Received: 3 March 2020 | Revised: 15 August 2020 | Accepted: 15 September 2020

DOI: 10.1111/are.14907

REVIEW ARTICLE

Aquaculture Research WILEY

Application of computer vision in fish intelligent feeding system—A review

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Funding information
The study presented in the manuscript is supported by the National Key Research and Development Program of China (Project No. 2019YFD0901000).

Abstract

Intelligent feeding will be an important mechanism for future aquaculture breeding, and the establishment of this system will also become a primary concern. At the same time, computer vision is rapidly developing as an effective intelligent feeding system. The combination of the two systems will contribute to increases in aquaculture, and their future development will be based on the innovation and implementation of existing technologies. This review summarizes the application and progress of computer vision in terms of all aspects of the intelligent feeding system, including underwater image preprocessing, fish target detection, fish weight and length detection, fish behaviour analysis and fish intelligent feeding decisions. We have summarized and analysed the methods used in each system to identify more ways to not hinder the senses of researchers and to expand the range of technologies that can be studied. The various research systems have progressed together, which has led to the establishment of intelligent feeding systems and the development of computer vision in intelligent feeding.

KEYWORDS

aquaculture, computer vision, fish behaviour analysis, fish intelligent feeding system, fish target detection, underwater image preprocessing

1 | INTRODUCTION

In recent years, with the rapid development of aquaculture, more people are paying attention to aquaculture (Goldburg et al., 2005). Fish account for the largest proportion of aquaculture, and aquaculture variety and quantity are also increasing (Bosma & Verdegem, 2011). By 2030, two-thirds of the world's fish are estimated to be supplied by aquaculture (FAO, 2018). Therefore, feeding and management of fish are important issues in aquaculture (Bank, 2013). Traditional fish feeding management costs are high (Verdal et al., 2018), labour productivity is low, environmental pressure is high, breeding risks are high, and feeding cannot be adjusted to the special conditions of fish stocks (Cressey, 2009; Edwards et al., 2015). These problems have become more serious over time. At the same time, the continuous increase in labour costs and the ageing of the labour force have exacerbated the issue of low production efficiency of fish farming. Efficient, precise and intelligent aquaculture is the future development direction for aquaculture (Goldburg & Naylor, 2005). Intelligent feeding solves some of the problems with traditional feeding. And the performance of intelligent feeding on all aspects is being gradually improved. Computer vision is an important technology for artificial intelligence (Hu et al., 2015) and has been integrated into all aspects of smart feeding. Computer vision technology can not only improve production efficiency and production quality but also effectively reduce manpower requirements (Liu et al., 2014). It has many applications in fish farming, such as fish target detection, fish measurement and behavioural monitoring. In Zion's review of computer vision in aquaculture (Zion, 2012) and Zhou's review of intelligent feeding methods in aquaculture (Zhou et al., 2017), two people summarized the solutions to aquaculture-related problems from different perspectives. Some of the traditional feeding problems are handled by smart feeding methods. For example, Navarro et al. discuss the relationship between length and weight of different fish species (Navarro et al., 2010). This can be used as a major indicator of fish growth structure and growth status, and is more accurate and effective than traditional feeding assessment of fish growth status. Rodríguez et al. used artificial neural networks and computer vision techniques to measure fish behaviour while rebuilding fish movements (Rodríguez et al., 2011). This also solves the problem that traditional feeding cannot monitor the behaviour of fish in real time, and cannot adjust the feeding strategy for fish behaviour changes. There are also many new methods for intelligent feeding in aquaculture that address many of the problems associated with traditional feeding and are mentioned in both reviews. Compared with traditional feeding, intelligent feeding reduces costs and has the same efficiency without subjective changes in the feeding strategy due to changes in the surrounding environment. When feeding at sea, intelligent feeding reduces the risks caused by uncertainties at sea (Wei et al., 2020). Intelligent feeding can also adjust the feeding system strategy in real time according to various environmental factors such as water temperature, water quality, weather and changes from fish growth and appetite to achieve optimal conditions for fish growth. To date, scholars have performed many studies on intelligent feeding, including factors affecting fish feeding, fish behaviour analysis, biomass prediction, size and quality measurements, and fish target detection.

There are many ways to establish a fish feeding system, collect information on it and finally obtain the best decision for feeding. Based on the process of intelligent fish feeding systems, this paper summarizes computer vision in underwater image preprocessing, fish target detection, fish weight and length detection, fish behaviour analysis, fish feeding decisions, etc. Each method has its own advantages, and the information obtained from each method is not the same. Over time, the technology will be updated. We hope to determine the direction of the next steps and combine the experience based on the preceding methods to contribute to the development of a follow-up fish feeding system.

2 | UNDERWATER IMAGE PREPROCESSING

Underwater image preprocessing is an integral part of building a complete fish feeding system (Zhou, Yang, et al., 2017). It helps in the identification and behavioural monitoring of fish, helping to more accurately determine the timing of feeding and the amount of feed. Undersea fish image preprocessing is also an important research tool in many fish target detection or behavioural analyses (Zhou, Zhang, et al., 2017).

Here, underwater image preprocessing mainly refers to underwater image enhancement. Underwater image enhancement methods generally include contrast colour enhancement or improved image defogging methods (Li et al., 2016). The improved image defogging method can restore the visibility and colour of degraded underwater images. Increasing contrast and brightness can result in improved underwater image details and display more realistic underwater images. In recent years, the methods to improve the defogging and enhancement of underwater images have gradually improved, and various methods have emerged. Traditional image enhancement methods (e.g. contrast-limited adaptive histogram equalization (CLAHE) (Jintasuttisak & Intajag, 2014), generalized unsharp mask (GUM) (Deng, 2011), a probability-based method (PB) (Fu et al., 2014) and dark channel prior theory (He et al., 2011)) are not necessarily suitable for processing in underwater images. The contrast of underwater images is very different from that of other images, and these traditional methods cannot be adequately adapted. However, based on the traditional image enhancement method, there have been many improvements or new methods that are effective in underwater images. Han et al. wrote a review (Han, Lyu et al., 2020). This paper presents the reason for underwater image degradation, surveys the state-of-the-art intelligence algorithms like deep learning methods of underwater image dehazing and restoration, demonstrates the performance of underwater image dehazing and colour restoration with different methods, introduces an underwater image colour evaluation metric and provides an overview of the major underwater image applications. Finally, they summarize the application of underwater image processing. This review provides a more comprehensive overview of the relevant content of underwater images.

Luczynski et al. improved the defogging algorithm in the air, the dark channel algorithm (DCP) (Luczynski & Birk, 2018). Global atmospheric light in the air is white, while underwater colour decays severely. Make improvements to this specific situation and correct the overall RGB of the picture. However, the dehazing algorithm originally applied to the air can be applied to underwater images and to different underwater environments (including a remote operated vehicle (ROV) cage, the Gnalic shipwreck archaeological site and the DexROV mockup), displaying details of the original underwater image that significantly increase the amount of information and with improved robustness. While using white balance and image fusion methods to enhance the image, the quality of underwater images can also be improved with the help of improved underwater image defogging methods (Ancuti et al., 2018). White balance enhances an image by removing the undesired colour castings due to various illumination or medium attenuation properties while using multi-scale fusion of underwater image defogging. This method modifies the underwater image of the white balance to the appropriate input, redefines it using a weight map and finally multi-scales the original input and weight map to obtain the final enhanced underwater image. This method is robust and has a better effect compared with the methods studied by Lu et al. (2015), Fattal (2014), Gibson et al. (2012) and others. The above two researchers' research on underwater images is mainly to reduce the attenuation of underwater image colours, that is, to restore the colour of underwater images. The problem of underwater images goes far beyond this aspect. Li also studied the problem of improved dehazing and enhancement of underwater images (Li et al., 2016). Li proposed an improved defogging algorithm based on the principle of minimum information loss. This method mainly consists of three steps: global background light estimation, intermediate transmission map estimation and adaptive exposure map estimation. Then, using the histogram distribution based on the a priori to propose the contrast enhancement algorithm, after the simulation experiment, qualitative comparison, quantitative comparison and colour accuracy test, the performance of this method was determined to be good; however, there are still limitations. This method is not suitable for all underwater environments, the image is not denoised, and the distance between the object of the water surface has a certain influence on underwater imaging. Ghani et al. proposed a new method to improve contrast and reduce underwater image noise (Ghani, 2014). This method first modifies the image to two main colour models, RGB and hue, saturation and value (HSV). The stretching process of the RGB model conforms to the Rayleigh distribution, the histogram of the blue channel is stretched downward, the red channel extends upward, and the green channel is stretched in both directions over the entire dynamic range. The HSV colour model can significantly improve image contrast, reduce blue-green effects and minimize under saturated and supersaturated regions in the output image. This method was superior to the six most advanced methods at the time: HE (Senthilkumaran & Thimmiaraja, 2014; Yeganeh et al., 2008), ICM (Iqbal et al., 2007), UCM (Iqbal et al., 2010), CLAHE-Mix (Hitam et al., 2013), CLAHS (Eustice et al., 2002), and PDSCC (Naim et al., 2012). Fu et al. used a retinex-based enhancement method to enhance a single underwater image (Fu et al., 2014), primarily to address colour distortion, underexposure and blurring. Then, Zhou et al. used a multi-scale retinex (MSR) algorithm and a greyscale nonlinear transformation method to enhance the image (Zhou, Yang, et al., 2017). The MSR algorithm was first used to process an underwater image to eliminate the effects of dark colour and uneven illumination, and then, the normalized incomplete beta function was used to perform the greyscale nonlinear transformation. The optimal parameters (α and β) based on the image contrast measurement function are automatically selected by the particle swarm optimization algorithm (PSO). This method has a better effect than that to other classical enhancement methods, improving the contrast of underwater images and highlighting dark areas, which facilitates further analysis of these images. Ma et al. improved the CLAHE algorithm used by Jintasuttisak et al. (2014) to make this algorithm more suitable for underwater images (Ma et al., 2017). This method uses the CLAHE algorithm to obtain enhanced images of the YIQ and HIS colour spaces. Two key factors of the enhanced fusion algorithm are the mean and fusion coefficients of the Sobel edge detector. Ma et al.'s approach can provide high-quality underwater image enhancement, primarily for visual enhancement of contrast and entropy but with limitations that are more time-consuming than existing algorithms and have a peak signal-to-noise ratio (PSNR) of less than 30 dB. In recent years, due to the rapid development of deep learning, the application of deep learning methods in underwater images has gradually increased. Islam et al. present a conditional generative adversarial network-based model for real-time underwater image enhancement (Islam et al., 2020). To supervise the adversarial training, they formulate an objective function that evaluates the perceptual image quality based on its global content, colour, local texture and style information. Peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) are classic full-reference image quality evaluation indicators. Take Islam's research experiment results as an example, and compare the processing effects of different algorithms in underwater image enhancement research in Table 1. Han et al's research on underwater image processing and target detection uses a deep CNN-based method (Han, Yao et al., 2020). In this paper, a combination of max-RGB method and shades of grey method is applied to achieve the enhancement of underwater vision, and then, a CNN (Convolutional Neural Network) method for solving the weakly illuminated problem for underwater images is proposed to train the mapping relationship to obtain the illumination map.

TABLE 1 Quantitative comparison for average PSNR and SSIM values on 1K paired test images of EUVP data set

Model	PSNR Input:17.27 $\pm$ 2.88	SSIM Input:0.62 $\pm$ 0.075
Uw-HL	18.85 $\pm$ 1.76	0.7722 $\pm$ 0.066
Mband-EN	12.11 $\pm$ 2.55	0.4565 $\pm$ 0.097
Res-WGAN	16.46 $\pm$ 1.80	0.5762 $\pm$ 0.014
Res-GAN	14.75 $\pm$ 2.22	0.4685 $\pm$ 0.122
LS-GAN	17.83 $\pm$ 2.88	0.6725 $\pm$ 0.062
Pix2Pix	20.27 $\pm$ 2.66	0.7081 $\pm$ 0.069
UGAN-P	19.59 $\pm$ 2.54	0.6685 $\pm$ 0.075
CycleGAN	17.14 $\pm$ 2.65	0.6400 $\pm$ 0.080
FUnIE-GAN-UP	21.36 $\pm$ 2.17	0.8164 $\pm$ 0.046
FUnIE-GAN	21.92 $\pm$ 1.07	0.8876 $\pm$ 0.068

In the improved fogging and enhancement literature of the previously mentioned underwater images in Table 2, the main source of methods is to improve the existing image enhancement methods and each of them has its own advantages and disadvantages. Compared with the present method or other methods, we can clearly find that the processed images are bluish-green on the whole while others are overexposed or dark on the whole from the existed images or the data. After the improvement, these shortcomings are obviously emphasis handled, the overall tone appears normal, the image details are retained, and the amount of information contained in the image is also increased a lot. The technology keeps advancing and the result turns to be better, which is something we should be happy with. However, the general problem of underwater image enhancement cannot be completely solved. This is due to various degradation problems caused by the complex underwater environment, including colour distortion, image fogging, low contrast and severe noise. These degradation problems overlap and cross each other. At the same time, underwater images are diverse. Different types of water have different selection characteristics for light, so light has different degrees of attenuation in different waters. These attenuations result in different degrees of colour distortion in images taken in different waters. In addition, the current underwater image enhancement

TABLE 2 Summary of application methods of computer vision in underwater image preprocessing

Technical method	Data set	Judging index	Advantage	Limit point	Reference
Minimum Information Loss, Histogram Distribution Prior	Blue; Turquoise; Green	*MSE*, PSNR, entropy, patch-based contrast quality index (PCQI) (Wang et al., 2015), underwater colour image quality evaluation (UCIQE) (Yang et al., 2015), processing time (PT)	Can handle different underwater environment image; Less information loss; Fewer artefacts; Clearer details	The result is not perfect under low light; The distance from the scene to the water surface is not considered; Noise effects are not eliminated	(Li et al., 2016)
A variational framework for retinex,	Turquoise; Green; Black & white	*MSE*, PSNR, Information entropy, Comparison of image correction results, LE, WT, HE, CLAHE, GA-based	Address the colour distortion; Address the underexposure and fuzz problem; The proposed approach can enhance other kinds of degraded image; reduces the influence of low and uneven illumination	Image enhancement can also be improved, the computing speed still needs to be improved	(Fu et al., 2014) (Zhou, Yang, et al., 2017)
White balancing, Multi-scale fusion	Blue; Turquoise;		Better exposedness of the dark regions; Improved global contrast; Edges sharpness		(Ancuti et al., 2018)
Contrast-limited adaptive histogram equalization (CLAHE), enhancement fusion algorithm.	Blue; Turquoise;	Mean, contrast, entropy, colourfulness metric (CM), mean square error (*MSE*) and peak signal-to-noise ratio (PSNR)	Suppress noise interference, Improve the image quality, Provide more detail enhancement; Higher values of colourfulness restoration	Algorithm is more time-consuming, Different uniform lighting environment enhancement effects can be optimized	(Ma et al., 2017)
Improved Dark Channel Prior	Blue; Turquoise; Green	Comparison of image correction results,	Good performance and robustness against different conditions and water properties	Need to use bilateral filters to improve the computational cost and speed of DCP; Use white balance correctly to get shaded light	(Luczynski & Birk, 2018)
The revised image formation model	Blue; Turquoise;	Average errors; Comparison of image correction results, mean square error (*MSE*), peak signal-to-noise ratio (PSNR)	The method with the revised model outperforms those using the atmospheric model; The proposed method is better than HE (Senthilkumaran & Thimmiaraja, 2014; Yeganeh et al., 2008), ICM (Iqbal et al., 2007), UCM (Iqbal et al., 2010), CLAHE-Mix (Hitam et al., 2013), CLAHS (Eustice et al., 2002), PDSCC (Naim & Isa, 2012),	Deep nets should perform better than the estimation methods the author used;	(Akkaynak & Treibitz, 2019) (Ghani, 2014)
Deep Learning	EUVP Data set	PSNR, SSIM	Simple yet efficient; The performance of the model is good, and the processing effect is sometimes better.	The training model requires a large data set. The training time of the model is relatively long.	(Islam et al., 2020) (Han F L, 2020)

methods have different problems. For example, model-free underwater image enhancement methods often have problems of over-enhancement and under-enhancement, while model-based methods are superior to simple underwater imaging models and ignore many relevant parameters. This causes a large error in the recovered image. At the same time, although computer vision has achieved good results in many low-level vision problems, due to the lack of underwater data, there is still a lot of room for improvement in computer vision methods in the research of underwater image enhancement.

3 | INDIVIDUAL/GROUP TARGET DETECTION

Target detection of fish during aquaculture is important. Target detection can be used to target individual fish or fish stocks. Target tracking detection can track the trajectory of the fish, thus monitoring the behaviour of the fish, analysing the behaviour of the fish, determining the purpose of the fish and detecting abnormal behaviour (Huanda et al., 2011).

In the fish positioning and detection method developed by Boudhane and Nsiri (Boudhane & Nsiri, 2016), the preprocessing step involves enhancing and denoising underwater images. This is very common in underwater image enhancement and fish target detection research. The denoising process uses a Poisson–Gaussian mixture distribution. Subsequent automatic object detection uses the mean shift algorithm to segment the image, and then, each region of the segmented image is processed independently by statistical estimation by log-likelihood ratio tested. After a comparison of this method of the traditional method, the image preprocessed with this method has better image quality and a clearer effect. The underwater fish recognition framework proposed by Chuang consists of completely unsupervised feature learning technology and error-proof classifiers (Chuang et al., 2016). This nonrigid part model effectively determines the correct object matching part by using significant and slack markers. At the same time, the system optimization algorithm was further developed, and an index benefit function was introduced to select the decision parameter of some classifiers. High precision is achieved under a common data set, with high uncertainty and class imbalance. The tracking system proposed by Spampinato uses Gaussian mixture model and moving average algorithm to automatically detect fish and uses an adaptive mean shift algorithm to track fish (Spampinato et al., 2008). The detection and tracking accuracy are about 85%. Subsequent research by this author was also applied to this method. Pautsina et al. used a new infrared reflection system for indoor 3D tracking to automatically monitor fish (Pautsina et al., 2015). This method estimates fish distance based on the absorption effect of water on the near-infrared (NIR) range of light. The NIR illuminator is used as part of the infrared reflection (IREF) system to monitor fish behaviour in the dark. Although the method used can reduce hardware costs and is less computationally intensive than 3D coordinate estimation algorithms, the accuracy is not high, but it is acceptable for most fish monitoring applications. In addition, there is still much room for improvement. A robust deformable adaptive 2D model based on computer vision is proposed by Vanacloig et al. (2016). A new deformable tuna model suitable for fish can be installed on fish to ensure that tuna is extracted instead of other fish or creatures. The same study by Muñoz-Benavent et al. also proposed a tuna-sized fish bending model (Muñoz-Benavent et al., 2018). This method uses a deformable model based on the stereo vision system and the profile of the fish belly side. The model proposed by Muñoz-Benavent, such as the model proposed by Vanacloig, can also be used to test specific fish. Huanda et al. used the multi-objective moving object tracking algorithm based on linear programming proposed by Jiang et al. (2007) to track the moving targets of fish in aquarium Huanda et al. (2011). This algorithm solves the occlusion problem of the object by introducing various constraints, thereby improving the tracking accuracy. Body colour analysis and monitoring and swimming speed and acceleration monitoring were performed on a number of fish tracked to examine the health of the fish and changes in the growth environment.

TABLE 3 The evaluation results of fish detection

Video	P(%)	R(%)	Number of occlusions	OR(%)	ODR(%)
D1(pH = 6)	99.41	99.26	395	3.95	92.41
D2(pH = 7)	99.75	99.44	205	2.05	92.68
D3(pH = 8)	98.23	98.85	325	3.25	91.38

The flow of the red snapper multi-fish tracking algorithm is as follows (Zhao et al., 2019). In the detection stage, they use the Otsu adaptive segmentation algorithm to extract fish targets based on the background subtraction method, following which the fish tracking feature parameters can be obtained based on the fish geometric features. In the tracking stage, the Kalman filter is employed to first estimate the motion state, and then, the cost function is constructed from the position of the fish body, target area and the direction information. Finally, fish school tracking is realized by the interframe relationship matrix. Among them, the experimental results of target detection under three different water qualities are shown in Table 3. The definition is as follows:

$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$OR = \frac{\text{total number of occlusions}}{\text{total number of target}}$$

$$ODR = \frac{\text{successful number of occlusion detection}}{\text{total number of occlusions}}$$

where TP is the total number of fish targets that are correctly identified in all frames, FP is the total number of fish targets that are error-detected and FN is the total number of mis-detected fish targets.

TABLE 4 Summary of application of computer vision in fish target detection

Technical method	Data set	Judging index	Advantage	Future work	Reference
Unsupervised learning algorithms	Fish4Knowledge data set	Average precision (AP); average recall (AR); accuracy(AC);	High accuracy; high uncertainty and class imbalance; reduces the requirement of human interference;	Make stereo imaging and object part matching helpful to each other;	(Chuang et al., 2016)
Fish bending model	The author shoots at the bottom of the cage	Fitting Error Index (FEI)	High precision; Accurately detect fish of a certain species;	Overlapping fish;	(Muñoz-Benavent et al., 2018) (Vanacloig et al., 2016)
The CamShift algorithm	the EcoGrid videos	Detection Success Rate (DSR); False Negative (FN); False Positive (FP);	In addition to target recognition and tracking, there are other functions.; Satisfactory accuracy;	Improve algorithm efficiency;	(Spampinato et al., 2008) (Liu et al., 2019)
The IREF system	The author uses water tank for experiments	Fish coordinates estimation accuracy; Depth estimation error;	Can detect overlapping fish; Can be detected in low visibility environments; lower hardware cost, less computationally	Correct the speed of the fish by changing the position of the fish and the speed of the water; Can collect more information about fish	(Pautsina et al., 2015)
A Linear Programming Approach	The author uses water tank for experiments	-	Solved the problem of object occlusion; Improve tracking accuracy;	Image quality needs to be improved;	(Huanda et al., 2011)
Data association	The author uses water tank for experiments	P;R;OR;ODR; the correct tracking rate and correct recognition rate	Effectively improve the tracking performance of the fish school under occlusion.	The movement regulation of fish schools under different water quality environments	(Zhao et al., 2019)
Deep learning	From Underwater ROV for marine organisms fishing; A fish school detection method based on YOLO	P;R;	The detection and classification are accurate and fast enough; assist the robot to achieve underwater working operation. Fish detection is also very accurate in dark scenes with far away.	The detection effect of this method applied to computer is not better than other methods.	(Junyu et al., 2018) (Han F L, 2020)

Liu et al. took the bionic fish as the research object and tracked its movement position (Liu et al., 2019). The motion estimation by an improvement mean shift algorithm is added to track the path of the bionic fish on xPC-Target platform. According to dual-target setting, two-dimensional coordinates are converted to three-dimensional coordinates. Han et al.'s research is not only about detecting underwater organisms, but also including more accurate classification (Han, Yao et al., 2020). After the image processing, a deep CNN method is proposed to perform the underwater detection and classification, and according to the characteristics of underwater vision, two improved schemes are applied to modify the deep CNN structure. Shen et al. (Junyu et al., 2018) proposed a deep learning-based method of fish swarm monitoring and positioning by combining computer vision of a deep learning method, and this approach has good detection and recognition ability in complex scenes and environments with weak light intensity.

The target detection of fish is also a special case of nonrigid target detection. The method used for nonrigid target detection can be used as a reference to fish target detection to improve its use or to ensure it is used correctly (Jiayan et al., 2014). In the fish target detection and tracking method described above, the target tracking algorithm used by Huanda et al. (Jiang et al., 2007) is an algorithm for nonrigid target tracking originally applied to water (Huanda et al., 2011). As long as the algorithm is properly transplanted, it can be applied to fish target detection and tracking. At the same time, due to the uncertainty of the underwater environment and the interference of underwater vision (Baig & Gokhale, 2015), the underwater target detection and tracking method have limited limitations in underwater applications, and it is possible to achieve multiple attempts and improvements.

We summary the fish target detection in Table 4, which can more clearly compare the differences between the various methods. The fish target detecting and tracking experimental environments mainly include the laboratory environment (Huanda et al., 2011) and the natural purse Seine environment (Chuang et al., 2016; Boudhane & Nsiri, 2016). The main difference between the them is the interference from the natural environment. Especially in the natural environment, the background mostly contains rocks, corals, Seine nets and other disturbances or muddy water quality, compared with the laboratory environment. These interference conditions make the impact on identifying the fish, so the preprocessing of underwater images in the early stage is needed and helpful (Boudhane & Nsiri, 2016). Since different species of fish have differences in the body shapes, the models established for fish bodies in different literatures are not universal, but the identification in the background of confusion is beneficial, and fish can be detected and tracked more accuracy, with better robustness. There are many difficulties in fish target detecting and tracking, including fish body bending during fish movement, different body angles to the camera, multiple fish overlapping (Baheti et al., 2016; Brazil et al., 2017) or objects blocking (Feng et al., 2019; Koh & Kim, 2017). The influence of the environment and the influence of fish movement have caused the difficulty of detecting and tracking fish targets to rise linearly (Baheti et al., 2016; Brazil et al., 2017). In the computer system, there is a specific value of the matching accuracy and the number of matches. This value will decrease as visibility decreases (Zhang et al., 2020). But in the human visual system, humans can still accurately recognize visual features despite changing light conditions. This is an aspect worthy of researchers to explore the particularity of the human perception system and apply it to computer vision technology.

4 | ESTIMATION OF THE WEIGHT AND LENGTH OF FISH

The length and weight of fish are important parameters in different growth stages of fish. Effectively measuring the length and quality of fish is of great significance of judging the growth of fish (Eric et al., 2007; Robert & Lymbery, 2005; Moutopoulos & Stergiou, 2002). Traditional manual measurement methods are time-consuming, laborious and invasive, affecting the growth of fish (Marcelo et al., 2015). However, the rapid development of computer vision technology provides an effective method of measuring the relationship between fish length and quality (Torisawa et al., 2011), and provides the possibility to determine feeding strategies and changes from the breeding environment (Li et al., 2019). Therefore, many researchers use computer vision technology to measure the length and weight of fish (Romero et al., 2015).

Bayesian stratification method was proposed by Froese to estimate the length–weight relationship (LWR) of fish (Froese et al., 2014). In particular, estimates are provided for the LWR parameters a and b in general as well as by body shape. Konovalov trained two instances of LinkNet-34 segmented convolutional neural network (CNN) (Konovalov et al., 2019). Two instances include fish masks with excluded fins and tails and whole-fish masks. The two CNNs were applied to the rest of the images and yielded automatically segmented masks. The one-factor and two-factor simple mathematical weight-from-area models were fitted on 1,072 area-weight pairs from the first two locations, where area values were extracted from the automatically segmented masks. Torisawa et al. performed 3D measurements on fish (Torisawa et al., 2011), including determining the length and length distribution of fish. This method uses two cameras for monitoring and uses the direct linear transformation (DLT) method to estimate the length of individual fish and the frequency distribution of the length to facilitate the management of farmed fish. However, 3D vision technology requires complex algorithms to measure the length of the same fish, and the computational efficiency of the algorithm is a huge challenge (Perez Garcıa et al., 2018). In addition, under normal circumstances, the body of the fish is not static or has been in a straight state. Therefore, Muñoz-Benavent et al. proposed a tuna-sized fish bending model (Muñoz-Benavent et al., 2018), which can also be used to measure fish length. Table 5 lists the comparison results between the automatic measurement and the real value of different tuna models. Among them, M1 is the comparison model used by Atienza-Vanacloig et al. (2016), and M2, M3 and M4 are the new models proposed by Muñoz-Benavent.

TABLE 5 Muñoz-Benavent's automatic system measurements and ground truth statistical comparison for the different tuna models

	M1	M2	M3	M4
Successful fitting in left video	41,014	48,017	48,312	57,167
Successful fitting in right video	43,962	51,059	51,236	60,750
Automatic measurements	3,845	4,170	4,811	6,706
Automatic measurements per minute of recording	28	31	36	50
Computing time	11h 04'12''	11h 10'54''	11h 56'57''	17h 37'03''
Welch's ANOVA test p-value	0.0012	0.5127	0.5192	0.5278
Kolmogorov–Smirnov test p-value	0.0017	0.1081	0.1503	0.1544

Taken together, all of the above studies can use computer vision technology to measure the length of fish. However, the estimation of fish weight often depends on the model of the relationship between body length and weight. Although some researchers have studied the body length–weight relationship model, the phenotypic changes in fish are often not fixed, and it is difficult to express many changes with fewer parameters. A complex algorithm such as a deep learning network model can be constructed to solve the problem of inaccurate weight estimation caused by large changes in fish body length and fewer parameters. In addition, because the quality of fish is the key to the amount of bait feeding on aquaculture (Batzina et al., 2020), it has also become a part of the aquaculture intelligent feeding system that cannot be ignored.

For many years, fish growth models have been able to roughly represent the relationship between fish body length and weight (Demirci et al., 2020; Vincenzi et al., 2020). In addition to using classic statistical models, computer vision methods can also be used to estimate fish weights. The system designed in the form of measuring instruments of physical weight and directly presented on the user's computer (Qashlim et al., 2019). The edge of the object is obtained by contour detection, and the required parameters and bounding box are obtained. Each bounding box edges measured using pixel scale and formulation using Weight Fish Estimation equation. Place the camera at a fixed distance from the fish body and take images of the fish from two angles (Islamadina et al., 2018). The fish is segmented from the background through the growth area algorithm. And extract features of the segmented image. The actual value of the fish sample measured manually is used as the standard, and the value calculated by the computer vision method is calibrated. Also in the earlier period, the study of fish weight classification based on the relationship between fish weight and shape parameters was relatively rough (Odone et al., 2001). The image measurements are taken from top and side views of live fish sliding through a transparent channel. After the training stage, in which a support vector machine learns the relation between fish weight and shape parameters from a small number of examples, the system is able to grade fish at the rate of three fish per second.

5 | FISH BEHAVIOUR ANALYSIS

For aquaculture, one of the way to determine the optimal farming strategy is to observe changes in behaviour (Cade et al., 2020). Changes in the behaviour of fish may be related to their own hunger status, changes in water quality and water temperature, and effects of natural enemies or peers. The behavioural changes caused by different factors need to be observed and summarized to be clear, and then, the growth of the fish population can be optimized by changing the environment or stabilizing the environment. In Table 6, we summary the literature on the use of different computer vision methods to analyse fish behaviour (Rosa et al., 2020).

Spampinato et al. mainly identified fish and abnormal fish behaviour (Spampinato et al., 2010). The fish species tracked by the tracking system are mainly used to understand abnormal behaviour. The tracking layer is used to calculate the fish trajectory, and the classification layer correlates the trajectory with the fish species and then clusters the trajectories to detect abnormal behaviour of the fish. Based on computer vision technology, Papadakis et al. designed a new system to quantify the behavioural changes in fish under various pressures of silver (Papadakis et al., 2012). This system can determine a fish's feeding or escape according to the interaction of the fish and net (including inspection and bite) under different conditions. This method can also quantify and expose any type of chemical stress factor (such as toxins and any industrial agricultural waste materials). In addition to the pressures studied by Papadakis and others, man-made noise may also have a negative impact on fish. The method used by Sadoul can calculate two indicators of fish behaviour through video and analyse the activity of fish populations (Sadoul et al., 2014). The Reynolds model, which was originally applied to flocks and herds, was tested for fish stocks to obtain a true value of the dispersion and swimming speed of each fish. By modifying these two indicators based on fish behaviour, relevant behavioural changes can be quantified. Zhao's kinetic energy model can be adjusted based on the speed of the fish, the steering angle and the area in which it is located so that it has improved performance in the detection of special behaviours (Zhao et al., 2016). This study avoids the complex tracking of individual fish due to the reflection of the surface light flow and can be used to determine the overall condition of the fish population. Xiao et al. monitored water quality based on the swimming speed of fish (Xiao et al., 2015). The tail-beat frequency (TBF) is related to the swimming speed. So it was tested. At the same time, to improve the method, the wall-hitting rate (WHR) is used to characterize behavioural avoidance after exposure. The results showed that TBF can reliably assess water quality. Similarly,

TABLE 6 Summary of application methods of computer vision in fish behaviour analysis

Technical method	Data set	Judging index	Advantage	Future work	Reference
Clustering	Ecogrid Images	Correct Rate (CR) and Error Rate (ER)	Can analyse the abnormal behaviour of fish	Establishing a probabilistic model of typical behaviour by analysing trajectories and also at modelling the scene and at correlating the computed trajectories with this model	(Spampinato et al., 2010)
Statistical analysis	The author uses three water tanks for experiments	Fish interaction (inspection and biting)	Successfully test behavioural changes caused by various stresses; inexpensive and efficient computer vision system;	Eliminate interference by analysing behavioural changes	(Papadakis et al., 2012)
Reynolds model	The author uses water tanks for experiments	Ptot;Adiff;*SD*; (Sadoul et al., 2014)	Sensitive, non-invasive, simple, widely applicable	-	(Sadoul et al., 2014)
a modified kinetic energy model(KEM)	The author built the Rearing Tank and monitoring platform	Human observation; special behaviours including emergent gathering and scattering caused by some stimuli	The good performance in detection of special behaviours	Only verified the feasibility of KEM, there is still room for improvement	(Zhao et al., 2016)
The Wall-hitting rate(WHR)& Tail-beat frequency(TBF)	The author uses water tanks for experiments	Number of fish& Toxin concentration	Reliable toxicity assessment;	Using multiple recorders with multi-angle view to obtain additional data	(Xiao et al., 2015) (Terayama et al., 2017)
T-tests and descriptive statistics	The author uses water tanks for experiments	Significant results; behaviours per observation period by trial	Have some help with the management of farmed fish	Needs to be conducted in the area of the abilities of fish species to adapt to changing environments over an extended period of time; the effects of increased water temperature on the vegetative and biotic prey structure of lakes	(Walberg, 2011)

Terayama proposed a measurement method of tail-beat frequency (TBF) and coast phase (CP) of fish swimming for isolated fish in a school of fish with visual tracking (Terayama et al., 2017), and according to representative features such as TBF and CP to analyse the movement of fish. Walberg studied the effects of elevated water temperatures on the feeding behaviour and living environment of warm water fish (Walberg, 2011). Behavioural changes were recorded, and observation bias was reduced by using scan samples and ethics maps. This recorded the significance and average number of behaviours of Pomoxis nigromaculatus and Ameiurus melas in seven behavioural states. These behavioural states include the following: Combined Feeding, Floating In Open, In Plant Cover, In Brick Cover, Outside Brick, Searching and Swimming.

Fish behaviour monitoring is an important part of a fish feeding system to determine appetite and changes from the surrounding environment. Based on these behavioural changes, the timing and amount of feed the fish took in can be determined, and the living environment of the fish population can be adjusted to the best condition as soon as possible.

Feeding behaviour is the most important area of study for researchers, and they have proposed lots of methods to describe this behaviour clearly, such as swimming speed, swimming direction, and the distribution of path in different depth. In such consideration at the same time, computer vision technology based on deep learning which developed rapidly became the most popular analysis method. The common way is that researchers quantify the feeding behaviour through images or videos which recorded by 2D or 3D camera. Obviously, compared with other methods such as biology sensors and sonar, computer vision is cheaper and easier to make it practicable. Predictably, besides mentioned behaviour, it has implications for studying how to combine behaviour and physical indices closely, for example, to explore the important influence of inner mechanism on the feeding behaviour in different lighting density. This requires not only the video data, but also need to collect the environmental quality parameters. Digging the law from the heterogeneous data fusion to provide precious decision is the meaningful research field in feeding system.

In summary, fish behaviour monitoring is an important part of the fish feeding system, which can be used to judge the hungry situation of the fish and the changes in the surrounding environment. These behavioural changes can be used to determine fish feeding time and feed food amount, and to adjust to optimize their living environment as quickly as possible.

6 | FISH INTELLIGENT FEEDING DECISION

The traditional automatic feeding machine provides a certain amount of feed at regular intervals according to the preset procedure of the keeper and can only be used as a substitute for manual feeding. This machine does not change the feeding strategy in real time based on changes in fish behaviour or environmental changes. Therefore, this traditional automatic feeding is not an intelligent feeding (Alanärä et al., 1996). With the continuous development of artificial intelligence technology, current intelligent feeding is based on various computer vision technologies, sensors and other methods to adjust the program for aquaculture feeding.

Liu et al. determined the feeding behaviour of fish based on the computer vision feeding activity index (CVFAI) (Liu et al., 2014). The CVFAI collects some data, and feeding activity analysis is based on the sum of the strengths of the different frames caused by fish movement. The authors defined the overlap coefficients to calibrate the computational errors caused by the overlap between the fish bodies in the image and proposed a method to filter out the effects of surface reflections on the previous results. According to these data, Liu et al. measured the feeding activities of fish. Atoum et al. continuously controlled the rearing of fish in aquaculture ponds through an effective visual signal processing system (Atoum et al., 2015). Its intelligent feeding mainly includes judging whether fish need to provide the amount of feed and feed. This system initially detects the amount of feed using an associated filter applied to the best local area within the video frame, followed by a SVM-based refinement classifier to suppress the feed of false detections. The intelligent feeding machine designed by Atoum et al. can not only determine the amount of feed the fish needs but also use negative feedback to judge whether the amount of feed fed is too much for the next feeding. In order to minimize food waste and maximize feed conversion rate, AlZub designed an adaptive intelligent feeding machine based on fish behaviour (AlZubi et al., 2016). AlZubi et al. divided an aquarium into a feeding area and a common area. Using the adaptive feeding algorithm, the fish could feed automatically after entering the feeding area, and the fish also could be trained to automatically feed in the feeding area when they are hungry. Zhou's method can use near-infrared computer vision and neuro-fuzzy models to control fish eating (Zhou et al., 2018). Zhou et al. used Delaunay triangulation and image texture to describe and quantify the indicators of fish feeding behaviour in NIR images. At the same time, an adaptive network-based fuzzy inference system (ANFIS) was established based on fuzzy control rules for automatic feeding. However, computer vision requires a high standard for the external environment, and it is difficult to determine the intensity of fish feeding activity in the dark or turbid water through only direct visual observation (Mallekh et al., 2003). Guo et al. (2018) used koi as the experimental object and proposed a method of monitoring fish feeding behaviour based on the shape and texture characteristics of fish images and a back propagation (BP) neural network, and this method provided guidance of precise feeding control in aquaculture. The improved kinetic energy model used by Zhao can quantify the feeding intensity of fish (Zhao et al., 2016). The model is obtained from the discrete degree of fish school and spatial behaviour characteristics. The degree of dispersion is determined by the speed and rotation angle of the fish school (extracted by optical flow method) and the entropy value of the whole-fish school. The spatial behaviour characteristics are calculated based on reflection area of the water surface.

At present, fish feeding decision is mainly based on changes in fish behaviour, including fishtail swing frequency and movement speed. At the same time, some studies will adjust the feeding decision based on the remaining amount of feed. By collecting data related to fish feeding, the hunger of fish stocks can be judged, and feeding decisions can be adjusted based on these data. Also, according to the amount of overfeed caused by the previous feeding decision, the following feeding decision can also be adjusted to meet the optimal condition after a long time of attempting history. But what has to be considered is that the underwater environment is dim and fuzzy. This will affect the data collection. At present, some researchers use computer vision methods to decide the feeding of fish, which is optimistic about the excellent performance of computer vision methods of other research areas. At the same time, the researchers also hope that through more accurate fish feeding decisions, while ensuring the optimal growth state of the fish, the waste of feed is minimized, and the fish grows uniformly to minimize food competition (AlZubi et al., 2016; Atoum et al., 2015).

7 | CONCLUSION

This review summarizes the application of computer vision technology in intelligent feeding, including underwater image preprocessing, fish target detection, fish weight and length detection, fish behaviour analysis and fish intelligent feeding decisions. Each of these aspects has an impact on the establishment of a smart feeding system (Jia, 2019). Underwater image preprocessing enhances image contrast while preserving underwater image details, which can provide powerful input for subsequent research (Han, Yao et al., 2020). Fish growth status can be expressed using changes in fish body length and weight. Part of the fish feeding decision is related to the feeding behaviour of the fish, and changes from the length and weight of the fish can express the quality of the feeding decision. Appropriate feeding decisions can keep the fish's growth trend excellent (Sheng-Wen et al., 2021).

Fish feeding is the most important part of future aquaculture and has many influencing factors (Gasco et al., 2020; Zaki et al., 2020). Fish lives in the water, which is very different from the air that humans have been in contact with for a long time. After underwater image processing, an underwater image is restored to the well-known water image of the greatest extent, making subsequent processing more convenient (Han, Yao et al., 2020). Subsequent processing methods can also be carried out by means of additional water image processing, and the effect is improved and more familiar. Fish live underwater, move fast, are susceptible to environmental disturbances and are difficult to observe. To reduce human interference, monitoring the camera needs to occur to a fixed environment. In regard to monitoring, fish target recognition and target tracking are essential. The conversion to fish in different areas of the water has a certain impact on the monitoring of fish targets. This scenario can be studied through other nonrigid target detection and tracking methods (Huanda et al., 2011). All published papers on transplantation are successful methods, but the number of researchers behind this failure is uncountable. Therefore, similarities should be sought in the process of method transplantation and should not be tried blindly. Expanding the monitoring area, not limiting the method of a fixed environment, innovating and implementing methods can provide greater research space for future research (Junyu et al., 2018; Han, Yao et al., 2020). Among the methods we have summarized, there are relatively few documents related to the detection of fish weight and length. Especially, weight-related research is less, because in the past research, weight-length research occupies a relatively large part. As long as the length of the fish is calculated, the weight of the fish can be roughly inferred according to the growth model formula (Irigoyen-Arredondo et al., 2016; Lamprakis & Kallianiotis, 2003). The use of cameras and other equipment is an important part of fish monitoring and behaviour analysis (Zhao et al., 2016, 2019). We can only use machines to analyse how they move in relation to the state of fish. Therefore, a behavioural analysis of fish is the most important step (Mao et al., 2015). At present, researchers have analysed fish behaviours by detecting external factors, such as hunger status, water temperature and water quality (Papadakis et al., 2012; Walberg, 2011; Xiao et al., 2015). These are undoubtedly important factors influencing the growth of fish, and we hope to identify additional factors that affect the growth of fish to ensure the best quality fish at the lowest cost. With sufficient research in the above areas, we believe that the establishment of a smart feeding system for fish is no longer a problem. After considering the above aspects, we can monitor the growth status of fish at any time, provide the most suitable environment, make feeding decisions according to the physiological needs of fish and provide the best feeding strategy for fish in different growth stages and types.

Research progress of the different aspects of this topic differs, and the advanced level of technology also has obvious limitations. For example, underwater image processing, research and technology are increasingly advanced (Islam et al., 2020; Zhou, Yang, et al., 2017). In comparison, the detection of fish quality and length is limited, there is few people studying this issue, and the technology is limited. The development of fish quality and length detection technology is slow. In the communication with the management and feeding staff of aquaculture, we learned that the weight of fish is estimated to be a pond of fish, and the whole is weighed. This is different from the purpose of computer vision to accurately estimate the length and weight of fish. The actual demand is relatively small, so the progress of the research will be relatively slow. These two aspects are different. In the process of establishing an intelligent feeding system, each aspect has a certain impact on it. On the one hand, even a short board will result in a study of the entire system becoming stagnant, which is the 'buckets effect'. Therefore, we hope that in the research related to intelligent feeding, all aspects can be coordinated, and the development of intelligent feeding is rapid, convenient and comprehensive.

The development of computer vision technology is moving fast, and many new machines or technologies need to be improved in the application of intelligent feeding system need to improve their effort and efficiency, which can be gradually strengthened with time, energy and knowledge (Hu & Wei, 2015; Obe & Omojola, 2015). But there is no single technology that can work through the whole intelligent feeding system but a part of it. This is not easy to overcome, each part has its own role which is completely different than the others, the use of technology also has their own function, using a single technology to solve all the problems is nearly impossible. Therefore, the establishment of the whole system is relatively tedious, and the complexity of the final system will increase by space, which needs optimization. At the same time, most of the applications of computer vision technology are used above the water, when it transplanted under the water it could have many difficulties (Ancuti et al., 2018; Spampinato et al., 2008). The technologies mentioned in the literature, some used to use above the water, but also the contrast experiment shows that it is not suitable for underwater image after modified. The technology that suits to the underwater environment needs to be groped. Aquaculture is one of the main sources of protein (Gasco et al., 2020). Intelligent feeding can assist the success of aquaculture. Intelligent feeding system is one of the important means to achieve the best feeding efficiency in aquaculture. With the premise of no increase in human labour, the growth state of fish could be monitored at any time, and the fish can be fed in the optimal environment with the lowest feeding cost and achieve the optimal growth efficiency.

With the rapid development of computer vision, research on intelligent feeding has gradually increased. Especially for the update of traditional methods, the research progress of intelligent feeding has made great progress. More computer vision methods can help achieve true intelligent feeding. In the future, the research of computer vision will not stop, which also gives a lot of room for the development of intelligent feeding. We hope for more intelligent algorithms in the future that will be applied to the aquaculture industry. At the same time, with the development of the aquaculture industry, more people will study more advanced technologies.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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How to cite this article: An D, Hao J, Wei Y, Wang Y, Yu X. Application of computer vision in fish intelligent feeding system—A review. *Aquac Res*. 2020;00:1–15. https://doi.org/10.1111/are.14907