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Broiler weight estimation based on machine vision and artificial neural network

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ABSTRACT

1. Machine vision and artificial neural network (ANN) procedures were used to estimate live body weight of broiler chickens in 30 1-d-old broiler chickens reared for 42 d.
2. Imaging was performed two times daily. To localise chickens within the pen, an ellipse fitting algorithm was used and the chickens' head and tail removed using the Chan–Vese method.
3. The correlations between the body weight and 6 physical extracted features indicated that there were strong correlations between body weight and the 5 features including area, perimeter, convex area, major and minor axis length.
5. According to statistical analysis there was no significant difference between morning and afternoon data over 42 d.
6. In an attempt to improve the accuracy of live weight approximation different ANN techniques, including Bayesian regulation, Levenberg–Marquardt, Scaled conjugate gradient and gradient descent were used. Bayesian regulation with R^2 value of 0.98 was the best network for prediction of broiler weight.
7. The accuracy of the machine vision technique was examined and most errors were less than 50 g.

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KEYWORDS
Machine vision; artificial neural network; body weight; broiler

Introduction

One of the most important parameters that give valuable information to broiler producers about growth rate and uniformity, feed conversion efficiency and occurrence of disease problems is body weight. Furthermore, for the farmers, prediction of the average weight and spread of weights some days in advance is necessary to schedule broiler pick-up and slaughter (Lott *et al.*, 1982; Turner *et al.*, 1984; Flood *et al.*, 1992). Assessment methods of the live weight of chickens are therefore important from several points of view. Usually, weighing is carried out manually which is stressful to the birds, labour intensive and time consuming and unsatisfactory from an ergonomic point of view. Moreover, the accuracy of data recording and analysis are subject to human error and could be affected by numerous factors, namely inspector fatigue. Thus, many attempts have been made to find an alternative to the manual weighing procedure.

Since 1991 filming with top-view cameras has been known as a non-disturbing method for monitoring animals and provides a way to implement algorithms in research and field applications (Van der Stuyft *et al.*, 1991). Computer-controlled systems for the remote monitoring of livestock have the potential to increase production efficiency and improve animal health and welfare (Van der Stuyft *et al.*, 1991; Frost *et al.*, 1997). In the image analysis technique neither the chickens need to be moved nor the farmer to be involved during the rearing period. Furthermore, since the only equipment within the pen is the camera and a light for illumination, cost and maintenance are minimised. Computer vision systems for automatic monitoring of animals are a novel approach, which have been developed and applied in various animal species to provide objective quality measurements (Aydin *et al.*, 2010; Tasdemir *et al.*, 2011; Kashiha *et al.*, 2014; Abdanan Mehdizadeh *et al.*, 2015; Neves *et al.*, 2015). Some researchers previously studied the ability of machine vision systems to capture a large number of images, relate them through statistical analysis to animal weight on a daily basis and determine accurate daily changes in measured parameters. Schofield *et al.* (1999) and White *et al.* (2004) showed that there was a linear relationship between body weight and top-view body area of pigs. In the aforementioned studies a single linear regression equation was used to estimate the live body weight of animals from the body area based on the interpretation of individual images. Kashiha *et al.* (2014) used computer-assisted digital image analysis to estimate automatic weight of individual pigs. According to reported results, pig weight could be estimated with an accuracy of 97.5% at group level (error of 0.82 kg) and 96.2% individually (error of 1.23 kg). Zion *et al.* (1999) reported that computer vision could differentiate fish of different species and there was also a good correlation between the view area in pixels and mass of three species of fish. Kuzuhara *et al.* (2015) conducted a study for predicting body weight and milk properties in lactating Holstein cows using a three-dimensional camera system. High correlations were found between the observed and predicted value of body weight (R^2 = 0.80) based on linear regression equations. The objective of this study was to process digital images to evaluate the capability of artificial neural networks (ANNs) in estimating body weight of live broiler chickens.

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Materials and methods

Management of experimental birds

A total of 30 1-d-old broiler chickens (Ross, mixed sexes) were obtained from a local hatchery and reared at Ramin Agriculture and Natural Resources University of Khuzestan in the animal husbandry station up to 42 d. The birds were reared in three different floor pens measuring 1 m × 1 m (10 birds/m^2) on wood litter. They were allowed to have access to a commercial diet that followed NRC (1994) and water for the full duration of the experiment. Ambient room temperature during rearing was 33°C in the first week and then every week the temperature decreased 2°C. The light during the first 3 d of rearing was 24 h and after that until the end of the breeding period 23 h light and 1 h darkness was given.

Imaging and weighing

To capture images and collect weight data, a special box was constructed to hold each bird while photographs were taken. This had a floor area measuring 50 cm × 36 cm, so the bird had sufficient space to move and stand freely during image capturing. A Samsung digital camera (SM-N9005, Korea) was used to capture individual images of the broilers. The camera was installed centrally above the bird at height of 0.5 m above the floor. This distance was set to ensure the scale of all images to be the same during the experiment. Imaging was conducted twice daily. A total of 84 images were recorded from each of the birds for image analysis at respective day of data collection. To make a clear outline of the birds, a dark background (floor) was used to have strong contrast between the chicken and the background. The capturing images at this stage were used to develop the ANN model; after that all of the acquired parameters were calibrated in a way so they were valid for non-invasive weight prediction inside the pen. In this regards, the same camera was employed and installed about 2.0 m above the ground to record video of broiler chickens inside pens. Each sample consisted of a 5 min video footage twice daily, from 7:00 to 8:00 h and from 16:00 to 18:00 h. During the video capturing, sufficient light was provided to achieve a good balance between the outline having shadows.

Image processing

Processing of images is important to increase measurement precision and analysis validity. The captured videos and images were processed offline in the MATLAB 2013A environment to analyse the outline of 6 body features of the broiler's body surface. The image colour was changed into greyscale and the contrast enhanced so that the images looked brighter. To separate the images from the background, an adaptive threshold was utilised (Otsu, 1979). To remove and avoid discontinuities and isolated areas due to presence of artefacts in the background and inside the images caused by shadows from the feathers and the head, erosion and dilation approaches were applied. The dilation adds while erosion erases pixels at the boundaries of the images and consequently these two functions remove unnecessary noise. After segmentation a white area corresponding to the shape of the animal on a black background was acquired. The head of the chicken was removed using the Chen–Vese model (Gao *et al.*, 2014) and the feature parameters including area, perimeter, convex area, major axis length, eccentricity and minor axis length were extracted using the Image Process Toolbox (Wang *et al.*, 2008).

Artificial neural networks

The back propagation neural network (BPNN), which is also referred to as the multilayer perceptron, is the most general-purpose and commonly used neural network. Feedforward neural networks (Rumelhart *et al.*, 1986) provide a general framework for representing non-linear functional mappings between a set of input and output variables. In this paper, different three-layer (one input layer, one hidden layer and one output layer) BPNN training algorithms (Levenberg–Marquardt algorithm, the gradient descent algorithm, the Bayesian regulation algorithm and the scaled conjugate gradient algorithm) were built and compared using the Matlab Neural Network Toolbox for weight estimation of live chicken (Demuth *et al.*, 2005). The BPNN receives information in the input layer by input vectors, passes this information through neurons and finally gives a certain output value in the output layer. The input layer in this study had 6 neurons corresponding to 6 features: area, perimeter, convex area, major axis length, eccentricity and minor axis length (Wang *et al.*, 2008).The transfer functions employed were the tangent sigmoid and pure line for hidden and output layer, respectively. The number of neurons used in the hidden layer was selected based on trial and error, following an initial selection using the equation below (Abdanan Mehdizadeh *et al.*, 2014). The output layer had one neuron which is the weight of the chicken.

$$n_h = \sqrt{n_i + n_o}, \tag{1}$$

where n_h,n_i and n_o are the number of neurons in the hidden layer, input layer and output layer, respectively. Two-thirds of the randomly extracted data points were used for training and the remaining data points were used as testing patterns.

Results and discussion

In order to find the location of the broiler chickens, segmentation was the first step to process images. To localise chickens within the pen, an ellipse fitting algorithm using Generalised Hough Transform was utilised (Davies, 1989). Subsequently, the chickens' body was extracted as ellipses (Igathinathane *et al.*, 2008). Figure 1(a) shows broiler chickens locations identified in ellipses. Afterwards it was binarised (Figure 1(b)) to eliminate the background (Yang, 1994). Due to the frequent movement of the head positions, an error was introduced into the body weight calculation. Previous studies had shown that measuring the pig (Brandl and Jørgensen, 1996) and chicken (De Wet *et al.*, 2003) with head included would introduce an additional error on body weight prediction. Therefore, head and tail of chickens were removed using the Chan–Vese method (Figure 1

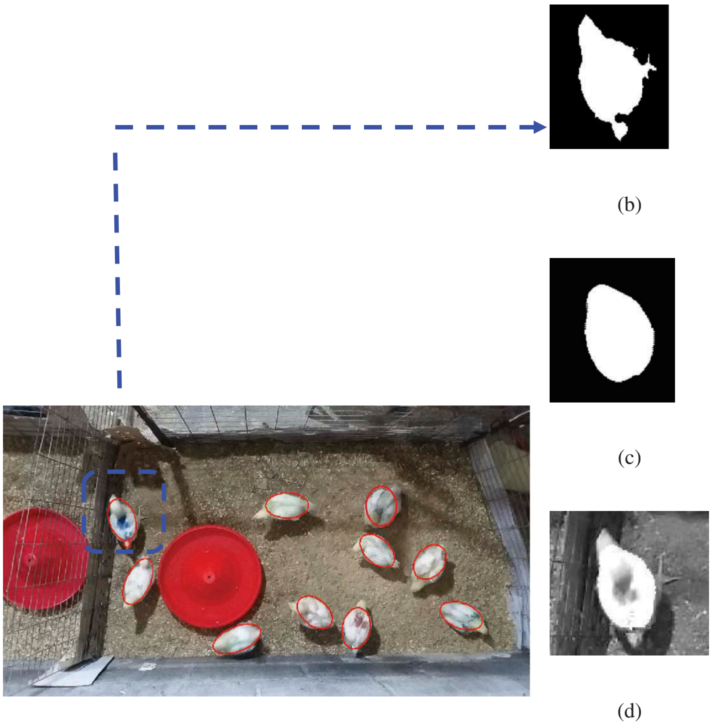

Figure 1. (a) Ellipses fitted to chickens' body; segmented image (b) before and (c) after applying the Chan–Vese method; (d) overlaying the body of segmented on grey level image.

(c)). It can be perceived from Figure 1(d) that the head and the tail of the chicken were effectively removed.

A paired *t*-test was performed to determine whether there was any statistically significant difference between morning and afternoon data for 6 body measures as well as real weight of broiler chickens. No significant difference ($P > 0.05$) was found between the morning and afternoon data over 42 d (data not shown) and morning and afternoon data were treated equally to develop the ANN models. Furthermore, the relationship between body dimensions and body weight affects the accuracy of weight estimation in two-dimensional measurements. Therefore, the correlations between the body weight and 6 extracted features were investigated and results are presented in Table 1. The value of 0.21 in Table 1 indicates that there is no correlation between body weight and eccentricity; however, the 5 remaining features (area, perimeter, convex area, major and minor) with correlation coefficient greater than 0.93 show a strong relationship with body weight. This result is in agreement with Wang *et al.* (2006) who have shown that a number of physical features, such as area, width, length and perimeter, extracted from pig images, were correlated with the pig live weight, and among which the area had the best correlation. Thus, the input layer in this study was changed to 5 neurons corresponding to 5 features: area, perimeter, convex area, major and minor to train the ANN.

Table 1. Correlation coefficients between area, perimeter, convex area, major, minor, eccentricity and weight.

	Area	Perimeter	Convex area	Major	Minor	Eccentricity
Perimeter	0.98					
Convex area	0.99	0.98				
Major	0.97	0.99	0.97			
Minor	0.96	0.98	0.96	0.96		
Eccentricity	0.22	0.26	0.22	0.34	0.10	
Weight	0.98	0.95	0.98	0.94	0.93	0.21

The performance of the ANN for the prediction of broiler body weight by the gradient descent algorithm, the scaled conjugate gradient, the Levenberg–Marquardt and the Bayesian regulation algorithm using the aforementioned features are illustrated in Figure 2. The Bayesian regulation and the Levenberg–Marquardt algorithm performed very well on the prediction of broiler weights. Although the lowest root mean square error (RMSE) of gradient descent was observed at the lowest number of neurons in the hidden layer, the gradient descent had higher RMSE than the Bayesian regulation algorithm. Therefore, the Bayesian regulation was used as the best network for prediction of broiler weight.

It is essential to emphasise there were no significant differences between errors in the training and testing stage, especially when considering that the samples with which the models were tested were not seen during the training stage. This indicates that the 4 training algorithms were able to generalise what was learned during the training stages. Table 2 presents the errors for each of the models. The training algorithm showing the best performance in the prediction of weight was the Bayesian regulation algorithm with RMSE of 80.68, 82.37 and 82.30 for the training, testing and total data set, respectively. The Levenberg–Marquardt algorithm was the second best with RMSE of 89.63, 91.59 and 90.51 for the training, testing and the total samples, respectively. Craninx *et al.* (2008) have conducted research to predict rumen fermentation pattern from milk fatty acids using ANNs. These authors found that

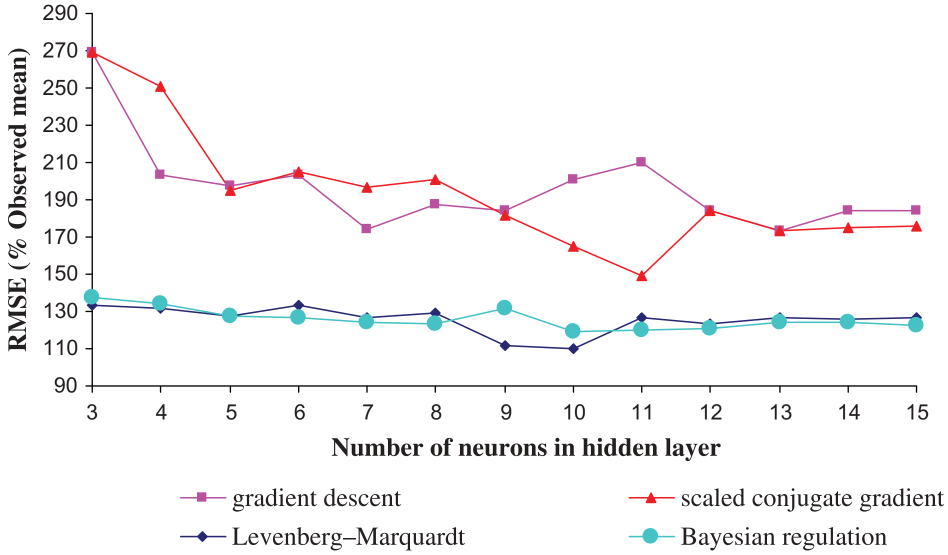

Figure 2. RMSE of testing stage of the ANN model developed for predicting weight of chickens using the gradient descent algorithm, the scaled conjugate gradient, the Levenberg–Marquardt and the Bayesian regulation algorithm for 1–15 neurons in the hidden layer.

Table 2. Prediction error comparison of optimal number of neurons in the hidden layer in weight estimation for different training algorithms.

		Training		Test		Total	
Training algorithm	Number of neurons in the hidden layer	R^2	RMSE	R^2	RMSE	R^2	RMSE
Gradient descent	7	0.946	150.66	0.941	157.12	0.942	154.57
Levenberg–Marquardt	10	0.98	89.63	0.979	91.59	0.979	90.51
Scaled conjugate gradient	11	0.967	115.10	0.963	121.63	0.965	118.41
Bayesian regulation	9	0.984	80.68	0.983	82.37	0.983	82.30

Table 3. Occurrence of the (absolute) error of prediction of body weight in 4 weight ranges.

Category	Error (|e |, g)	Occurrence %
I	50	56.1
II	50–100	20.1
III	100–150	14.5
IV	150–250	9.3

the Levenberg–Marquardt algorithm performed very well on the training data but showed higher RMSE on the test data. In addition, they also declared that the scaled conjugate gradient algorithm performed very satisfactorily for both test and training data. Therefore, the scaled conjugate gradient algorithm was chosen as the learning algorithm for the ANN.

Figure 3(a–d) shows the result of predicting broiler chicken weights for the independent test data using different training algorithms: (a) Bayesian regulation; (b) Levenberg–Marquardt; (c) Scaled conjugate gradient and (d) gradient descent. The R^2 values for these training algorithms were 0.98, 0.97, 0.96 and 0.94, respectively. The higher R^2 value for Bayesian regulation for unseen data (test data) pointed to the predictive ability of Bayesian regulation as the best ANN.

The accuracy of the machine vision technique was examined using the error ($M_{observed} - M_{predicted}$) and the frequency of occurrence for each error for 371 data points as shown in Figure 4. The sign of the error was kept to show whether the predicted mass was larger or smaller than the manual mass. According to Figure 4, more negative values for estimation of broiler weight can be seen than positive values which means, ANN overestimated broiler weight. To detail the information reported in Figure 4, the prediction errors were divided into 4 ranges as follows with a frequency of occurrence as given in Table 3. Most errors were less than 50 g and only a few cases (9.27%) gave an error above 150 g; therefore the proposed method could generally predict weight of live broiler with errors less than 50 g. This result is similar to that obtained by Mollah *et al.* (2010) for live weight estimation of the broiler using digital image analysis.

Conclusion

In this research, a technique for automatic weight estimation of live broiler chickens using machine vision and ANN was proposed. To localise chickens within the pen, an ellipse fitting algorithm was used, and head as well as tail of chickens removed using the Chan–Vese method. Through the images, 6 physical features including area, perimeter, convex area, major, minor and eccentricity were extracted and of these 5 features (area, perimeter, convex area, major and minor) showed a strong correlation with body weight. In an attempt to improve prediction of live weight different ANN techniques, including Bayesian regulation, Levenberg–Marquardt, Scaled conjugate gradient and gradient descent, were utilised. Bayesian regulation with R^2 value of 0.98 was the best network for prediction of broiler weight. The accuracy of the machine vision technique was examined and the most errors were less than 50 g.

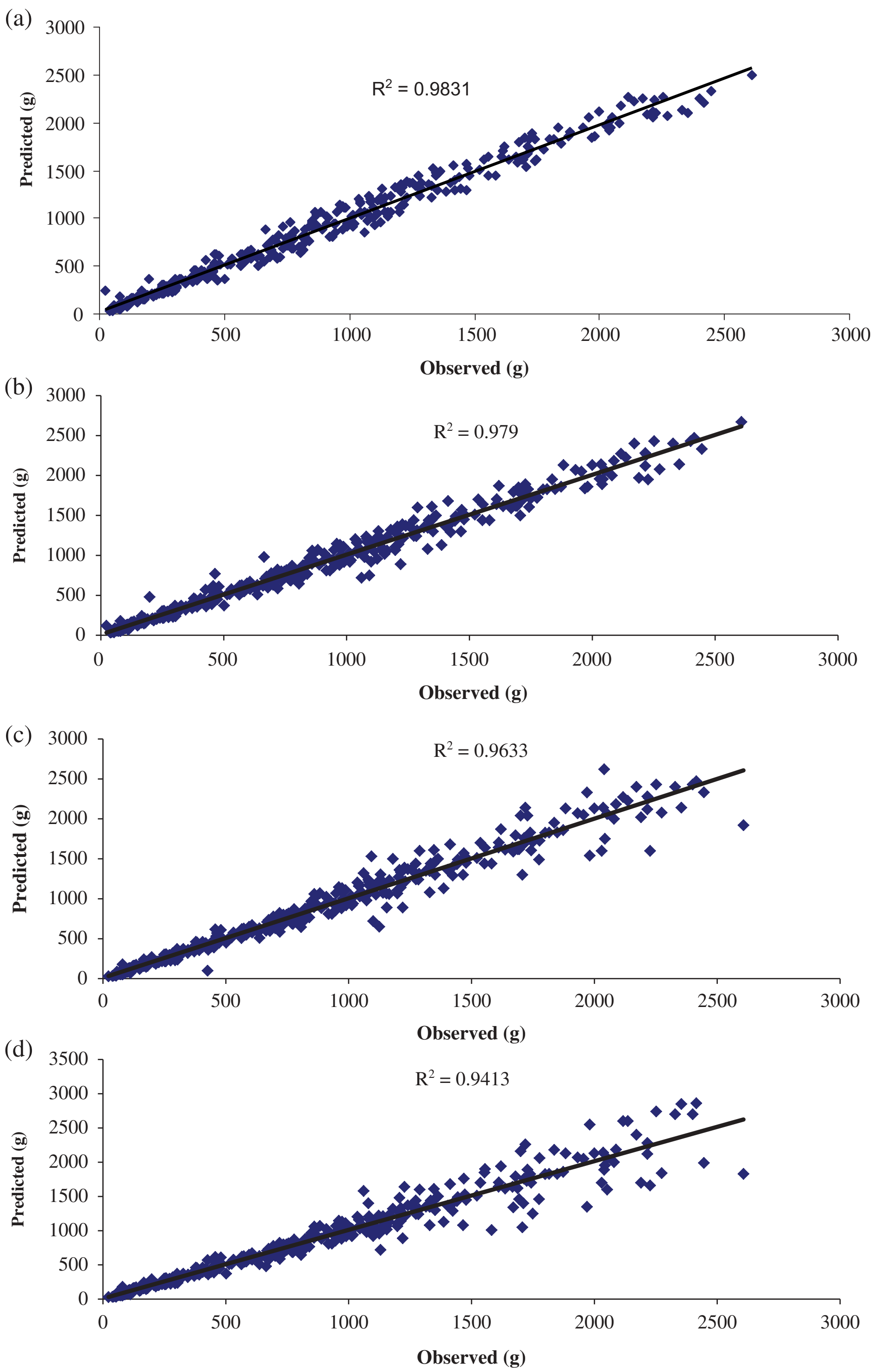

Figure 3. Prediction of the weight of chickens for the independent test data using different training algorithms: (a) Bayesian regulation; (b) Levenberg–Marquardt; (c) Scaled conjugate gradient; (d) gradient descent.

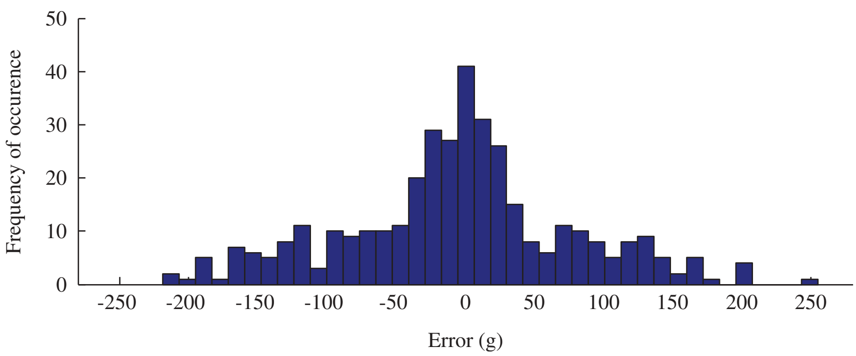

Figure 4. Frequency of occurrence of error for weight estimation.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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