other factors, making it difficult for foreground segmentation. Appropriate tuning images and new algorithms such as deep convolutional neural networks for crowed counting could be used to resolve this issue. Due to low frame rate, entrance/exit of the view field of fish is frequent, making traditional multitarget tracking algorithm infeasible. Therefore, it is necessary to use a high frame rate camera to improve the accuracy. The algorithms for counting fish are presented in Table 2.

Direct fish biomass estimation

Direct fish biomass estimation means that fish biomass weight (M) can be obtained directly by fish biomass volume (V) times fish biomass density (ρ), namely $M = \rho{\cdot}V$, and the fish biomass volume can be obtained directly by laser scanning system. With the rapid development of machine vision system, the combination of laser systems with visual methods has been widely used for object inspection. Since the mid-1990s, the laser scanning technology known as light

Table 2 Principal methods for counting fish

Methods	Machine vision systems		Fish species	Results or accuracy	References
	Camera	Illumination			
Neural network	2D	—	Synthetic fish	94% accuracy	Newbury *et al.* (1995)
	2D	—	Fish	95% accuracy	Zheng and Zhang (2010)
	2D	LED light	Fish fry	98.73% accuracy	Fan and Liu (2013)
Data fitting	2D	Artificial light	Fish fry	95% accuracy	Zhu (2009)
Area counting	2D	LED light	Fish fry	Above 95% accuracy	Labuguen *et al.* (2012)
	2D	LED light	Fish fry	Relative error 7.4%	Wang *et al.* (2016)
Curve evolution	2D	LED light	*Turbot* fish fry	Approaching 100%	Wang *et al.* (2015)
Fish localization	2D	Natural light	—	97.1% recall	Li *et al.* (2016)
Image thinning	2D	LED light	—	Error less than 6%	Le and Xu (2017)
Connected Component	2D	Fluorescent	*Guppies, Mollies*	Accuracy up to 96.64%	Hernández-Ontiveros *et al.* (2018)
	2D	Natural light	—	Error less than 10%	Fabic *et al.* (2013)
Object tracking	2D	Natural light	—	81%	Erikson and Mario (2005)
	2D	Natural light	—	Accuracy as high as 85.72%	Spampinato *et al.* (2008)
	2D	Artificial light	*Sablefish*	Precision of 83.8%	Fier *et al.* (2014)
	3D	LED light	—	Accuracy 88%	Chuang *et al.* (2014)

detection and ranging (LiDAR) has developed rapidly in aquaculture, which can quickly obtain scanning object surface model. Compared with photogrammetry which needs personal interpretation to obtain characteristics of objects, the laser scanning technique makes automatic and intensive sampling of target surface possible in a short time (Pfeifer & Briese 2007). Laser with certain patterns is applied to measure distances between objects and sensors. A laser scanner can project structural light onto the surface of objects, and a large amount of XY or XYZ coordinates of object's surface can be obtained to represent its shape, which has been widely applied in agriculture (Igathinathane *et al.* 2010), especially in aquaculture. A digital camera with laser was first proposed to monitor flatfish spatial distribution (Duarte Ortega *et al.* 2007). Assuming that the fish density is the same that of waters, this technology was adopted by Almansa *et al.* (2012) to monitor total fish biomass transformed by volume of fish layer. However, fish size and density were not considered. Afterwards, Almansa *et al.* (2015) utilized laser scanning system to measure total biomass of Senegalese sole with different fish size and density, the coefficient of variation was less than 7.2%. And Lopes *et al.* (2017) also described an autonomous system based on a camera and two red line lasers (projectors) equipped with a line beam to perform indoor fish farming biomass estimation in real time with approximate 5% to 17% of relative error.

The laser scanning technology has proven to be a noninvasive and promising tool for estimating total fish biomass almost in real time. Although the limitations that laser scanner with automatic image analysis has are homogeneity of illumination and the presence of unwanted noise such as bubbles, the laser scanner system is convenient and feasible to allow operations to be repeated periodically and frequently for discarding bad images for biomass estimation. However, fish biomass estimation depends on the values of density and volume. An approximate real biomass density value and the developments of specific image analysis software are necessary to improve the accuracy. In addition, the laser scanner system is a large, heavy machine. Therefore, there is need to integrate inertial measurement device to simplify the platform implemented in intensive aquaculture for fish biomass estimation.

Machine vision based on infrared light

Infrared light known as nonvisible light is an electromagnetic wave whose wavelength between 760 nm and 1 mm. With advances in computer technology, machine vision based on infrared light has developed rapidly, which has been used to count fish in aquaculture. It provides a noninvasive means for counting fish and analysing behaviour, which is relatively simple and plays an important role in the development of effective method for fish biomass estimation. Machine vision based on infrared light includes fish counter and near-infrared (NIR) camera for fish biomass estimation.

The fish counter that is not affected by visible light intensity was developed in the early 1990s, consisting of a scanner unit, control unit and computer (Shardlow & Hyatt 2004), as shown in Figure 2. The infrared beam net in scanner unit is generated between two scanning plates inside frame where a series of infrared light diodes are positioned to send infrared light beams to receivers on other side. The fish are forced to swim through the scanner unit, breaking a finely spaced lattice of infrared beams and generating shadow silhouette (Cadieux *et al.* 2000; Ferrero *et al.* 2014). However, the infrared light attenuates more rapidly in waters than in the air, especially in the turbid waters, which prevents physically infrared light from penetrating waters to reach scanner units. The effect of turbidity on infrared counter was studied by Santos *et al.* (2008), but it did not determine the critical threshold of water turbidity. In addition, some scholars not only studied the effect of turbidity on accuracy of infrared counter but also investigated passage rates of fish (Baumgartner *et al.* 2010; Baumgartner *et al.* 2012). In summary, fish counter can work effectively in dark environment. However, the short penetration of the rays through the water especially turbid water, restricts its application scenarios. Additionally, fish may be reluctant to swim across such a narrow space (Tillett *et al.* 2000) and small fishes are difficult to be detected (Broersen 2009). Moreover, no difference occurs for counting when many fish pass through simultaneously infrared counter because these fish are detected as single fish. Therefore, the developments of hardware and software of fish counter are still needed to further improve accuracy.

Near-infrared (NIR) camera has been used for monitoring fish feeding behaviour in tanks or cages (Zhou *et al.* 2017; Zhou *et al.*, 2018a, 2018b). It has been used to track fishes in three-dimensional environment (Pautsina *et al.* 2015; Saberioon & Cisar 2016; Saberioon & Cisar 2018). The principle is based on the absorption of near-infrared light in water resulting different brightness (Zhou *et al.*, 2018a). Counts of analysed fish from images can be generally provided as a by-product. Compared with stereovision systems, the near-infrared camera system requires no calibration, providing information in real time even if there is relatively dim light. Although it can be used to identify position in 3D space, fish occlusion remains a problem in high-density rearing units. The system combined with other imaging systems need to develop to resolve this issue. Additionally, the system provides the opportunity to develop a practical and affordable method for 3D tracking of fish movements. However, because of absorption, refraction and scattering of near-infrared light (Lin *et al.* 2017), it has lower accuracy of vertical dimension. Therefore, there is a need to improve the capacity to track fishes under conditions of high illumination levels or longer distances.

Acoustics-based methods

Compared with light waves, acoustic waves can travel long distances through water (Martignac *et al.* 2015), making it the best way to remotely detect and identify objects in waters. With the development of acoustics technologies, the application of acoustics as a remote sensing tool has rapidly increased, particularly in protection zones. Recently, acoustics has been widely used in spatio-temporal distribution behaviours (Tanoue *et al.* 2008; Zare *et al.* 2017), species detection (Langkau *et al.* 2012; Mizuno 2015) and fish stock assessment without causing the stress to fishes (Boswell *et al.* 2010; Guillard *et al.* 2012; Jung & Houde 2014; Djemali & Laouar 2017). According to data acquisition methods for fish biomass estimation, acoustics can be divided into active acoustics and passive acoustics (Pujiyati *et al.* 2016).

Active acoustics

The principle of active acoustics is that the transmitter unit emits sound waves at a certain frequency into the waters to remotely detect targets. Active acoustics enables to rapidly sample large water volumes. In addition, it can nonintrusively work in dark and turbid waters. Active acoustics technology has been widely used in the investigation and assessment of fishery resources, and the main instruments can be mainly divided into echosounder and sonar camera (Shen *et al.* 2018).

Echosounder

Echosounder can be used to detect targets in waters through the physical characteristics of the target and the water medium. The acoustic waves emitted by the transducer of echosounder propagate in waters. When these waves encounter targets whose density is different from that of environments during transmission, they will be reflected and returns to the receiving array, which is called echo signal. These echo signals scattered back to the transducer are converted back into voltage parameter recorded for analysis (Stanton 2012), as shown in Figure 3. The echosounder has been widely used in fisheries (Lucas & Baras 2000; Guillard *et al.* 2004; Loures & Pompeu 2015; Lin *et al.* 2016b), especially for fish density estimation. By physical characteristic that echo-signal strength is proportional to fish number, the number of

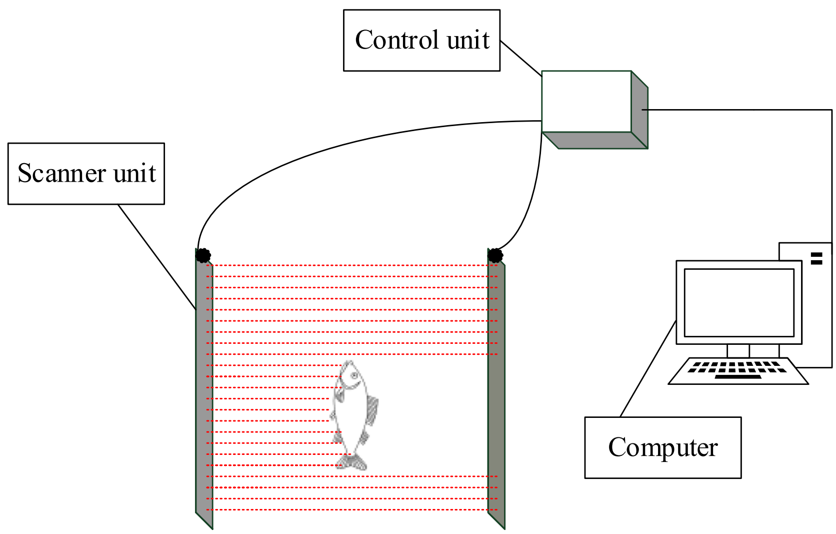

Figure 2 The infrared counter system

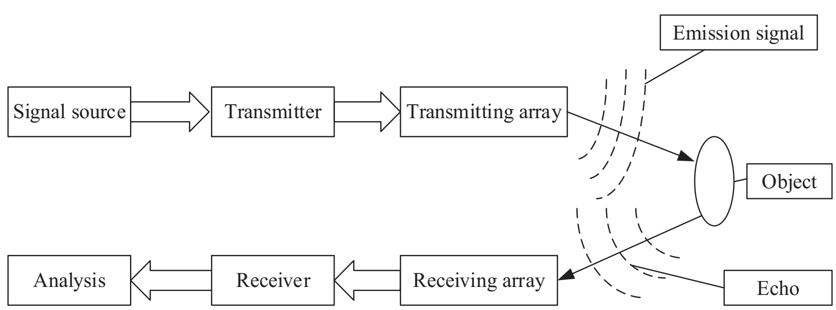

Figure 3 The principle diagram of the echosounder

the fish can be estimated by some techniques such as echo-counting and echo-integration (Johannesson & Mitson, 1983). Currently, the target strength (TS) of fish in natural state can be measured by split-beam technology. When fishes are relatively dispersive and the density is low enough, the echo-counting method is used to measure fish density by dividing the fish number obtained directly from the echosounder by the water volume of the investigation area. Generally, the echo-integration method is used to estimate the number of fishes by dividing the integral value of the echo intensity of fish shoal within the sampled unit area by the TS value of an individual, which is suitable for that when fish are congregating distribution and cannot be easily identified as single fish (Simmonds & MacLennan, 2005).

The split-beam echosounder at certain frequency has been used to assess fish biomass in rivers (Matveev 2007), lakes (Emmrich *et al.* 2010; Lian *et al.* 2018), shallow reservoirs (Djemali *et al.* 2009; Djemali *et al.* 2017) and estuaries (Boswell *et al.* 2008b; Guillard *et al.* 2012). The fish TS plays an important role in fisheries acoustic surveys to convert acoustic data to the number of fishes (Murase *et al.* 2011). However, specific TS/length regression functions have not been determined for different fish species (Godlewska *et al.* 2009). Additionally, understanding factors that influence the fish TS is an essential prerequisite for improving accuracy (Coetzee *et al.* 2008; Zare *et al.* 2017). The above-mentioned echosounders are ineffective to work when echoes are from overlapped fish and reverberant environment such as small tank. A cross-correlation technique based on multiscattering has been proposed to count fish in tanks (De Rosny & Roux 2001; Conti & Demer 2003), where the average effect of the scatters on the acoustic echoes of cavity interfaces are measured to count fish. From multiple reverberation time series, acoustic total scattering cross section of free-swimming fish was proposed by Conti *et al.* (2006) to count fish and monitor growth rate in a tank. In addition, individual fish height was extracted from a time-of-flight analysis of fish echo shape using narrow-bandwidth echosounder for monitoring weight in cages, instead of the relationship between backscattered energy and fish length (Soliveres *et al.* 2017).

Commonly cited advantages of echosounder include that it can rapidly and noninvasively sample large water volumes. However, vessel avoidance and seasonal distribution contributed to biased density estimates. There is a need to sample by small vessels at the appropriate time to limit the potential biases (DuFour *et al.* 2018). Sampling intensity is needed to achieve reasonable levels of precision. In addition, there is a need to filter the noise of the original acoustic image by effective data processing algorithms, and professional trained personnel is required to interpret acoustic data (Boswell *et al.* 2007).

Sonar camera

Sonar camera known as imaging sonar is a recent adaption to convert sound into video images by acoustic sensors. The schematic diagram of imaging sonar is shown in Figure 4. Imaging sonar has the advantage that images can be obtained in dark or turbid waters. Acoustic signals from imaging sonar data are processed to show shapes and outlines of fish by image processing while also providing information on swimming speed or direction (Boswell *et al.* 2008a). Sonar cameras such as dual-frequency identification sonar (DIDSON) and adaptive resolution imaging sonar (ARIS) have been widely used in behaviour monitoring (Rakowitz *et al.* 2012; Becker *et al.* 2013), size measurement and counting (Kang 2011; Petreman *et al.* 2014; Tuser *et al.* 2014; Lin *et al.* 2016b). The area or volume density method is commonly used for fish counting. For example, the formula of volume density method is calculated as follows (Jing *et al.* 2017),

$$N = \left(\sum_{i=1}^{n} N_i \bigg/ \sum_{i=1}^{n} V_i \right) \cdot V \tag{4}$$

where N and N_i denote the total number of fish and the fish number of each route from images through the target tracking and counting methods, respectively. V and V_i represent water storage and the volume swept by sonar camera of each route in units m^3, respectively. n is the number of routes in boat trajectory.

The DIDSON operates at two discrete frequencies consisted of a higher frequency that can produce higher resolution images of objects from close ranges and a lower frequency that detect targets from further ranges with lower resolution images (Burwen *et al.* 2010). Sonar camera could work in almost zero-visibility conditions, which has recently attracted increasing attention (Holmes *et al.* 2006; Kang *et al.* 2012; Hightower *et al.* 2013). Han *et al.* (2009)

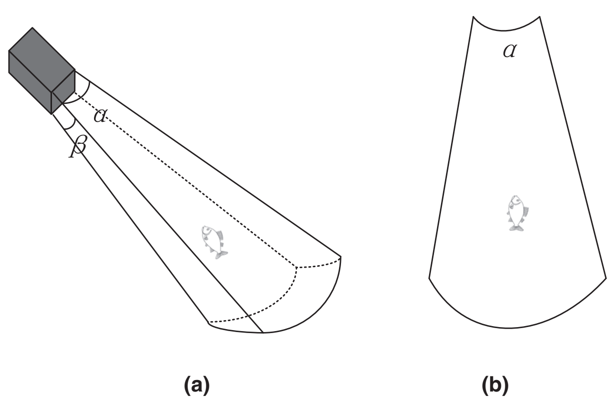

Figure 4 (a) A fish is in the field of view of imaging sonar technique. (b) the imaging results are shown: α is the horizontal view angle and β is the vertical view angle of imaging sonar technique

performed DIDSON systems to automatically count and size free-swimming farmed fish with error of 0–2.4 cm. And Zhang *et al.* (2014b) used DIDSON systems to assess behaviour and length of 10 cultured Chinese sturgeon in cages. But the maximum length found by acoustics was approximate to the length by manual measurement. Jing *et al.* (2017) also proposed the DIDSON to monitor fish abundance with <5% error. In addition, the ARIS was adopted by Shahrestani *et al.* (2017) to count successfully large free-swimming fishes with precision rate of no less than 94%. And García-Magariño *et al.* (2017) utilized a novel agent-based simulator called ABS-FishCount to count fishes through underwater acoustic sensors' network in a wide area.

The sonar cameras can obtain images whose quality approximates that of images obtained by optical cameras even in dark or turbid waters without injury to the fish. These images are sufficient to show shapes and outlines of fish in their habitats (Becker *et al.* 2011). However, the side scan range of the DIDSON is limited and the fish inclination angle in vertical direction may lead to reductions for length measurement (Zhang *et al.* 2014b). Using the maximum length value in each frame as the total length of fish is necessary. In addition, the sonar image is based on echo strength and slant distance from camera's transducer to targets. Therefore, it is very important to deploy the camera head and adjust sonar parameters properly for getting fine image data. Moreover, the environment conditions such as waves and bubbles, can affect the quality of the video images. It is preferable for the sonar camera to operate during good weather days or stay as stationary as possible. Finally, the extreme complexity of acoustic-based procedures, expensive software and processing large data remain major challenges (Shahrestani *et al.* 2017). Hence, special image processing software such as deep learning can be used to address these challenges. If paired with optical video camera systems, the sonar camera identifications could be verified by video images to realize the application of multidimensional information fusion in fisheries.

Passive acoustics

According to Lin *et al.* (2018), passive acoustics is a technology that can be used to listen to sounds by hydrophones that do not emit acoustic signals into waters. The schematic diagram of passive acoustics is drawn in Figure 5. Passive acoustics take advantage of the fact that many species of fishes can produce naturally sounds in various conditions (Gannon 2008). Generally, low-frequency hydrophones that typically convert sound pressure into electrical signals recorded by data acquisition system are utilized to detect and monitor sounds (Rountree *et al.* 2006). Passive acoustics is an active field of ichthyological study in fisheries surveys (Luczkovich *et al.* 2008). The sounds produced by fishes are used to analyse fish behaviours (Mann *et al.* 2008) and quantify fish abundance by specific algorithms.

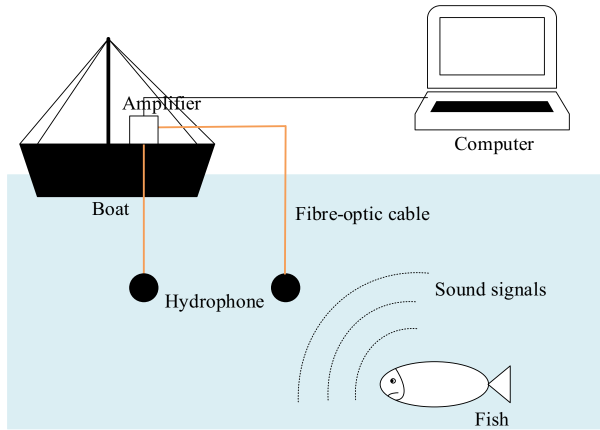

Figure 5 The schematic diagram of passive acoustic work

The cross-correlation technology has been used in communication networks for identifying and localizing nodes. An essential statistical method called the cross-correlation technique for signal processing was proposed to estimate number of fishes in the sea (Rana *et al.* 2014). In this work, the fishes are considered the sources of Chirp Signal. In addition, passive acoustic combined with active acoustic have recently been developed by Rowell *et al.* (2017) to estimate fish abundance or biomass from sound levels at fish spawning aggregations. The results demonstrated that the densities of soniferous fishes could be estimated by sound levels recorded by passive acoustic.

Passive acoustics can be an attractive alternative or supplement to count fishes, which has the ability to collect remotely and inexpensively data over long periods of time (Mann & Lobel 1995). However, the sounds of most species are not produced continuously but produced more commonly at night or during periods of specific behavioural activities such as feeding. At what distance these sounds could be detected is dependent on sound source levels and environmental sound levels. These challenges make interpretation of the results more difficult than those derived from active acoustic (Rowell *et al.* 2015). The potential of passive acoustics has been hampered by a widespread lack of familiarity with the technique and methodologies. Therefore, new developments of hardware and software should be considered to further improve or advance management of fish populations. In addition, in a realistic environment, the environmental noise is mostly periodic noise but fish sounds are random signals. Removing environmental noise using supervised and unsupervised approaches is necessary to improve the accuracy of passive acoustics method.

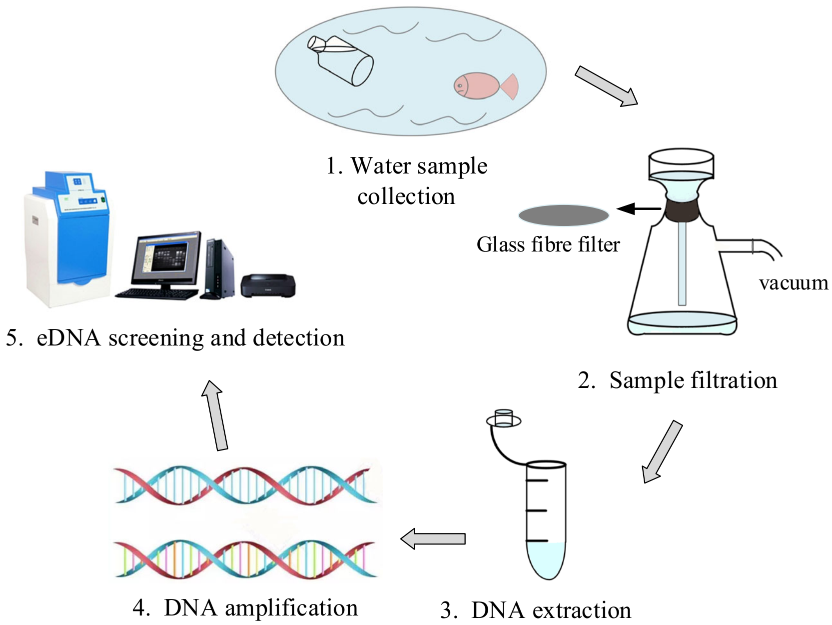

Figure 6 Major steps associated with processing aquatic eDNA samples

Environmental DNA (eDNA)-based methods

The word 'eDNA' has first appeared in the paper of Rondon *et al.* (2000). The eDNA means that the DNA can be extracted from environmental samples without the need to first isolate any interested organism, and it includes the DNA of environmental microorganisms, faeces, urine, mucus, extracellular DNA resulting from the natural death organisms, subsequent destruction of cellular structure and others (Levy-Booth *et al.* 2007; Pietramellara *et al.* 2009). According to metagenomics concept, eDNA technology mainly refers to methods of sequencing analysis with genomic DNA from environmental samples using a set of species-specific primers and probe. Some advances in quantitative real-time polymerase chain reaction (PCR) and next-generation high-throughput sequencing technology further expand application of eDNA technology from the microbiological field to zoological and botanic fields, bringing innovations in research methods and ideas in traditional ecology. There are relatively few studies on aquatic biomass assessment, an important reason is that aquatic animals are mobile, easy to hide and hard to catch in *situ*. However, the eDNA technology provides possibility for aquatic biomass assessment. Fish biomass assessment from water samples involves some basic steps, as shown in Figure 6, and the detailed content of each step is described by Evans and Lamberti (2018). Additionally, the eDNA technique can be used to investigate the presence or absence of aquatic inhabiting lakes and ponds (Doi *et al.* 2015a), rivers (Ikeda *et al.* 2016) and marine habitats (Miya *et al.* 2015) and estimate aquatic distribution and biodiversity (Blaalid *et al.* 2012; Thomsen *et al.* 2012; Thomsen & Willerslev 2015).

The eDNA technology for fish biomass assessment was first proposed by Takahara *et al.* (2012). They assumed that biomass of aquatic vertebrates is proportional to the quantity of eDNA released by vertebrates into waters at a rate. With Type II regression and Type I regression, the carp biomass could be estimated by concentrations of eDNA copies. The results demonstrated that the *carp* biomass was positively correlated with the concentration of eDNA. Since that time, Lacoursière-Roussel *et al.* (2016a, 2016b) had attempted to use the concentration of eDNA for fish abundance estimation in different experimental water sites. In addition, Pilliod *et al.* (2014) elucidated the influence of some factors such as fish size, number, behaviour and water temperature on the concentration of eDNA. Doi *et al.* (2015b) proposed droplet digital PCR (ddPCR) to estimate fish biomass for different numbers of common carp. Compared with quantitative real-time PCR (qPCR), the proposed ddPCR could be more accurate, particularly at low concentration of eDNA. Additionally, Doi *et al.* (2017) utilized two different models to evaluate concentration of eDNA for the abundance of *P. altivelis*. The possible effect of fish size and age on the relationship between the eDNA and fish biomass is not considered. To address this issue, Mizumoto *et al.* (2018) studied the relationship between eDNA concentration and biomass in different age and size of fish, and the results showed the eDNA concentration was significantly correlated with fish size and density.

These studies indicate the great potential of eDNA technology as a useful and cost-effective tool for fish biomass estimation. However, the limiting factor may be the 'knowledge gap' about how environmental conditions such as water chemistry and temperature affect eDNA concentration (Bohmann *et al.* 2014; Murakami *et al.* 2019). Further study should elucidate how fish biomass and environmental conditions influence eDNA dispersion and degradation. In addition, there are some disadvantages such as PCR inhibition for eDNA analysis and false positives of eDNA from wastewater contamination. In future applications, such disadvantages of eDNA technology should be considered. From a technical standpoint, the choice of filters to capture eDNA is also important. At present, the research about the eDNA is still in its infancy, the future development and applications of the eDNA can make significant impact on cost-effective fish biomass estimation.

Resistivity counter-based methods

Resistivity counters have been used as a noninvasive tool to monitor migratory fish populations in waters, which can provide essential information for abundance or biomass. If there is an electric potential between two electrodes in fresh water, a small current is passed through these electrodes. But the small current is affected by the presence of fish because the fish's resistance is lower than water resistance near the electrodes. The resistivity measurement can be carried out by placing two face-to-face conductive plates underwater. When the fish pass through these electrodes, the resistance between two plates will be recorded. The electrical resistivity counter was first proposed by Lethlean (1954) to count fishes automatically. When fish pass through one or more pairs of electrodes in surrounding water, the characteristic changes in electrical resistance will be detected and recorded (Forbes *et al.* 1999; Eatherley *et al.* 2005). The basic schematic view of resistivity counter is shown in Figure 7. The electrical resistivity counters have been extensively applied to monitor fishes at specific points such as rivers or fish passage. The information that the resistivity counters provide has been widely used to monitor long-term trends in fish abundance by scholars (Moores *et al.* 1984; Sheppard & Bednarski 2015). In addition, resistivity counters have also been applied to monitor the impact of environments on migration (Jensen *et al.* 1986; Alabaster 1990) and evaluate fishway utilization and performance.

Resistivity counters have been used as a nondestructive tool for fish counting in certain circumstances. However, some disadvantages such as missed, false and multiple counts, have been noted for electronic resistivity counters (Chatain *et al.* 1996). Resistivity counters also count many fish that pass through simultaneously electrodes as single fish. The resistivity counters combined with optical sensors should be considered to improve accuracy. In addition, the conductivity of fish is relatively stable, while the conductivity of waters varies greatly with discharge. Therefore, the amplitude of signal produced by a fish of a given size at a certain distance above the electrode varies with the conductivity of

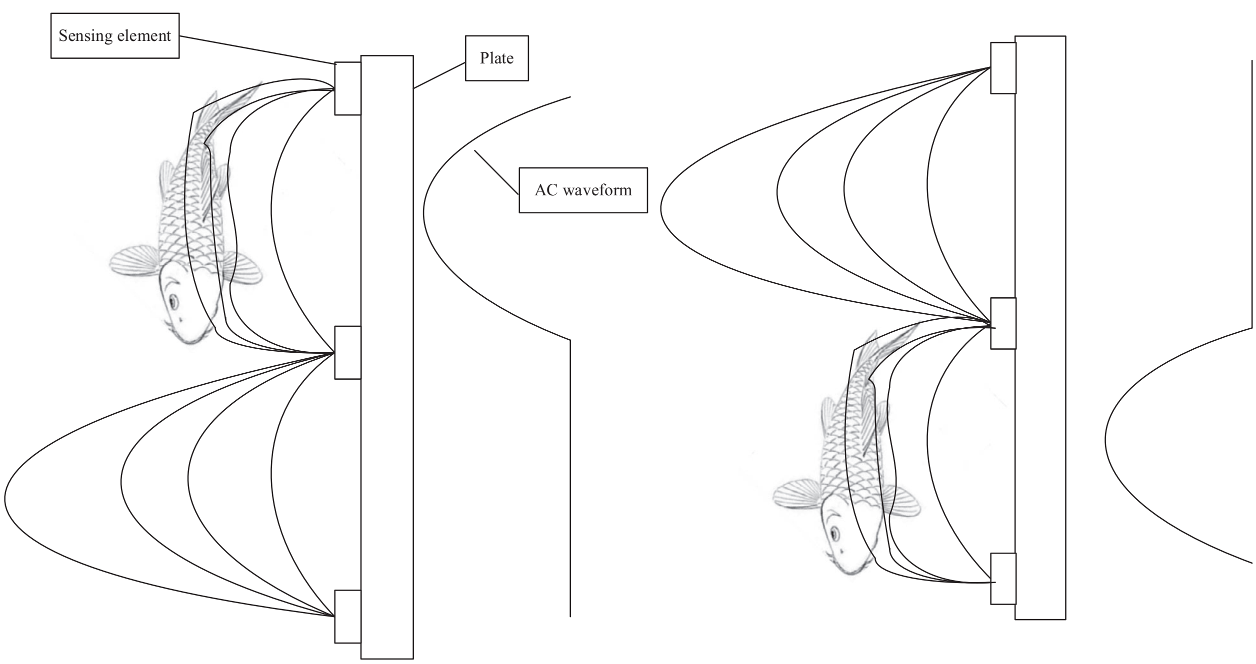

Figure 7 The schematic view of resistivity fish counter using three metal strips

waters, and it becomes smaller as water conductivity increases. For this case, automatic compensation for conductivity variation is necessary so that the detected electrical resistance of fish remains constant regardless of the conductivity of waters. The advantages and disadvantages of each noninvasive method are summarized in Table 3.

Challenges and future perspectives

The information on fish biomass during different growth periods is critical because it allows managers to optimize feeding demands and make effective decisions. However, the acquisition of fish biomass information is very difficult and challenging. One of the major reasons is that fishes are sensitive and freely move in an environment where lighting, visibility and stability are not controllable. Another reason is that estimating fish biomass should not disturb fish growth or cause the stress to fish, which limits the application of some technologies. Manually sampling is usually time-consuming, laborious, invasive and inaccurate. Therefore, using rapid, cost-effective and noninvasive methods for fish biomass estimation is imperative for intensive aquaculture. With the developments of new information technology such as advanced sensors and big data, machine vision, acoustics, environmental DNA and resistivity counter have been developed to improve the automation level in precision fish farming. These noninvasive methods have been applied for fish biomass estimation. However, special limitations of each method still exist. We forecast several different trends in fish biomass estimation to further improve the level of precision farming:

1. *Combining machine vision with acoustics technique* – Machine vision has been widely used as an alternative to measure fish size especially in dead zones where acoustic equipment is inaccessible. However, acoustics techniques being independent of light intensity can be used to count fishes. Therefore, the combination of acoustics technique with machine vision can noninvasively provide information on fish biomass.
2. *Using remote satellite image and geographic information systems (GIS)* - Remote sensing information is often accompanied by the development of prediction models. The remote sensing satellite has been used to estimate chlorophyll in oceans or freshwater, the positive linkages between chlorophyll and fish productivity have been demonstrated (Ware & Thomson 2005). Therefore, remote sensing satellite combined with other information derived from GIS could be further used for fish biomass estimation.
3. *Improving the effectiveness of object recognition using information fusion technique* – The information fusion technique based on colour and thermal images has been used to address the problem about similar colours of objects and backgrounds (Gan *et al.* 2018). To some extent, fish detection is difficult because its colour resembles the background in which they live in. Therefore, a multimodal imaging platform consisting of colour and thermal cameras with the advanced deep learning algorithms could be developed to detect fishes for achieving better biomass estimation.
4. *Expanding and improving the capabilities of underwater acoustic sensors* – A set of underwater sonar sensors named ABS-FishCount simulator was designed to count fish number in a wide area (García-Magariño *et al.* 2017). In future study, the simulator can be extended to measure fish size for the total weight estimation, which can be useful for biomass estimation in aquaculture.

Conclusion

This paper reviews the current development in different noninvasive methods including machine vision, acoustics, environmental DNA and resistivity counters for fish biomass estimation. Based on extensive literature analysis, the paper discusses the advantages and limitations of each method and presents a comparison summary in Table 3. As a rapid, objective and repeatable tool, machine vision can monitor fishes remotely without the stress to fish. However, the application of machine vision based on visible light is limited by the light intensity, object occlusion and other factors. This issue could be solved by machine vision based on infrared light as it can work in relatively poor lighting environment. However, the drawback of infrared systems is the short penetration of the rays through the water, especially in turbid waters. The machine vision based on laser scanning can be used to directly assess fish biomass, but this method can work only for relatively inactive species that remain motionless in bottoms of tank. Compared with machine vision, the advantages of acoustics are that they can work in nearly zero-visibility conditions and rapidly sample large water volumes; therefore, acoustics are highly suitable for use in large-volume culture systems with low light intensity. However, imaging sonar is adversely affected by environmental conditions (e.g. wind, waves and bubbles) or fish density. In addition, it is necessary to trawl for verifying species composition for echosounder. The advantage of eDNA is that it has lower cost and high accuracy. However, the lack of knowledge on how environmental conditions affect eDNA is limiting its current development and applications. The resistivity counter is rapid and nonintrusive, but it is unable to identify species and only work for large fish. With the in-depth integration of information technology and aquaculture, the fusion of optical technology combined with other techniques, some new improved

Table 3 Advantages and disadvantages of different noninvasive methods

Technique	Principle	Application	Advantages	Disadvantages	References
Machine vision					
Single camera	Visible light	Mass counting size	Objectivity, repeatability, high special resolution, cost-effective, in real time	Susceptible to environmental interference and overlaps, the distance between fish and camera is relative constant	Viazzi *et al.* (2015), De Verdal *et al.* (2014), Balaban *et al.* (2010a), Balaban *et al.* (2010b), Hufschmied *et al.* (2011), Costa *et al.* (2013), Hernández-Ontiveros *et al.* (2018)
Stereovision	Visible light	Mass counting size	Objectivity, repeatability, high special resolution, the distance between fish and camera is not constant	Requires complicated processing procedures, not in real time, expensive, susceptible to environmental interference and overlap	Martinez-de Dios *et al.* (2003), Chuang *et al.* (2014), Beddow *et al.* (1996), Odone *et al.* (2001), Odone *et al.* (1998), Denney *et al.* (2017), Shortis *et al.* (2013), Lin *et al.* (2016a)
Laser scanner	Laser based on visible light	Biomass weight size	Repeatability, in real time, directly estimates fish biomass without relying on fish size	Susceptible to illumination irregularities or the presence of unwanted objects	Storbeck and Daan (1991), Mathiassen *et al.* (2011), Almansa *et al.* (2012), Almansa *et al.* (2015), Lopes *et al.* (2017)
Infrared counter, near-infrared camera	Infrared or near infrared	Counting mass size	Cost-effective, regardless of visible light intensity	The short penetration, refraction and scattering of infrared rays	Ferrero *et al.* (2014), Baumgartner *et al.* (2010), Saberioon and Cisar (2016), Saberioon and Cisar (2018)
Acoustics					
Active acoustics	Echosounder	Counting weight	Rapidly sample large volumes of water, regardless of turbidity and light,	Difficulty in species identification, restricted study areas, expensive software, depends on TS/length regression	Lian *et al.* (2018), Djemali *et al.* (2017), Zare *et al.* (2017), Murase *et al.* (2011), Conti and Demer (2003), Conti *et al.* (2006), Soliveres *et al.* (2017)
	Sonar camera	Counting size	High special resolution, independent of turbidity and light	Complex procedures, expensive software, affected by environmental conditions	Han *et al.* (2009), Zhang *et al.* (2014b), Shahrestani *et al.* (2017), García-Magariño *et al.* (2017)
Passive acoustics	Bio-acoustic	Counting biomass	Inexpensive, regardless of turbidity, light	Highly variable sound, insensitivity for silent target	Rana *et al.* (2014), Rowell *et al.* (2017)
eDNA	PCR	Biomass	Cost-effective	Susceptible to environmental conditions such as temperature, PH	Lacoursière-Roussel *et al.*, (2016a, 2016b**)**, Doi *et al.* (2017)
Resistivity counter	Resistance changes	Counting	Low cost	False, multiple counts	Moores *et al.* (1984), Sheppard and Bednarski (2015)

algorithms and special processing software will be developed for estimating noninvasively fish biomass to meet the automation level of precision breeding.

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