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Automatic mass estimation of Jade perch *Scortum barcoo* by computer vision

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ABSTRACT

The aim of this study was to test and evaluate a 2D computer vision technique that estimates the mass of Jade perch *Scortum barcoo* swimming freely in a tank of a recirculation aquaculture system. The first step of this study, which is described in this paper, was to build up a relationship between the fish shape and its mass in order to be able to estimate the mass of the fish by vision techniques. A set of 120 images of fish outside the water was captured and different features were extracted by using computer vision techniques. Regression analysis was used on the training dataset in order to generate the best model that estimated accurately the mass of the fish. Single-factor regression equation using the area of the fish without considering the fin tail proved adequate for measuring the mass of Jade perch *S. barcoo* and revealed a coefficient of determination (R^2) of 0.99. When applied to the evaluation dataset, the mean relative error was $6 \pm 3\%$ compared to the value measured by a weighing scale. This suggests that the calculated model can be used in a second step to estimate the biomass of fish moving freely in a tank without causing any stress or damage to the fish.

1. Introduction

Monitoring the mass of the fish is essential for effective management in aquaculture farms. Information about fish mass enables the farmer to calculate the daily feed ratio and the fish stocking density. In addition, harvesting and grading fish is dependent on the fish mass and the mass distribution among the fish population.

The most common method to estimate the mass of a fish population is to net fish samples from a tank and weigh them. However, this method is labour intensive and according to Klontz (1993) is also 15–25% inaccurate.

Furthermore, this method is stressful for the fish and may even injure the animal (Pickering and Christie, 1981; Maule et al., 1989). Stress can lead to significantly lower feed intake during the days following the harvest, and therefore in a reduced growth rate. Other fish farmers try to avoid interfering with the fish and use growth prediction models based on initial stocking density, size and mortality rate. This method is based on assumptions because it takes data from initial and final fish populations without measuring the fish during the time of farming, and therefore the method is prone to large errors (Beddow and Ross, 1996).

The relationship between fish shape and mass has been extensively and for a long time investigated (Spencer, 1898; Huxley, 1924; Le Cren, 1951). Spencer (1898) estimated the weight (W) of the fish based on the length (L) and a constant including volume of the fish and specific gravity (q): $W = qL^3$. Huxley (1924) substituted the cubic function with a variable exponent (n) in order to consider the allometric growth: $W = qL^n$. Beddow and Ross (1996) manually measured the conventional dimensions of the lateral profile of Salmon and used 52 parameter multifactor regressions to accurately predict the mass of the fish.

The increased use of image processing in aquaculture as of the mid-1980s (Zion, 2012) opened up the possibility to estimate the weight of fish automatically and without the need to remove the fish from the water. Up to now, different techniques have been used for automated mass estimation of fish both outside the water and inside their aquatic environment.

Poxton and Goldsworthy (1987) used image analysis to determine the projected trunk area of turbot and to develop a logarithmic weight–area relationship. Strachan (1993), instead, extracted the length measurement of fish by computer vision from their binary image on a conveyor. The error in length measurement of fish was ±3% compared to manual measurements. Zion et al. (1999) found out that fish mass can be closely estimated from their image area.

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Fig. 1. Recirculating aquaculture system at Aqua4C lab.

The correlation coefficients between the mass and image area of grey mullet, carp and St. Peter's fish were respectively 0.954, 0.986, and 0.986. Odone et al. (2001) used a support vector machine to define the relation between fish weight and shape parameters with an error of ±3%. The images were taken from both top and side view and 13 parameters were used to train the support vector machine. Balaban et al. (2010a,b) used image processing to predict the mass of different salmon species (Alaskan, Pink, Red, Silver, Chum) with coefficients of determination varying between 0.93 and 0.99 and showing that each species has a different model for mass estimation.

Computer vision is therefore a powerful method to capture and estimate the mass of fish objectively and in real-time. However, there is no a general method to estimate the mass of every species and the optimal relation needs to be estimated for each species individually.

The objective of this paper was to determine the best model for predicting the mass of Jade perch *S. barcoo* with the aim of using this model in a second step in order to estimate the biomass of fish swimming freely in a tank.

2. Materials and methods

2.1. Animals and housing

The experiment was carried out in the Aqua4C lab at the KU Leuven (Fig. 1) and conducted on Jade perch *S. barcoo*, farmed by Aqua4C. A recirculating aquaculture system was used which consisted of 4 tanks, each with a capacity of 1600 l and equipped with a mechanical filter, a nitrifying trickling filter to maintain NH_3-N and NO_2-N levels, two water pumps, a pH pump, an electric heater (Elecro 8 kW), UV unit (Bio-UV 30), an oxygen reactor and a denitrifier to maintain NO_3-N levels. The oxygen, temperature and pH were monitored continuously and were kept between 6.5–7 mg/l, 27 °C and 7.2–7.5, respectively. On each tank one belt feeder was mounted and the daily feed ratio was given continuously over a 12 h period. The feed was a slow sinking extruded 2 mm pellet (42% protein and 12% fat) that was composed of vegetable products. The fishes were a F1 generation from wild Jade perch obtained from a hatchery in Queensland (Australia).

2.2. Data collection

During the three months of the experiment, 15 Jade perch *S. barcoo* were pictured and weighed outside the water in eight measurement sessions with an interval of approximately 10 days.

During each measurement session, each fish was netted, sedated with 70 ppm tricaine methane sulfonate (MS-222) in a water basin and placed on a polystyrene board in a room without windows and illuminated only by fluorescence light.

The fishes were manually and individually identified and then pictured from top view from a distance of 80 cm by using an Olympus C770UZ camera (Olympus Corporation, Tokyo, Japan). The pictures were taken with a focal length of 6 mm, exposure of 12.5 ms, ISO of 200 and a resolution of 2288 × 1712 pixels. Afterwards, each fish was weighed manually by using a Kern 572 weighing scale with a precision of 0.1 g in order to associate a weight value to each picture.

At the beginning of the experiment the mean fish mass was of 92.0 ± 53.4 g, while it was 298.5 ± 98.0 g at the end of the experiment. Overall 120 measurements of fish were collected. The minimum mass of the measured fish was 29.7 g, while the maximum mass measured was 491.0 g, with an average of 182.6 ± 97.1 g.

The setup was remounted at the beginning of every measurement session. In order to compensate small variations in the different measurements, a black square was painted on a polystyrene board. This square was used to compensate the small variations in the setup of the different measurement sessions.

2.3. Image processing

An algorithm was applied to each of the images in order to extract the shape features of the fish and in order to relate the features to the mass estimation.

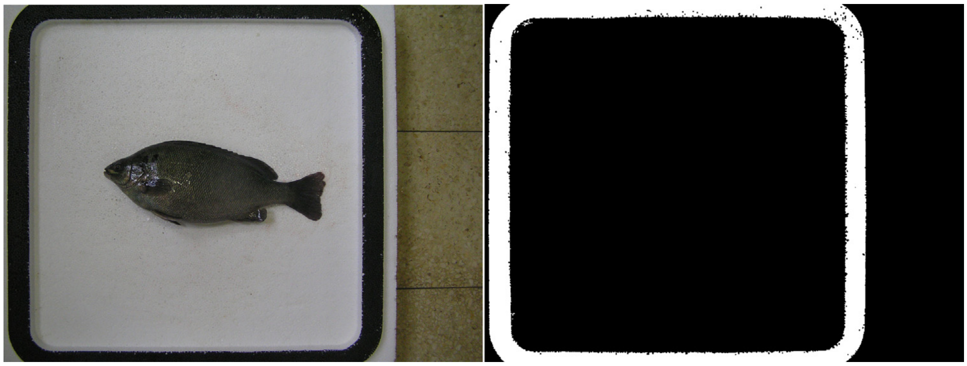

Fig. 2. Original image (left) and detected black painted square.

Fig. 3. Fish binary image.

The image processing consisted of four consecutive tasks. First, the painted black square was detected in the image. Then, the fish was segmented from the image background. Afterwards, shape analysis was applied to the contour of the segmented image in order to remove the fin tail. Last, the height, length and area were extracted from the segmentation mask of the fish both with fin tail and without. The image processing was developed in Matlab 2012b (MathWorks, MA, USA).

2.3.1. *Black painted square location in the image*

The first step in the image processing algorithm consisted in finding the location of the black painted square in the image I by using a colour image input and resulted in an automatically detected bounding box, the smallest rectangle containing an object. The colour image was represented by a matrix of the red (R), green (G) and blue (B) colour spectrum (RGB-image). The image was segmented in order to remove the background (Yang, 1994) by using an adaptive threshold (Otsu, 1979) for each of the colour spectrums. The binary image was calculated as a bitwise AND operator of the three image component.

Afterwards, the ratio between height and width of the bounding box (the smallest rectangle containing an object) was calculated for each of the connected objects resulting from the colour threshold segmentation. The object with the biggest size and whose height/width relationship was closer to 1 was considered the black painted square (Fig. 2). The area (A_{bb}), the width (W_{bb}) and the height (H_{bb}) of the bounding box were then used to rescale the fish shape measurement.

2.3.2. *Fish segmentation*

After the bounding box was detected, the next step consisted in segmenting the fish from the background. The original image I was cropped inside the black painted square that had been detected in the previous step, and a new image I_c was obtained. The binary image was segmented by using an adaptive threshold (Otsu, 1979) for each of the colour spectrums. The biggest connected object was considered the fish, while the other objects were filtered out.

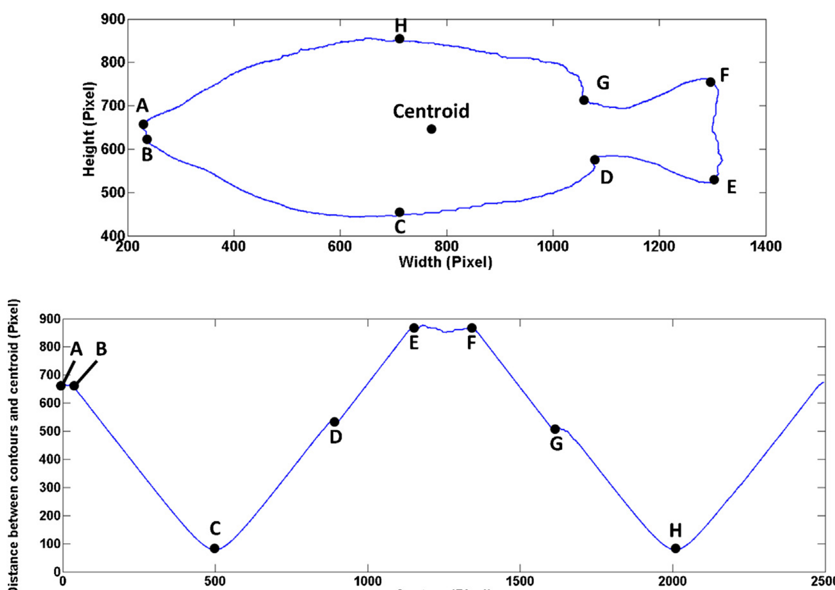

Fig. 4. Contour of the fish extracted from the binary image (top) and the calculated distance between the contour and the centroid (bottom). This distance was used to remove the tail fin from the image (pixels between D and G).

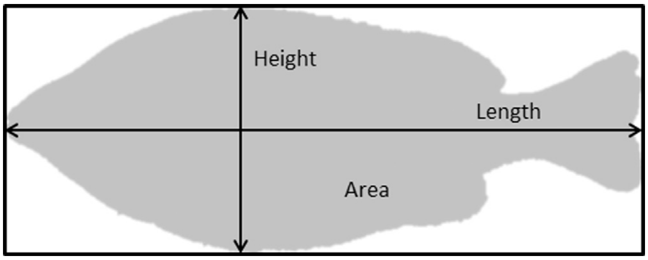

Fig. 5. Parameters extracted from the binary image: area (grey), height and length of the bounding box.

Afterwards, pixels inside the contour of the fish that were not identified as part of the fish, were filled in. The orientation of the fish binary image was calculated as the angle between the x-axis and the major axis of the ellipse that had the same second moment as the region. The image was rotated by the orientation of the fish binary image in order to have the binary imaged orientation parallel to the x-axis of the image (Fig. 3).

2.3.3. Removing the tail fin

The tail fin of the Jade perch *S. barcoo* has a lower specific mass compared to the other parts of the fish body and may influence the modelled mass estimation. Therefore, the fin tail was removed automatically by using shape analysis of the fish binary image. Another approach to eliminate the effect of the fins would have been to calculate a different specific mass coefficient for the fin tail, but since the mass of the fins contributed in minimal part with the overall mass, it was preferred not to consider it in the equation.

As a first step, the contour of the binary image was extracted. The binary image was searched from top left until a fish foreground pixel was found; this pixel was the starting pixel for the contour. The eight-neighbourhood of the pixel was searched in counter clockwise direction. The first fish foreground pixel found was the next pixel of the contour. This procedure was repeated until the first element of the contour was detected.

As a second step, the distance d between the pixel of the contour and the centroid was calculated (Fig. 4). The minima (C, H) were calculated from d. By looking at the first and the last peak between (C, H), the points (D, G) were defined. These points were then used to remove the area of the fins from the area of the body.

2.3.4. Shape features extraction

From the fish binary image with tail, the area – the number of white pixel in the image – (A_1) the length (L_1) and the height (H_1) of the bounding box were extracted and used to develop the model (Fig. 5).

From the fish binary image without tail, the area (A_2) the length (L_2) and the height (H_2) of the bounding box were extracted as well.

In order to correct the small variations in the different measurements due to the remounting of the setup for each of the measurement sessions, the values were rescaled by using the constant dimension of the painted black square as follows:

$$A_1 = \frac{A_1}{A_{bb}}; \quad A_2 = \frac{A_2}{A_{bb}} \tag{1}$$

$$L_1 = \frac{L_1}{L_{bb}}; \quad L_2 = \frac{L_2}{L_{bb}} \tag{2}$$

$$H_1 = \frac{H_1}{H_{bb}}; \quad H_2 = \frac{H_2}{H_{bb}} \tag{3}$$

2.4. Precision of measurement

In order to test the precision of the measurement technique, each of the 15 fish was pictured consecutively every 15 s on one measurement session for a total of 5 pictures per fish. During this session, the fish was positioned in different angles and the height of the camera was changed. The errors associated with the automatic measurement of area, length and height were analysed statistically by calculating the standard deviation of the repeatedly measured values for a single fish and the percentage of this value in relation to the mean.

2.5. Regression analysis

The relationship between the Jade perch *S. barcoo* area (A), length (L), height (H) and weight (W) could be expressed in form of mathematical models. Based on literature, the most common models to predict fish mass by means of image processing were (Zion, 2012):

$$\text{Polynomial}: \quad W = a + bA + cL + dH \tag{4}$$

$$\text{Linear}: \quad W = a + bA \tag{5}$$

$$\text{Power curve}: \quad W = aL^b \tag{6}$$

Linear regression analysis was used to determine the models' coefficients. In order to calculate the linear relationship in the power curve model, the model was converted in logarithm form and afterwards it was converted back ($c = \log(a)$).

$$W = aL^b \iff \log(W) = c + b\log(L) \tag{7}$$

In order to avoid model over-fitting, the data were divided into two datasets. The first dataset containing the measurements of 7 fish (56 images) was used to determine the constants of the models. The second dataset containing the measurements of 8 fish (64 images) was used to validate the models' performance and the prediction error.

To evaluate and compare the models in addition to the coefficient of determination (R^2), the following measurements were used in this study:

The root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{\sum_N^{i=1}[W_{\text{estimated}.i} - W_{\text{measured}.i}]^2}{N}} \tag{8}$$

The mean absolute error (MAE):

$$\text{MAE} = \frac{\sum_N^{i=1}|W_{\text{estimated}.i} - W_{\text{measured}.i}|}{N} \tag{9}$$

The mean absolute relative error (MARE):

$$\text{MARE} = \frac{\sum_N^{i=1}|W_{\text{estimated}.i} - W_{\text{measured}.i}|/W_{\text{measured}.i}}{N} \times 100 \tag{10}$$

The maximum absolute error (MXAE):

$$\text{MXAE} = \max_{i=1}^{N}(|W_{\text{estimated}.i} - W_{\text{measured}.i}|) \tag{11}$$

The maximum relative error (MXRE):

$$\text{MXRE} = \max_{i=1}^{N}\left(\frac{|W_{\text{estimated}.i} - W_{\text{measured}.i}|}{W_{\text{measured}.i}}\right) \tag{12}$$

3. Results and discussion

3.1. Precision of measurement

Table 1 shows an example of the results for the measured areas. The table shows that the measurements presented a high precision: the relative error ranged from 0.2% to 2.8% to the rescaled area and the mean error was $0.6 \pm 0.6\%$.

Similar results were obtained for the measured length and height. The error for length ranged from 0.2% to 2.8% with a mean

Table 1
Precision of measurement for the area value.

Fish	Area measurement					Mean ± std	Error as % of distance
	1	2	3	4	5		
1	0.5736	0.5698	0.5696	0.5694	0.569	0.57027 ± 0.00170	0.3
2	0.0926	0.0931	0.093	0.0932	0.0927	0.09294 ± 0.00022	0.2
3	0.1077	0.1073	0.1071	0.1074	0.1076	0.10741 ± 0.00022	0.2
4	0.0863	0.0852	0.0855	0.0861	0.0865	0.08593 ± 0.00047	0.6
5	0.0893	0.0887	0.0891	0.0899	0.089	0.08921 ± 0.00040	0.4
6	0.0811	0.0808	0.0805	0.0817	0.0809	0.08100 ± 0.00042	0.5
7	0.0495	0.0484	0.0482	0.0485	0.0478	0.04847 ± 0.00057	1.2
8	0.0588	0.059	0.0595	0.0599	0.0604	0.05951 ± 0.00058	1.0
9	0.0707	0.0724	0.0707	0.0713	0.0725	0.07152 ± 0.00080	1.1
10	0.07213	0.07217	0.07236	0.07205	0.07176	0.07209 ± 0.00019	0.3
11	0.0504	0.0505	0.0502	0.0506	0.0503	0.05039 ± 0.00014	0.3
12	0.063	0.0632	0.0631	0.0633	0.0634	0.06320 ± 0.00014	0.2
13	0.0462	0.0462	0.046	0.0466	0.0465	0.04627 ± 0.00022	0.5
14	0.5362	0.5017	0.5143	0.5357	0.5386	0.52529 ± 0.01468	2.8
15	0.0388	0.0391	0.0388	0.039	0.0389	0.03892 ± 0.00015	0.4

error of 1.2 ± 0.8%. The height error ranged from 0.4 to 3.7% with a mean error of 1.5%.

The small errors in the precision may be caused by the fact that the fish were moved in order to repeat the measurement. Changing the position compared to the previous measurement, it may be that the body of the fish was more flattened or compressed in the following measurement. Errors may also occur in the image processing algorithm.

3.2. Regression analysis

Linear regression analysis was used to fit the mathematical models' coefficients. The results of the fitting Eqs. (4)–(6) for fish both with and without fin tails are shown in Table 2.

In the power curve model, the relationship between the logarithm fish length and the logarithm fish mass was calculated and then transformed back.

Table 3 shows the error of the models' mass prediction in the training dataset, using the fish with the fin tail. The results suggest that all the models were not significantly different from the manually measured values (P-value < 0.01).

Both the linear model and the polynomial model performed better than the power curve model. This is evident since the mass of the fish is not only determined by length, but also by volume and density and therefore using the area as a parameter can improve the mass prediction accuracy.

Table 4 shows the error of the models' mass prediction in the training dataset using the fish shape without the fin tail. The performance measurements suggest once again that using the area is necessary in order to achieve better predicted values.

When comparing Table 3 and Table 4, it becomes evident that the results of all three models were better when the tail fin is removed from the image, confirming the hypothesis that the tail fin negatively influences the mass modelled due to its different specific mass. The developed mathematical models for estimation of Jade perch *S. barcoo* mass were validated in the validation dataset, using instances not used in the mathematical model development. The estimation errors were determined and reported in Table 5 for the fish with tail fin and in Table 6 for the fish without tail fin.

The coefficient of decision (R^2) for all models indicated the positive correlations between the masses measured by the weighing scale and masses estimated by the models. The results from the validation confirmed also that using only the length of the fish results in less accurate values than using the area; this observation applied to using the fish with or without tail fin. It was furthermore confirmed that removing the tail fin results in more accurate values.

The linear model that uses only the area of the fish without fins has a performance (R^2 = 0.99, MARE = 6%, MXRE = 19%) similar to the polynomial model (R^2 = 0.99, MARE = 5%, MXRE = 17%) and better than the power curve model (R^2 = 0.96, MARE = 10%, MXRE = 28%). The area of the fish is sufficient to predict the mass and, compared to height and length of the fish, more robust to be calculated.

The linear model had a mean error estimation of 6 ± 3% of the fish mass measured with a maximum error of 19%.

Figs. 6 and 7 show respectively the relation between the fish area and mass and the relation between the fish length and mass in the linear and power curve model.

In Fig. 6, it is noticeable that the relation between area and mass starts to diverge when the fish is getting heavier. Area and mass could diverge because the fish stop to grow in area after a certain mass is reached and instead start to grow in thickness.

Table 2
Coefficients of the mathematical models fitted by regression analysis on the fish with and without tail fin.

Equation	Model coefficients with tail fins				Model coefficients without tail fins			
	a	*b*	*c*	*d*	*a*	*b*	*c*	*d*
Polynomial	−27.39	5660.10	−188.14	−241.68	84.22	8500.00	−489.59	−999.12
Linear	4654.40	−103.59	–	–	5364.50	−121.26	–	–
Power curve	1735.24	3.26	–	–	3272.47	3.21	–	–

Table 3
Error in estimation of Jade perch *Scortum barcoo* weight and related statistical values in the training dataset using the fish shape with tail fin.

Equation	RMSE (g)	MAE (g)	MARE (%)	R^2	MXAE (g)	MXRE (%)	P-value
Polynomial	10.9	8.2	4	0.99	21.5	18	<0.001
Linear	11.5	8.6	6	0.99	22.7	20	<0.001
Power curve	16.9	12.9	8	0.97	25.5	32	<0.001

Table 4
Error in estimation of Jade perch *Scortum barcoo* weight and related statistical values in the training dataset using the fish shape without the tail fin.

Equation	RMSE (g)	MAE (g)	MARE (%)	R^2	MXAE (g)	MXRE (%)	*P*-value
Polynomial	8.9	6.0	4	0.99	15.4	16	<0.001
Linear	9.3	6.3	5	0.99	16.9	17	<0.001
Power curve	14.0	8.5	7	0.98	22.5	24	<0.001

Table 5
Error in estimation of Jade perch *Scortum barcoo* weight and related statistical values in the validation dataset using fish shape with tail fin.

Equation	RMSE (g)	MAE (g)	MARE (%)	R^2	MXAE (g)	MXRE (%)	*P*-value
Polynomial	10.8	8.9	5	0.99	21.9	19	<0.001
Linear	11.9	9.7	7	0.98	23.2	21	<0.001
Power curve	19.1	13.7	12	0.96	28.0	34	<0.001

Table 6
Error in estimation of Jade perch *Scortum* weight and related statistical values in the validation dataset using fish shape without tail fin.

Equation	RMSE (g)	MAE (g)	MARE (%)	R^2	MXAE (g)	MXRE (%)	*P*-value
Polynomial	9.3	6.3	5	0.99	17.5	17	<0.001
Linear	9.9	6.9	6	0.99	17.7	19	<0.001
Power curve	17.1	10.6	10	0.96	26.0	28	<0.001

The results show that it is possible to use only side view images to estimate accurately the mass of Jade perch *S. barcoo*. These results are comparable to other studies that use different species of fish. The correlation coefficients between the mass and image area of grey mullet, carp and St. Peter's fish were found to be respectively 0.954, 0.986, and 0.986 (Zion et al., 1999). The area is a simple feature that can be robust enough to estimate the fish mass but retaining the same accuracy compared to more complex methods. Odone et al. (2001) used 13 parameters to define the relation between fish mass and shape parameters with an error of ±3%. Using more feature variables to estimate the mass of the fish can improve the results but also make it less robust and prone to error.

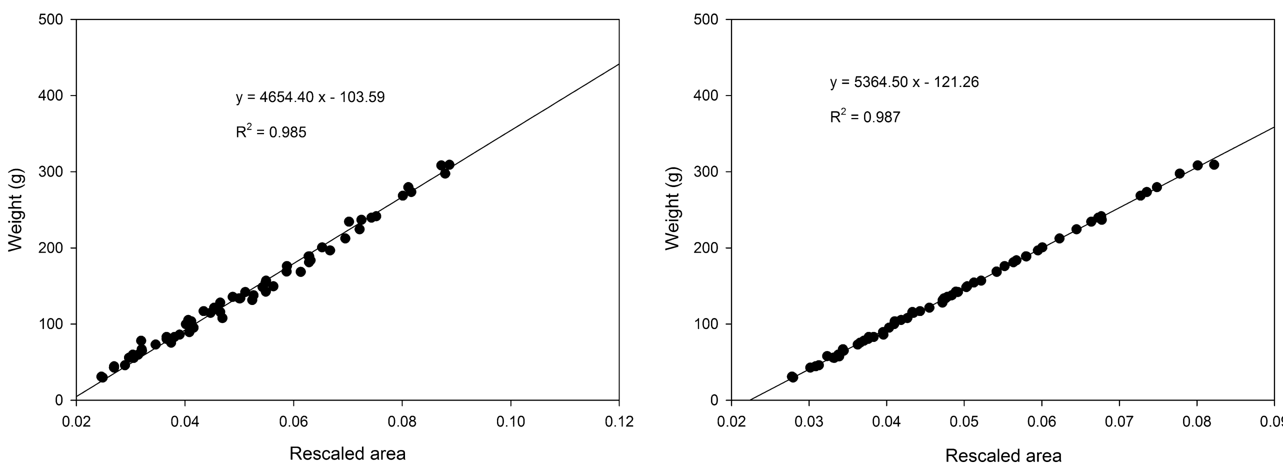

Fig. 6. Relation between area and weight of Jade perch *Scortum barcoo* with tail fin (left) and without tail fin (right) in the validation dataset in the linear model.

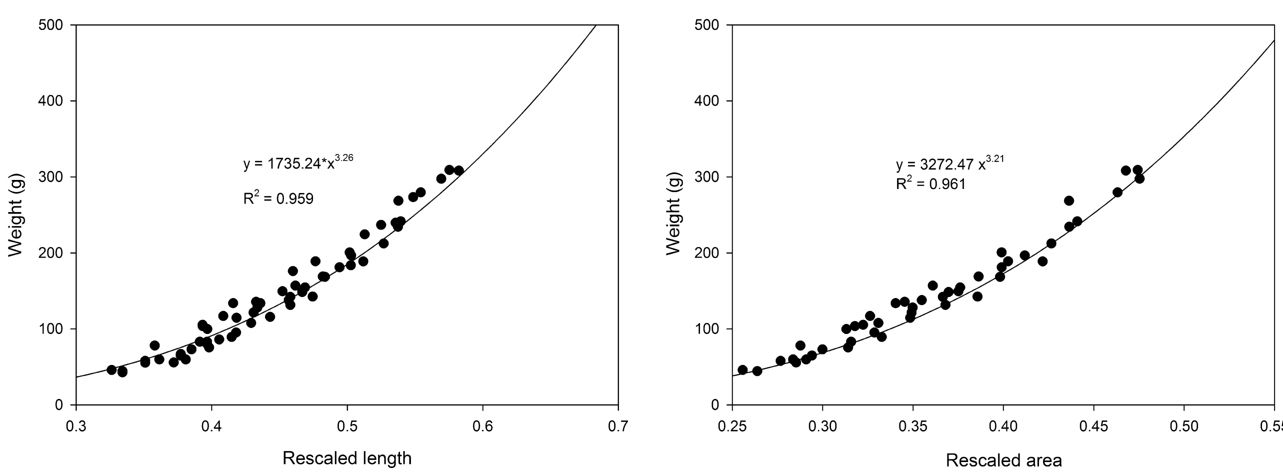

Fig. 7. Relation between area and weight of Jade perch *Scortum barcoo* with tail fin (left) and without tail fin (right) in the validation dataset in the power curve model.

4. Conclusion

The paper illustrated that 2D computer vision techniques can be used to estimate accurately the mass of Jade perch *S. barcoo* by measuring the area of the fish from side view.

The linear model that used only the area as feature variable shows comparable results (R^2 = 0.98, MARE = 7%, MXRE = 21%) to the polynomial model that used the area, the length and the height (R^2 = 0.99, MARE = 5%, MXRE = 19%) and performed better than the power curve model that used only the length of the fish (R^2 = 0.96, MARE = 12%, MXRE = 34%).

The results of the model can be improved by removing the tail fin from the calculation (R^2 = 0.99, MARE = 6%, MXRE = 19%).

The area of the fish is sufficient to predict the mass and, compared to height and length of the fish, more robust to be calculated.

This model can therefore be the first step towards the development of an automatic monitoring tool that can estimate the fish mass when the fish is swimming freely in the water. With an automatic system in place, the fish do no need to be harvested and therefore suffer no stress or weight loss caused by harvesting procedures. The next step is now to apply the selected model to free fish underwater.

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