Application of Machine-vision to assess weight of fish (Case study: *Oncorhynchus mykiss*)

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Introduction

Computer Vision(CV) is a relatively young discipline which has been widely used to automate quality evaluation (Baxes, 1994;Luzuriaga *et al*., 1997).CV inspection of fish and fish products can provide efficient, consistent and cost effective alternative, so efforts focused on speed and accuracy of machine vision as a substitute for human inspection of foods (Brosnan and Sun, 2002).Machine vision is explained as the construction of explicit informative and meaningful descriptions of a physical object via image analysis (Dowlati *et al*., 2012). Actually it encloses the capturing, processing and analysis of two-dimensional images, and by modeling human vision electronically perceives and understands images (Timmermans, 1998; Sonka *et al*., 1999).

With the development of image processing many researchers used machine vision to evaluate fish physical parameters. Machine vision was used to calculate the weight, the uniformity ratio and the count of shrimp (Balaban *et al*., 1994). Fish species classification by color, length, texture and orientation in a processing line has also been used by researches (Hu *et al*., 2012; White *et al*., 2006; Storbeck and Daan, 2001; Strachan, 1993a; Strachan *et al*., 1990).Furthermore, digital image processing has been used to develop objective criteria to predict flesh redness from the spawning coloration of fall chum salmon (Hatano *et al*.,1989).

Fish and fish products are one of the most important parts of protein demand around the world and in recent decades total amount of consumed fish has dramatically increased significantly. Fish products are about 16% of human diet all around the world (Alsalvar *et al*., 2011). Fisheries management and research often require the use of biometric relationships in order to transform data collected in the field into appropriate indices (Ecoutin and Albaret, 2003). Weight calculations are very important in fisheries stock assessments or measuring fish biomass in fish farms. In addition, weight-based population analysis (WPA), currently used in fisheries stock assessments rely on weight of fishes (Ueda *et al*., 2001). The most useful relationship for estimating weight is Length-Weight relationship which estimate weight based on fish length (Gerami *et al*., 2013). Measuring length requires catching fish from aquatic ecosystem which causes stress and mortality. Machine visions can be invented a new method for estimating weight without requiring manipulating fishes. This study tries to evaluate the relationship between weight of fish and visual features derived from image processing and present best fit relationship between weight and visual features.

Materials and methods

Seventy five live specimens of *O.mykiss* were obtained from fish farm in Sepidan, Fars, Iran. All individual specimens weighted separately with accuracy 0.1 g. Lightroom with indirect lighting (Cloudy sky) improved to shot images. Lightroom formed from a dome with 90 cm diameter that its inner space was glossy and white. Samples were placed under the dome and 150 W GE Tungsten Halogen lamps were designed surroundings, so that direct light did not affect the samples. Beam lamps reflected to the sample after irradiation to the inner space of the dome, therefore no shadows were formed around it. After weighting of each specimen, pictures were taken by digital Canon IXUS 960IS (12 mega pixels; 3000×4000) in the red, green and blue channels from left side of samples. The camera was placed at a height of 45 cm above the sample. Image data transferred to a laptop (CPU core 2dou 2.53GH, 4GB RAM) and analyzed by MATLAB (Matrix Laboratory) version R2009a.Image analyzed as represented in Fig. 1.

The designed program extracted 7 features from the image which include Length, Height, Area, Perimeter, Equivalent Diameter, Major and Minor Axis Length. To calculate area, Grayscale image preformed and black and white pixels were equal to 1, were counted. Boundary pixels between black and white regions in Grayscale image were utilized for calculating perimeter. Equivalent diameter equals with the diameter of a circle which its area is equal to the area of the desired shape. Therefore equivalent diameter calculated by following formula:

$$\text{Equivalent Diameter} = \sqrt{\frac{4 \times \text{Area}}{\pi}}$$

Major and minor axis length was equivalent to the largest and smallest axis of the oval surrounded by sample fish, respectively. Extracted data converted to cm^2 for calculating area and cm for other features.

Linear and multiple regressions were used for modeling between fish external features and weight. Modeling factors included length, height, area, perimeter, equivalent diameter, major and minor axis length and grain elongation. These factors were assayed with linear, logarithmic, exponential and power method. 70 percent of data was used to obtain a model and 30 percent was assigned for evaluating the equations.

Coefficient of determination (R^2), adjusted Coefficient of determination (R^2_{adj}), Standard error of estimate (SEE) and F test computed to find best fit model.

$$R^2 = \left[1 - \frac{\sum_{i=1}^{N}(Y_{exp,i} - Y_{pred,i})^2}{\sum_{i=1}^{N}(Y_{exp,i})^2}\right] \times 100$$

$$R^2_{adj} = 1 - \left[\frac{(1 - R^2)(N - 1)}{(N - K - 1)}\right] \times 100$$

$$SEE = \sqrt{\frac{\sum_{i=1}^{N}(Y_{exp,i} - Y_{pred,i})^2}{N - 2}}$$

Y_{exp} represent original fish weight, Y_{pred} was weight estimated by regression, N was sample size and K was the number of independent variables.

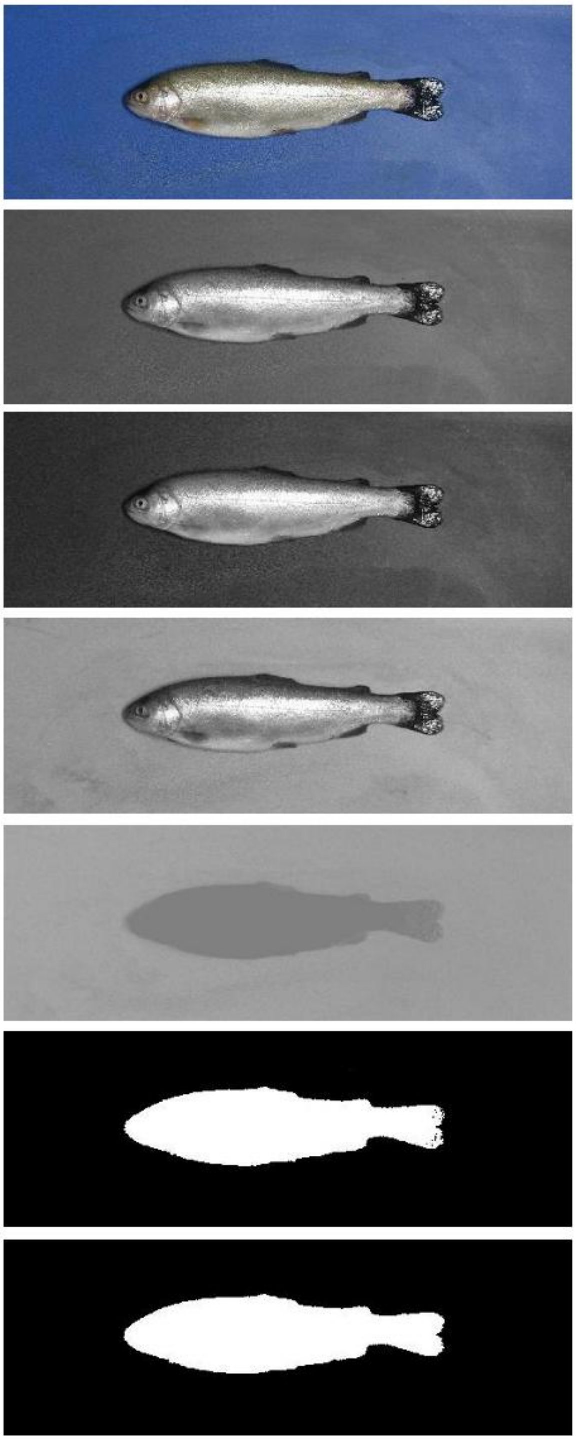

Figure 1: Sort by: Original form, R, G and B color model, one color channel median filter, C_b image component, Grayscale image, Noise reduction.

Best sub-categories method was used to find goodness of fit of the model in multiple regressions. Models evaluated by R^2, regression t-test, R^2_{adj}, SEE, F test and VIF. VIF represented level of linearity between independent Variables:

$$\mathrm{VIF_j} = \frac{1}{1 - \mathrm{R_j^2}}$$

Where j is j^{th} independent variable and R^2_j is the coefficient of determination of the regression between j^{th} independent variable as the dependent variable and other independent variables. Afterwards, percent error of estimated fish weight was calculated by following formula:

$$E = \frac{|Y_{pred} - Y_{exp}|}{Y_{pred}} \times 100$$

Regression graph of estimated fish weight basis original fish weight was plotted for 30 percent of test data. Regression equation was compared with y=x which represent real regression of original fish weight. The significance of these two models evaluated by F test and Graphpad prism 5 software:

$$F = \frac{a_1 - a_2}{\sqrt{SE^2_{a_1} - SE^2_{a_2}}}$$

Eventually, 90% confidence intervals for estimated models were calculated by following formula:

$$Y_{exp} = Y_{pred,i} \pm t_{\frac{a}{2},n-1} \times SEE(\sqrt{1 + \frac{1}{N} + \frac{(X_i - \overline{X})^2}{\sum_{i=1}^{n}(X_i - \overline{X})^2}}$$

Where X is independent variables extracted form image processing, $\bar{X}$ is average of each independent variables extracted form image processing, a is level of probability and SEE is Standard Error of the Estimate. Microsoft excel 2010, SPSS 18 and MATLAB software were used to analyze data.

Results and discussion

According to the visional features extracted from image processing, average±standard deviation of total length, height, area, parameter, equivalent Diameter, major axis, minor axis, full stomach fish weight and grain elongation of samples were calculated 24.16±6.56 cm, 5.86±1.70 cm, 105.46±53.56 cm^2, 65.48±19.01 cm, 11.15±3.16 cm, 24.29±6.65 cm, 186.24±128.71 g and 0.24±0.02, respectively.

Univariate Linear Regression equations derived from length, height, area, perimeter, equivalent diameter, major and minor axis length in four categories: Linear, logarithmic, exponential and power. These equations are represented in Table 1. Results indicated that power regression based on area was the best fit equation according to R^2, R^2_{adj} and SSE (Table 1).

Multiple regression models based on fish weight and visional features were assessed. Minitab (version 15, Minitab Inc) used for modeling data. Based on R^2_{adj}, C_p value and standard errors, best fit models obtained and represented in Table 2.

Table 1:Relations of fish weight estimations with Univariate Linear Regression and statistical Analysis.

Categories	Number	Model	R^2	R^2_{adj}	SEE
Liner	1	W= -262.35 + 18.49L	0.918	0.916	36.86
	2	W= -228.59 + 70.52H	0.887	0.885	43.27
	3	W= -63.86 + 2.36A	0.981	0.980	84.58
	4	W= -232.12 + 6.34P	0.903	0.928	86.83
	5	W= -247.53 + 38.78ED	0.924	0.927	86.03
	6	W= -257.9 + 18.21MAAL	0.918	0.922	85.85
	7	W= -229.92 + 75.21MIAL	0.892	0.904	88.62
logarithmic	8	W= -1021.3 + 383.6Ln(L)	0.834	0.831	52.41
	9	W= -393.4 + 336.2Ln(W)	0.784	0.780	59.78
	10	W= -627.11 + 180.8Ln(A)	0.827	0.824	53.53
	11	W= -1272.4 + 352.14Ln(P)	0.812	0.809	55.75
	12	W= -156.16 + 361.49Ln(ED)	0.827	0.823	55.54
	13	W= -1015.5 + 381.18Ln(MAAL)	0.835	0.832	52.26
	14	W= -378.30 + 339.47Ln(MIAL)	0.792	0.788	58.67
exponential	15	$W = 4.46e^{(0.14L)}$	0.959	0.959	42.49
	16	$W= 5.41^{(0.54H)}$	0.964	0.963	41.48
	17	$W= 22.29^{(0.02A)}$	0.914	0.912	70.03
	18	$W= 5.65e^{(0.05P)}$	0.939	0.938	59.26
	19	$W= 4.91e^{(0.29ED)}$	0.976	0.975	36.64
	20	$W= 4.69e^{(0.14MAAL)}$	0.950	0.949	45.84
	21	$W= 5.38e^{(0.58MIAL)}$	0.967	0.966	43.19
power	22	$W= 0.01L^{3.10}$	0.988	0.987	20.76
	23	$W= 1.10H^{2.78}$	0.979	0.978	26.21
	24	$W= 0.18A^{1.47}$	0.998	0.997	7.83
	25	$W= 0.001P^{2.857}$	0.973	0.972	32.49
	26	$W= 0.12ED^{2.94}$	0.998	0.997	7.85
	27	$W= 0.01(MAAL)^{3.06}$	0.982	0.981	22.98
	28	$W= 1.26(MIAL)^{2.81}$	0.985	0.984	25.52

*W is weight of fish, L is length, H is height, A is area, P is perimeter, ED is equivalent diameter, MAAL is major axis length and MIAL is minor axis length.

Table 2: Best fit multiple regression models for full stomach fish weight.

Number	Model	Statistical coefficients	Intercept	L	H	A	P	ED	MAAL	MIAL	GA
1	W=59.8+3.27L-7.5H+4.55A-0.573P-40.3 ED+5.98MIAL+267 GA	t value	0.84	0.89	-0.43	25.26	-1.57	-3.47	-	0.68	0.79
		VIF	-	487.03	720.19	75.15	39.20	1095.15	-	161.40	33.67
2	W=53.2+4.60L-11.4H+4.55A-0.400P-32.3 ED-3.21MAAL+300GA	t value	0.75	0.94	-0.61	25.30	-.094	-3.26	-0.67	-	0.88
		VIF	-	848.49	816.50	74.80	52.97	793.17	833.59	-	33.54
3	W=91.3+2.94L+4.50 A-0.379P-35.9ED-2.20MAAL+ 114GA	t value	2.78	0.73	-	28.73	-0.90	-4.54	-0.49	-	0.77
		VIF	-	585.32	-	57.46	52.59	512.49	734.35	-	6.42

*W is weight of fish, L is length, H is height, A is area, P is perimeter, ED is equivalent diameter, MAAL is major axis length, MIAL is minor axis length and GA is grain elongation.

Maximum coefficient of determination and maximum proximity between numbers of factors involved in model and C_b value; were selected as best fit models. Table 2 shows t value and VIF value of best fit multifactor models for full stomach fish weight. VIF value in all 3 models is more than 1 which represents the interaction effect of independent variables on each other.
Fig. 2 shows the assessment of y=x line for regression. For this purpose, 30% of data were used to Evaluation Model. It is noted that accuracy of the weight estimate is very high in the lower weights and disparities with y=x line is very little.

Results showed that all data are in expected range with 90% confidence. According to the results, equation weight = $0.18A^{1.47}$ was selected as the most appropriate model.

Original full stomach fish weight and image processing weight estimation were calculated as 186.24 and 184.82 g, respectively. No significant differences were observed between image processing estimated fish weight and original fish weight (p value> 0.05).
Table 3 shows the weight separation biased on full stomach fish weight. Fish were divided into 9 categories, and error and separation percentage was calculated.

Result showed that, best fit model for estimating weight was founded based on calculating area. It is noted that for calculating area, caudal, dorsal, annual and ventral fins are contributing in fish weight and calculated in determination fish area. Weight estimate based on fish area is more accurate than other visional features and express the accuracy of image processing and written algorithm for calculating fish area. In addition, due to high accuracy of area, error percentage was less than 4.5 in all categories (Table 3). Manuchehri and Akrami (2008) sorted fish species based on length and weight which resulted 7.8 to 19.6 percentage errors in weight categories. Calculating weight by area is performed in other aquatic animals. Balaban *et al.* (1994) and Luzuriaga *et al.* (1997) demonstrated that the weight of white and tiger shrimp could be estimated based on view area and described three equations to correlate weight vs. view area.

Contrasting results are scarce for comparing fish species weight assessment based on view area. However computer vision based sorting fillets like color of shape analysis is widely has been studied and successful. Misimi *et al*. (2007) studied sorting fillets of Atlantic Salmon (*Salmo salar*) based on color and stated that there were no significant differences between computer vision and human inspector method. Strachan (1993b) recognized 18 demersal and five pelagic species by color and shape with computer vision and sorted them with a reliability of 100% and 98%, respectively. Storbeck and Daan (2001) applied machine vision to classify fish species and stated that more than 95% of the fish could be classified correctly by computer vision and a neural network program.

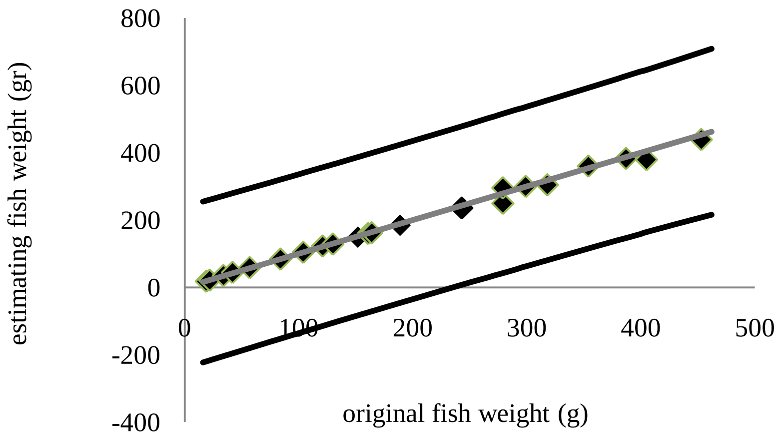

Figure 2: 90% confidence limits of predictability of fish weight.

Table 3: weight categories sorting full stomach fish.

Number	Weight categories	Number of fish	Number of sorted fish	Sorted percentage	Error percentage
1	Less than 50 g	14	14	100	4.32
2	50 to 100 g	7	6	85.71	3.75
3	100 to 150 g	13	12	92.31	3.87
4	150 to 200 g	12	11	91.67	2.71
5	200 to 250 g	4	4	100	3.55
6	250 to 300 g	10	8	80	4.22
7	300 to 350 g	4	4	100	2.08
8	350 to 400 g	5	5	100	1.4
9	400 to …	6	4	66.67	3.4
	Total	**75**	**68**	**90.67**	**3.25**

Result in this study showed that algorithm for generating fish area form images and assess weight have high accuracy for *O. mykiss.*

In conclusion, machine vision could be used to evaluate visual features of fish and estimate fish weight by a new method. More work is necessary on other fish species to validate this method for application this mythology in fisheries process.

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