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The Measurement of Fish Size by Machine Vision- a Review

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Abstract. Aquatic products are becoming increasingly popular because of their high nutritional value. Size information is an important parameter that can be used to measure the growth, weight, gender, grading and even species identification of fish. However, size information is a highly tedious and inefficient measure when conducted manually through traditional methods. Machine vision is a non-destructive, economic, rapid and efficient tool; hence, it is suitable to measure fish size. This review introduced methods and results for fish size measurement through machine vision. The paper is organised according to the measurement of body dimensionality: length measurement and area measurement. Simultaneously, the advantages, disadvantages and future trends of the system are discussed. With development in those areas, the size measurement by machine vision technology will become more effective. Machine vision system brings high accuracy and high efficiency and is easier than manual work. The methods reported can help researchers and farmers bring benefits for aquaculture.

Keywords: machine vision, fish size, fish length, fish area

1. Introduction

Fish and fish products play an important role in meeting human protein demand. To sustainably manage fish resources with high efficiency, fishers have to catch fish appropriately and obtain meaningful information [1]. One important piece of information is fish size^[2], which is a key parameter to appraise stock status, provide management advice and enhance economic benefits for an aquaculture enterprise^[3]. In fish culture, gathering fish size information to describe and manage the growth of fish is necessary to harvest the stock at the optimum time. Furthermore, length distribution of the fish can be used to predict a range of population-level characteristics^[4, 5] and to assess the stock scientifically during rearing^[6-8]. Whether for aquaculture or market purposes, fish grading is an important and frequent operation^[9]. During rearing, fish need to be graded by size; fishers can separate the fast growers from the slow ones to adjust the distribution of food and management to reduce cost^[10-12]. For fish farms to adapt to the market, fish should be sorted by size after harvesting to estimate the value. This step is necessary to set different prices and manage markets conveniently^[13-17]. Simultaneously, size information can be used to monitor quality in the food industry, which can help fishers assess the price. When many kinds of fish are reared in one pond or net, identifying different species is necessary; measuring size information is an important means to enable identification [14, 19, 20]. Size information enables identifying different genders [9, 19, 21] and even estimates the age [22] because of the size difference from different individuals of different genders. Size information can also be used in many other measurement issues. Fish weight is also an important and direct parameter to judge whether the fish is satisfactory [23-26]. Fishers or sellers can measure weight directly and use the high correlation between size and weight to

estimate the weight [16, 27, 28] . The size information also can help to measure biomass and morphology, such as volume [29] and even estimation of fat content [30] . Therefore, fish size is a meaningful parameter that is necessary to determine the size information.

Given the application of fish size, fishers have realised the importance of size information and started to measure fish size by traditional measurement methods. For length data, fishers sometimes estimate length by eye based on experience. Most use a ruler, which has high accuracy, or a roller grader, which is slightly faster [31] . To measure the area, fishers place the fish on a measuring board, draw the fish shape along its edges, and then calculate the amount of forms to estimate the area [31] . This process can also be conducted through electronic measuring boards. These methods are time consuming [32] , labour intensive and inaccurate, with subjective [26] and expensive operation [13] . These methods also cause considerable stress to the fish [4, 33] and raise the risk of related damage [14, 21] or hinder growth by reducing appetite [12, 15] of the fish. Therefore, a simpler, fast and scientific method is urgently needed to collect fish size data [34] .

Machine vision systems have been developed and used in various industries [35] . Machine vision is a non-destructive [5, 36] , rapid [30] , economical [6] , consistent [29] , objective, repeatable [26] , quantitative [37] , relatively efficient and robust tool [38, 39] . It can capture images in real time, analyse these pictures and make decisions to deal with certain questions based on the result [26] . Furthermore, machine vision has been used widely in aquaculture, such as health monitoring, disease detection, behaviour detection, species identification and so on. Fish size measurement by machine vision has been developed and has become popular because of its high efficiency [15] .

This study reviews methods of machine vision technology in fish size measurement, including fish length and fish area. The aim of this study is to converge all the methods, as well as discuss the advantages, disadvantages and future trends. In addition, the study helps other researchers promote the development of machine vision in aquaculture.

2. Image acquisition

For a machine vision system that measures fish size, obtaining images by image acquisition equipment is important. The image acquisition process relies on a specific environment. Several environments are discussed.

2.1 Sonar

Sonar is powerful tool used to obtain images in a wide range of areas [8, 40, 41] . It can be equipped on a ship or a fixed facility to measure fish schools or large fish [42] . However, image quality captured by sonar is not very high, and a sonar system is costly [43, 44] . The system is illustrated in Fig. 1.

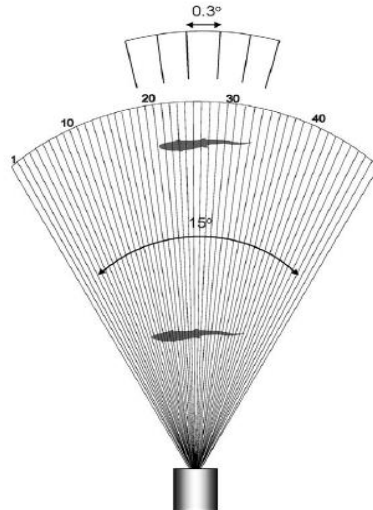


Fig. 1. Image acquisition by sonar [41]

2.2 Single camera

A single camera can be used to capture images. This camera can obtain a 2D image. This setup can be used when the fish is placed in a net, cage, pond or light box. Alternatively, the fish can go through the light box on a conveyor [32, 45], and the camera can be used under water. A single camera can easily obtain high-quality images. However, it can only capture 2D images. The structure is shown in Fig. 2.

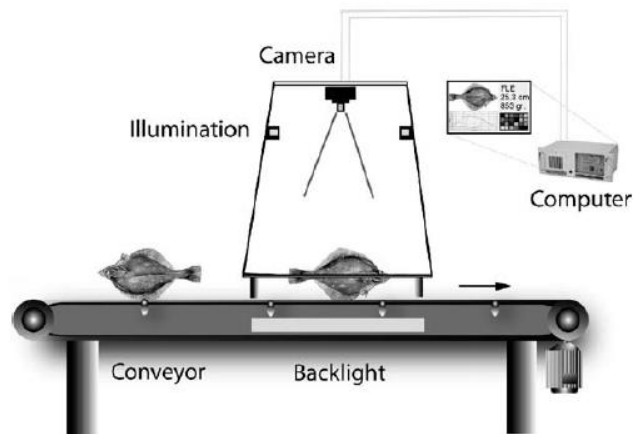


Fig. 2. Image acquisition by single camera [32]

2.3 Stereo camera

In this system, two cameras are placed side by side, which take and process two images synchronously [46]. The stereo camera can take images on a 3D plane. However, the cost of the system and the demands for system rigor are very high. The structure is shown in Fig. 3.

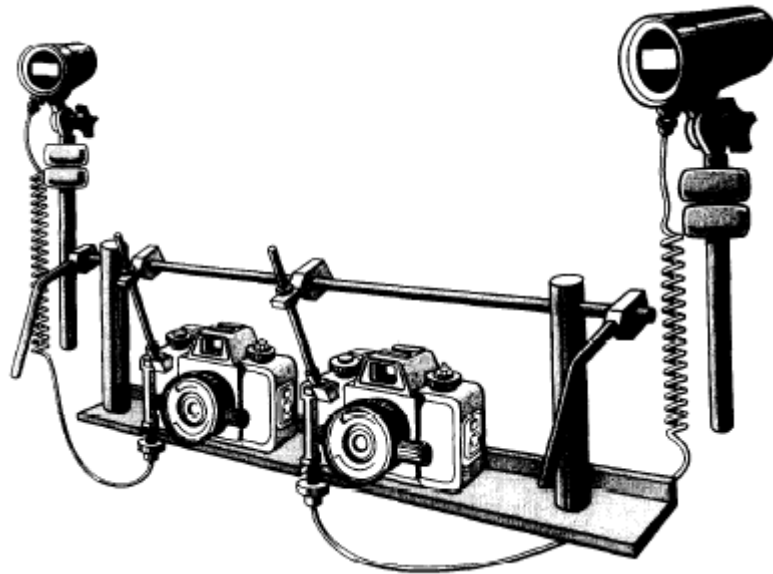


Fig. 3. Image acquisition by stereo-camera[46]

After the images are obtained by the machine vision system, the colour image is transformed to grey scale or to only its HSV values. The binary image is transformed after grey transformation. The interesting region is segmented from the background in binary images by global threshold [47, 48] or dynamic threshold method [42]. In the stereo-camera system, two image acquisition devices exist; two side-by-side cameras take two images synchronously. Two interesting regions are segmented in two images. Thus, machine vision can take the next step to measure the size information.

3. Length measurement

Given that fish length is one of the meaningful parameters of size measurement, many researchers have proposed methods of length measurement by machine vision. The methods are described in two fields: 2D and 3D. Methods in 2D mean that the image is 2D and the process is conducted on one plane using one camera. By contrast, 3D uses two or more cameras to capture images. In this method, 3D reduction or processing two or more images is needed. In this study, 3D methods rely on the stereo-camera system. The different methods are described as follows.

3.1 Length measurement in 2D

The length information can be reviewed in two parts according to the fish body structure. When the fish body structure can be regarded as a straight line and curve, the length can be measured by the linear measurement method and non-linear measurement, respectively.

3.1.1 Linear measurement

When the fish body can be regarded as a straight line, the length equals the line length. The fish length can be calculated by the relation between the fish body pixel length and image reference scale

[37] . The reference scale can be obtained through a square on the colour plate, which captures a photograph of the fish or separately by the same camera [3] . In Fig.4, A and B are the image length of fish and the colour plate, respectively. A' and B' are the actual length of fish and the colour plate, respectively. Thus, the actual fish length A can be calculated using Eq. (1):

$$A' = A * B' / B. \quad (1)$$

Thus, the next step is calculating the length of A [37, 48] .

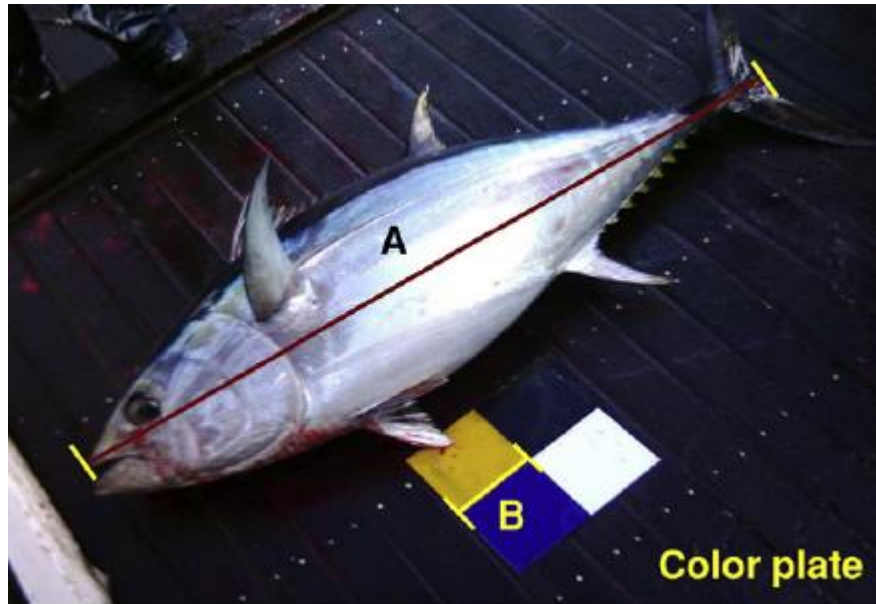


Fig. 4. Using relation between A and B to calculate fish length [37]

Many methods are available to calculate the length of A . For some fish, the body can be regarded as a linear structure; Therefore, the length of A can be described as a line measurement. According that, Hsieh et al [37] proposed that uses Hough transform to calculate the length of A around the tuna's snout to determine fork length in the image. The longest line measured by Hough transform in the image can indicate the length of the fish. Thus, transforms for every point from image space to Hough space are conducted; The collinear points in the image space are presented in the Hough space. Therefore, the weight of the largest peak is the length of fish in image, called A . The images are taken at different angles from the top and the horizontal direction of fish and corrected by projective transform to reduce the error. Different results are calculated because of the different angles and projective transform. The results were approximately $10.7 \pm 5.5\%$ and $5.6 \pm 4.7\%$ before and after correction by projective transform, respectively. For different angles, the best situation was direction angles between $315-0^\circ$ and $135-225^\circ$ and a top-view angle of more than 45° with an error of $2.4\% \pm 2.3\%$. The average error of testing 600 tuna images was $4.5\% \pm 4.4\%$.

Simultaneously, the best fitting rectangle can also calculate fish length. In the image, the fish is surrounded by an external rectangle, and the area of the rectangle is calculated. Then, we rotate the square constantly and recalculate the area until the minimum area of the rectangle is derived. Finally, the fish length is calculated by the length of the rectangle. Misimi et al [48] used this method to calculate the length and width of Atlantic salmon and Atlantic cod to estimate the change of size and shape during rigor mortis and ice storage with area, roundness and height information. Balaban et al [49] described the concrete method to build the rectangle and used this method to calculate the length of four salmon

species (pink, red, silver and chum) to weigh the fish stored in a light box through regression analysis with area and width information. The error was less than 0.5%. Balaban et al [50] used this method to calculate the ratio of the width/length of Alaska Pollock roe in a light box to identify if roes were single or double so that an appropriate equation could be chosen to estimate the weight. Lee et al [51] proposed a model of automatic vaccine injection for flatfish by computer vision in a light box. The injection site was different for various sizes; However, the site was related to the length and the width of the flatfish. The best fitting rectangle was used to calculate the length and width for the injection site.

Both the aforementioned methods are used to calculate the length of fish easily and intuitively when fish body is regarded as a linear structure. Otherwise, both these methods must have low accuracy. The first method uses the Hough transform, which can determine a straight line easily and with high accuracy in a fish image. However, the first method has high time complexity. In addition, this method demands high image quality. In the future, the count of points that need transformation will decrease, and the image quality will increase. The second method, which uses the best fitting rectangle, can also calculate the width information and can be used to assist the other method. Furthermore, the first method can ignore the image detail. However, the fins and tail can introduce significant error into the length and width information. In the future, the pre-processing of segment fins and tail will be adapted, such as morphological operations of opening and closing [52, 53].

3.1.2 Non-linear measurement

For certain types of fish, the body is curved; Therefore, the linear measurement methods shown in 3.1.1 must have a large error. To solve the non-linear measurement, many researchers purpose some methods. One of the methods is that the length is estimated by the key points, as shown in Fig. 5. The best line is found through several different points, which are the midpoints of the width along the length of the fish body. Strachan [31] used the key points method to measure the length of haddock on a conveyor. The paper determined the fish species as well as its orientation and length. The best line was found to measure the length of the fish image caught in a light box, which was composed of seven different midpoints in the image. Simultaneously, the best fitting rectangle method was used as a supporting tool to measure length. The length was calculated by the sum of distance between each of two adjacent points. A total of 35 haddocks were measured five times, and the error was less than 1%. Strachan [45] used a similar method to measure fish length to sort round fish and flatfish, which were transformed on a conveyor and with images caught in a light box. The colour and shape information were processed to identify the species. The length information was estimated to sort various species of fish, which was conducted by measuring the line, which was composed of 10 points. The error was less than 4%. White et al [32] used this method to identify the species of fish (round fish or flatfish) on a conveyor by the length-width ratio and colour information. Fish length was also calculated by 10 points. The length was measured 100 times in varying positions and rotations, and a result was obtained with less than 0.3% error. Jeong et al [54] introduced a vision-based automatic system to measure the body length and the width of flatfish in a light box. The length was estimated by a line composed of five points. The error was less than 0.2%. Lee et al [55] used this method to measure the length of sea cucumbers to estimate the weight. The line was composed of 10 points, and the length was estimated by the sum of Euclidean distance of each 2 points. The error of 300 measurements was less than 0.17%.

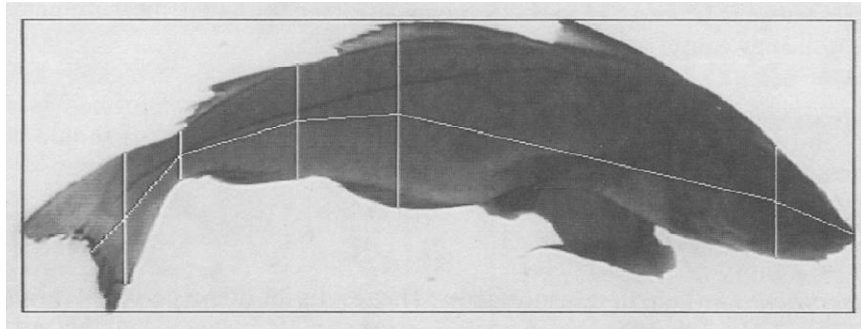


Fig.5. Key points of fish image. The points are the midpoints of width along the body [31] .

For the choice of the key points to compose the line, the best situation is selecting all the midpoints along the body length to connect a line. This method is called image thinning. Yamana et al [56] used this method to measure the size of Japanese sea cucumbers. Their study found a relationship between length and width information. For length measurement, the error was less than 7%. Han et al [57] used a dual-frequency identification sonar (DIDSON) image to count and measure the size of tuna. The best fitting rectangle method was used to segment the tuna from the image, and the image thinning method was used to calculate the length. The error was less than 3%. Pan et al [58] used area, perimeter, length and width information to estimate the weight of shelled shrimp in a light box. Image thinning was achieved by the MATLAB function *bwmorph* with parameter *thin*. Simultaneously, the weight was calibrated by an artificial neural network. Fan et al [59] counted zebra fish fry and calculated seven geometric features, such as area, perimeter and so on. The fish skeleton was described through image thinning, and the best fitting rectangle was used to segment the fish and calculate their width.

Both the aforementioned methods can achieve non-linear measurement of fish length. However, fish cannot avoid curling their bodies, and neither of the methods can solve this situation. For the key points method, the choices for points do not strongly rely on the detail of the image. Furthermore, the choice of special points can ignore the influence of fins. However, determining the position of the point is difficult; Other methods are needed, such as the best fitting rectangle. In the future, a larger number of points will be added to measure linear bent significantly. The image thinning method can describe the body structure clearly no matter the degree of fish body bend. However, the image thinning method has a high demand for image quality. Furthermore, fish fins significantly affect the results. Following the development, image pre-processing will improve, which will enhance image quality. In addition, additional algorithms and theories of eliminating fish fins will be proposed. All detailed information on the aforementioned methods is listed in Table 1.

Table1. Detailed information on methods of length measurement in 2D

Method	Object	Environment	Error	Reference
Hough transform	Tuna	-	<5%	Hsieh et al., 2011
Best fitting rectangle	Salmon, cod	-	-	Misimi et al., 2008(a)
	Salmon	Light box	<0.5%	Balaban et al., 2010(a)
	Roe	Light box	-	Balaban et al.,2012(a)
	Flatfish	Light box	-	Lee et al., 2013
Key points	Haddock	Light box	<1%	Strachan, 1993
	Round fish, flatfish	Light box	<4%	Strachan, 1994
	Round fish, flatfish	Conveyor	<0.3%	White et al., 2006
	Flatfish	Light box	0.2%	Jeong et al., 2013
	Sea cucumber	-	<0.17%	Lee et al., 2014
Image thinning	Sea cucumber	-	<7%	Yamana et al., 2006
	Tuna	-	<3%	Han et al., 2009
	Shelled shrimp	Light box	-	PAN et al., 2009
	Zebra fish fry	Tank	-	Fan et al., 2013

3.2 Length measurement in 3D

In recent years, a stereo video camera system was developed for fish length measurement [4] . This system provides the potential and high accuracy in estimating the length of free-swimming fish [5, 21] . Importantly, the stereo-camera system is not stressful and is non-invasive to the fish [4] . The stereo-video camera system is composed of two digital video cameras in underwater housing or two divers with two cameras to take images. The two cameras must be connected and synchronized to reduce error [24] . Fish length information can be calculated by operating a series of processes on two images acquired by the stereo-video camera system.

After pre-processing, fish length can be calculated by the relation between image and real world. Torisawa et al [60] used the direct linear transformation(DLT) method to calculate the 3D coordinate positions in the real world from the two 2D stereo-images recorded simultaneously by the stereo-camera system. The method transformed the fish head and fish tail coordinates in the image to the real world using Eq. (2,3), where u and v were the point coordinates in the image and the coordinates in the real world were described by X , Y and Z , respectively. L_1 - L_{11} werethe DLT parameters of each camera. Then, we calculated the distance of those two real-world points as the fish length. According to this calculation, two lengths were measured through the stereo-video camera system, and the final length was determined by the average of two lengths. Using this method, the fork length and length frequency distribution for tuna in a net cage were estimated. The error in measuring 107 tuna was less than 5%.

$$u = \frac{L_1X + L_2Y + L_3Z + L_4}{L_9X + L_{10}Y + L_{11}Z + 1} \quad (2)$$

$$v = \frac{L_5X + L_6Y + L_7Z + L_8}{L_9X + L_{10}Y + L_{11}Z + 1} \quad (3)$$

Fish length can also be measured by the relation between the fish length in the image, the distance from camera to fish and the distance between a specific point to the camera. Dunbrack [5] proposed a

method according to this theory to measure the length of sharks in the ocean, as shown in Fig. 6. LOS was a point coordinates in image on this common visual axis. The specific point S was determined when the Ep. (4) was set up while S was moving from UC to LOS. The fish length was calculated using Ep. (5), where DBC was the distance from camera to fish, L was the fish length in the image and D was the distance from UC to S. The final length was estimated by the average of both values that were calculated by both side camera systems using this method. The error was less than 1.6% through 13 test measurements.

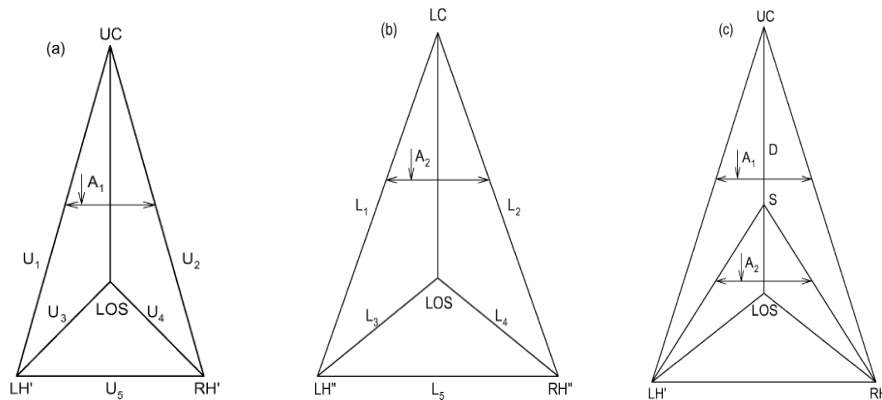


Fig. 6 (a) Upper camera. (b) Lower camera. (c) Angle is used to find S [5]

$$\angle LH'SRH' = \angle LH''LOSRH'' \quad (4)$$

$$FL = DBC \frac{L}{D} \quad (5)$$

A specific method can calculate fish length when the distance between the two cameras is known and the optical axes of the cameras are parallel. In addition, the stereo-camera system is a horizontal structure. Through this method, the fish length in each image can be calculated first by the relationship between the focal length, camera distance and the distance from camera to fish, as shown in Fig. 7. The fish length in the image was calculated using Ep. (6), and the final length was calculated by the average of the two image lengths. Finally, the actual length could be calculated by the relation between the image and the real world. Ruff et al [40] used this method to measure the fish length in a cage. Simultaneously, the image calibration was introduced by a colour plane. The error was less than 1.5%. Rooij et al [46] also used this method to measure fish length. Their paper introduced the specific theory and the steps of the method. The error with calibration was less than 3%. Petrell et al [61] used this method to measure the length of salmon in a cage and tank; the speed was also measured. Costa et al [62] used a similar method to measure the length of tuna in a sea cage. The specific theory was described by vector and matrix. Simultaneously, image calibration was introduced. The error corrected by the artificial neural network was approximately 5%.

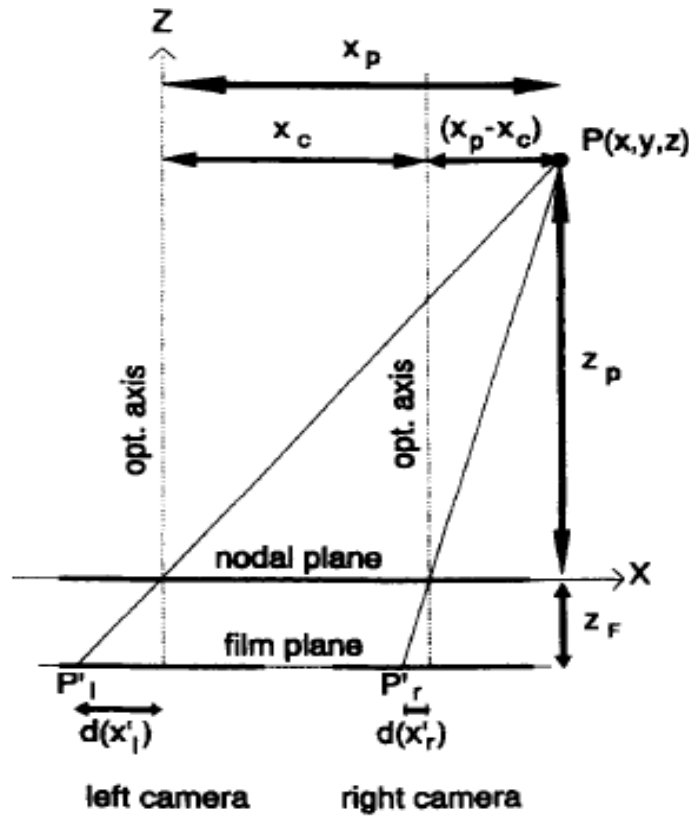


Fig.7. Point P was caught by Stereo video system [46]

$$FL = \frac{z_f \times x_c}{d(x'_l) - d(x'_r)} \quad (6)$$

Overall, the three methods can effectively measure length in three dimensions. They have a high accuracy; however, the stereo camera system also has disadvantages. The economic costs have to increase because of the two-camera system. Furthermore, the system must have high synchronicity. The DLT method is easy to achieve because only 11 parameters are needed for calculation. However, finding heads and tails of fish manually or by extra theory is necessary. In the future, an automatic process that does not require manual work to identify fish heads and tails will be proposed. The second method does not rely on the camera constant parameters. Furthermore, this method has a low demand for equipment rigor. However, the angle in both camera systems is highly difficult to calculate and needs a large number of iterations. With development, additional cameras will be equipped to increase the accuracy. The third method only needs two parameters for measurement, which are camera distance and distance from camera to fish. In addition, the method does not need many calculations. However, fish length was indirectly calculated by the fish length in the image; Therefore, it cannot estimate the bend. The third method has high demand for equipment rigor; The two camera systems must be parallel. In the future, a new method and theory on non-linear measurement will be added to the third method.

Detailed information on the aforementioned methods is listed in Table 2.

Table2. Detailed information on Methods of length measurement in 3D

Method	Object	Environment	Error	Reference
Method 1	Bluefin tuna	Cage	<5%	Torisawa et al.,2011
Method 2	Shark	Ocean	<1.6%	Dunbrack, 2006
Method3	-	Cage	<1.5%	Ruff et al., 1995
	-	-	<3%	Rooij et al., 1996
	Salmon	Cage, tank	-	Petrell et al., 1997
	Tuna	Cage	5%	Costa et al., 2006

Method 1 is the method that uses the direct linear transformation.

Method 2 is the method that shows the relation between the fish length in the image, the distance from camera to fish and the distance between a specific point and the camera.

Method 3 is the method that uses the relation between the focal length, camera distance and distance from camera to fish.

4. Area measurement

All the 2D and 3D methods are used to measure the length of fish. Fish length is an important parameter; simultaneously, area is a very meaningful parameter. Hence, methods of area measurement should be reviewed.

For a given species of fish, area information has a mathematical relationship with the length of fish. Thus, the area can be calculated by its length information. Newlands et al [63] used this theory to calculate the area information of tuna schools in the open ocean. The study introduced fish schools as ellipsoids, and the area was calculated by length. The error was approximately 5%.

Furthermore, the image area can be calculated by the actual pixel number of a fish region after a good segmentation. Then, the real area can be determined according to the relation between the image and real world. Iwamoto et al [64] used the method to measure the area of a fish egg. The study used real-time flow imaging and the classification system to capture images. Then, the image was processed to identify the species and development stage. Misimi et al [48] used this method to calculate the fillet area of cod and salmon in a light box. The area was used to estimate roundness, and the error was less than 6%. Misimi et al [47] introduced area measurement of salmon in a light box according to this method. The area information was one of the parameters used to grade the fish. Pan et al [58] calculated the area of shrimp to estimate the weight. The area was calculated using the MATLAB function *bwarea*. Gumus et al [27] used this method to calculate the area of trout in a light box. The area was used to estimate the weight by establishing a relation model. Balaban et al [49] measured the area of salmon and used this method to sort them. Simultaneously, the weight and volume dimension were estimated by the area information. Balaban et al [26] used this method to calculate the area of Pollock in a light box. The area information was used to estimate the weight, and the volume was calculated by the area. Balaban et al [50] also used this method to measure the area of roe in a light box. In their paper, the weight was estimated by the area, and length information was calculated. For area measurement, the error was less than 2.5%. Fan et al [59] used the method to calculate the area to count fry in a light box. The length, width and perimeter were also measured. Back propagation neural network and least squares support vector machine (LS-SVM) were used to count them.

Both the aforementioned methods can calculate the area effectively. For the first method, the area is calculated by the relationship with the length. This method does not need to calculate area directly, but

the length must be calculated. Therefore, this method does not rely on image quality. However, this method is achieved through the relationship with length; thus, the demand for accurate length is significantly high. Simultaneously, establishing the relation with length is complex. For the second method, the area is measured by the relation between the actual pixel number of the fish region and the real world. This method is more accurate and more effective than the first. The relation is easy to establish and can be found through the relation between a known object such as a colour plane and real world. However, one pixel can take a significant error; thus, this method strongly relies on image quality. Furthermore, fish fins and tails can influence the result. Therefore, image pre-processing is more important. Additional development will significantly improve the software and the speed of calculation, and new methods of area measurement will be proposed.

All detailed information on the methods is listed in Table 3.

Table3. Detailed information on methods of area measurement

Method	Object	Environment	Error	Reference
Method1	Tuna	Ocean	5%	Newlands et al.,2008
Method 2	Fish egg	-	-	Iwamoto et al., 2001
	Cod and salmon	Light box	< 6%	MISIMI et al., 2008(a)
	Salmon	Light box	-	MISIMI et al., 2008(b)
	Shelled shrimp	-	-	PAN et al., 2009
	Trout	Light box	-	Gümüş et al., 2010
	Salmon	-	-	Balaban et al., 2010(a)
	Pollock	Light box	-	Balaban et al., 2010(b)
	Roe	Light box	2.5%	Balaban et al.,2012(a)
	Fry	Light box	-	Fan et al., 2013

Method 1 uses the relationship with the length.

Method 2 uses the relationship between pixel number and real-world area.

5. Discussion and perspective

This study reviewed the methods of fish size measurement through machine vision. Length and area are important information that can help fishers manage fish scientifically and conveniently. This information could be used to calculate the volume and weight according to their relation; other information could also be calculated. Machine vision is more effective, economical and faster than traditional methods. Simultaneously, machine vision is more accurate; Overall accuracy is 10% higher than that of traditional methods. The size measurement is based on the two parts, which are fish length and fish area. The methods reviewed in this paper vary according to different platforms for different fields. Length measurement was reviewed according to 2D and 3D platforms; however, the 2D platform was used for area measurement. For length measurement, the methods were reviewed in two parts according to the body structure of fish in the 2D platform. One part considers the shape as a straight line measured as a linear structure, and the other considers the shape as a curve measured as a non-structure. In the 3D platform, the length measurement relies on a stereo-camera system. For area, fish are measured in 2D, and methods are described by the relationship with length and the amount of pixels in the image. All the methods used the image captured by the machine vision system, and the length or area information could be calculated. Given the difference of methods, the best one can be chosen to solve the

specific situation and can obtain the best effect.

Machine vision system can help fishers obtain size information of fish, is better than traditional methods and reduces labour. However, the machine vision system also encounters problems such as lack of accuracy. Although the system has low error, it is still unsatisfactory. This is particularly true in special situations such as when the fish body is curved; as a result, the accuracy is reduced. Simultaneously, the image quality captured by the system has a significant effect. A satisfactory image can result inefficient processing. However, the image must sometimes be taken under water; The reflection of light, volatility of water, variations in temperature, water mist and other factors not easy to control could increase the noise in the image and reduce the quality. Therefore, processing the image is difficult. Obtaining the length or area information through machine vision is complex, needs many iterations or vector operations and costs much time to achieve, resulting in poor time efficiency. Although several deficiencies exist, machine vision is also a powerful tool to measure fish size.

Although machine vision has only been developed in recent decades, it has already experienced a qualitative leap. Therefore, the application of machine vision in fish size measurement will also be developed further. The machine system may replace traditional methods to measure fish size. The development of hardware will result in high calculation speed, can solve complex calculation and can enable the adaption of an effective real-time system. The image acquisition device will also improve to capture high-quality images. Thus, processing could be reduced, and efficiency could be increased. The processing that the system uses for the image includes complex key steps, such as image denoising, image segmentation, image enhancement and image recognition. These steps are difficult and will be developed in the next several decades. In the future, these steps must be examined by researchers globally. Such a focus could improve the speed and efficiency of processing. Nowadays, mobile equipment has become widely used. Thus, machine vision systems could be used in mobile devices, which could bring convenience as well as sufficient real-time operations. Fish size information could be obtained directly by an image taken by mobile equipment. Simultaneously, the methods reviewed in this paper could be used in size measurement in other fields, such as leaf, fruit, live stock and even certain industrial equipment. Fish size measurement by machine vision is meaningful and can benefit aquaculture and improve economic value.

6. Conclusion

This study reviewed the methods of fish size measurement based on two parts: length measurement and area measurement. The advantages and disadvantages were discussed and the development was described. This study can be used as a research reference in promoting the aquaculture industry.

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