Engineering in Agriculture, Environment and Food xxx (2017) 1–6

Contents lists available at ScienceDirect

Engineering in Agriculture, Environment and Food

journal homepage: http://www.sciencedirect.com/eaef

Application of computer vision and support vector regression for weight prediction of live broiler chicken

Somaye Amraei [a], Saman Abdanan Mehdizadeh [a,*], Somayeh Sallary [b]

[a] Department of Mechanics of Biosystems Engineering, Faculty of Agricultural Engineering and Rural Development, Ramin Agriculture and Natural Resources University of Khuzestan, Khuzestan, Iran
[b] Department of Animal Science, Faculty of Animal Science and Food Technology Ramin Agriculture and Natural Resources University of Khuzestan, Khuzestan, Iran

ARTICLE INFO

Article history:
Received 4 June 2016
Received in revised form
13 December 2016
Accepted 24 April 2017
Available online xxx

Keywords:
Image processing
Support vector regression
Weight estimation
Broiler

ABSTRACT

A very important ingredient in the recipe for a productive broiler breeder flock is the collection of frequent and accurate body weights. To achieve this goal in this paper image processing and support vector regression (SVR) were used as a non-invasive method. An ellipse fitting algorithm using generalized Hough transform was performed to localize chickens within the pen and the head as well as the tail of chickens was removed using Chan-Vese method. After that from broiler images six features were extracted, namely area, convex area, perimeter, eccentricity, major axis length and minor axis length. According to statistical analysis between weight estimation of SVR and manual measurement of birds up to 42 days, no significant difference was observed ($P > 0.05$). The RMSE (root mean square error), MAPE (mean absolute percentage error) and the R^2 (correlation coefficient) value of SVR algorithm were 67.88, 8.63% and 0.98, respectively. This shows that machine vision along with SVR could promisingly estimate the weight of life broiler chickens.

1. Introduction

According to Food and Agriculture Organisation (FAO) global broiler meat production was estimated at 84.1 million tonnes in 2013. In order to meet the rapidly rising market demands for healthy animal food products, the number of animals in the herd should be increased. The increased number of animals per farm has resulted in welfare problems because it is difficult to care animals individually (HSUS, 2010). The animal weight plays an important role in the controlling factors which affect the output of the herd (Schofield et al., 1996). A very important ingredient in the recipe for a productive broiler breeder flock is the collection of frequent and accurate body weights. Weighing birds more than once a week will provide rapid feedback on how feed allocations are affecting body weight gains. When allocating feed, it is essential to look at how much weight the birds have gained in the last few 3–4 day periods and what they need to gain in the next 3–4 day period and beyond. To allocate feed accurately weight of the birds need to be known. Weight can be measured by catching the chicken(s) from the pen, putting them on the balance, read and record them. This is labour-intensive and stressful for both chicken and stockman, and in practice this means that chickens are seldom weighed more than once, during production. Furthermore, the steady accumulation of dirt on and below the scale platform results in inaccurate weight readings which are difficult to detect. Now days, there are technologies that can monitor animal continuously (DeShazer et al., 1988). Turner (1981) studied automatic weighing systems for several species (Lokhorst, 1996; Turner et al., 1983, 1984).

Among the various technologies, machine vision as a non-invasive method has widely been used in different field of agriculture (Chen et al., 2002). In this method, real-time images with digital cameras were captured and analyzed. Generally, to estimate weight of the animal, the body dimensions of the animal were measured automatically and a prediction function established using the relationship between these dimensions and the live weight of animal (Brandl and Jørgensen, 1996). The precision of these predictions should be high enough to obtain valid information. An image-based walk-through system was developed for live weight approximation in pig using the artificial neural network technique.

* Corresponding author.
E-mail addresses: saman.abdanan@gmail.com, s.abdanan@ramin.ac.ir (S. Abdanan Mehdizadeh).

http://dx.doi.org/10.1016/j.eaef.2017.04.003
1881-8366/

The results showed that the average relative error of the walk-through weighing system was around 3% (Wang et al., 2008). De Wet et al. (2003) used computer-assisted image analysis to quantify daily growth rates of broiler chickens and the relative error in weight estimation expressed in terms of the standard deviation of the residuals from image surface pixels was 10%, and 15% for the image periphery data. Alonso et al. (2013) presented a function to predict the carcass weight for beef cattle before the slaughter day with an average absolute error of 4.27% of the true value using artificial intelligence tools based on Support Vector Regression (SVR). Also Alonso et al. (2013) improved estimation of bovine weight trajectories using Support Vector Machine Classification. The objective of this study was to process digital images to investigate the possibility of estimating body weight of broilers using support vector regression.

2. Materials and methods

2.1. Animals and housing

In order to carry out the experiment, 20 birds from thirty 1-d-old broiler chickens (Ross, mixed sexes) were randomly selected. Birds were obtained from local hatchery and reared at Ramin Agriculture and Natural Resources University in the animal husbandry station for 42 days. The birds were kept on wood litter in 3 floor pens measuring 1 m × 1 m (10 birds/m^2). They were received a commercial diet based on NRC (1994) and also had free access to water for the full duration of the experiment. During rearing broilers, salon temperature was kept at 33 °C in the first week and then every week the temperature decreased by 2 °C. The light during the first three days of rearing was 24 h and after that until the end of the breeding period 23 h light and 1 h darkness was considered. Fences were used to separate each pen.

2.2. Image and weight data collection

SAMSUNG digital camera (SM-N9005, Korea) was used to capture individual image of the broilers. The camera was installed centrally above the floor of the box and pen at height of 0.5 and 2.0 m, respectively. Images were captured twice a day in two steps: (i) inside the pens and (ii) into the special box (50 cm × 36 cm). Therefore, 2440 images were recorded from individual bird inside the box and 84 images from the pens. To make a clear outline of the birds, and to have strong contrast between the chicken and the background, a dark background (floor) was used inside the box. The captured images were used to develop the SVR model; after that all of the acquired parameters were calibrated in order to make them valid for non-invasive weight prediction inside the pen using images from the pens. Finally, the same camera was employed and installed about 2.0 m above the ground to record video of broiler chickens inside the pens. Each sample consisted of a 5 min of video footage twice a day, between 7 and 8 a.m. and 4–6 p.m. During the video capturing, adequate light was provided to get a good balance between the outline having shadows. The capturing videos were separated into a sequence of JPEG files in frames.

2.3. Image processing

In order to increase the segmentation performance and find the location of the chicks, the first step was to pre-process the images. To eliminate light effects, histogram of the image was equalized using adaptive histogram equalization (Sherrier and Johnson, 1987). Afterward, the image was filtered using a 2-D Gaussian low-pass filter to remove noises. To eliminate the background, the adaptive thresholding method was preformed (Otsu, 1979). Thereafter, to remove small objects from the images, a threshold with area size of 500 pixelsˆ2 were applied on them (Gonzalez et al., 2004). Finally, to avoid discontinuities and isolated areas caused by artifact present in the background (light stains due to feces) and inside the images (shadows from the feathers and the head) erosion and dilation techniques (Gonzalez et al., 2004) were used. The dilation and erosion functions add and pare pixels at the boundaries of the images and consequently unnecessary noises were removed. After segmentation a white area corresponding to the exact shape of the animal on a black background was acquired. Head of chicken was removed using Chen-Vese model (Gao et al., 2014) and six feature parameters using the Image Process Toolbox including area, convex area, perimeter, eccentricity, major axis length and minor axis length were extracted (Wang et al., 2008). Schematic of imaging and feature extraction is represented in Fig. 1.

2.4. Support vector regression (SVR)

Support vector machine (SVM) is a supervised learning algorithm for estimating indicator functions and support vector regression (SVR) is a universalization of support vector machines to estimate real-valued functions established by Vapnik and others (Cortes and Vapnik, 1995; Vapnik, 1998). Support vector machines were developed to solve classification problems at first (Mehdizadeh et al., 2014). Then they were used in regression problems widely (Alonso et al., 2013).

SVR is obtained popularity due to many attractive features and promising empirical performance. The basic idea of SVR is that the data vector x is mapped into a high-dimensional feature space $\boldsymbol{f}$ by a nonlinear mapping, and then linear regression is performed to estimate an unknown continuous-valued function based on a finite dataset number.

The training dataset is expressed as follows:

$$S = \{(x_1, y_1), ..., (x_n, y_n)\} \tag{1}$$

Where x_i and y_i are input and the output vector values for ith input, respectively. A regression model is learned from these pairs and used to predict the target values of unseen input vectors. The performance of a function $\boldsymbol{f}$ will be measured by MAPE and RMSE defined as follows (Alonso et al., 2015):

$$MAPE(S, f) = \frac{100}{n} \sum_{i=1}^{n} \frac{|f(x_i) - y_i|}{y_i} \tag{2}$$

$$RMSE(S, f) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \frac{(f(x_i) - y_i)^2}{y_i}} \tag{3}$$

Among the several types of SVR, the most frequently used is ε-SVR (Smola et al., 1998; Vapnik, 1998). Finding a function f(x) with the most ε variation from the actually obtained targets y_i is the aim of SVR. The parameter ε controls the sparseness of the solution in a rather indirect way. In other words, as long as the errors are inside the ε-insensitive band (ε -tube) they do not make any problem. SVR performs linear regression in the high dimension feature space using ε-insensitive loss and at the same time, tries to reduce model complexity by minimizing $||\omega||^2$. Thus SVR is formulated as minimization of the following functional (Alonso et al., 2015):

$$\min \frac{1}{2}\|\omega\|^2 + C \sum_{i=1}^{n} \left(\xi_i + \xi_i^*\right) \tag{4}$$

ARTICLE IN PRESS

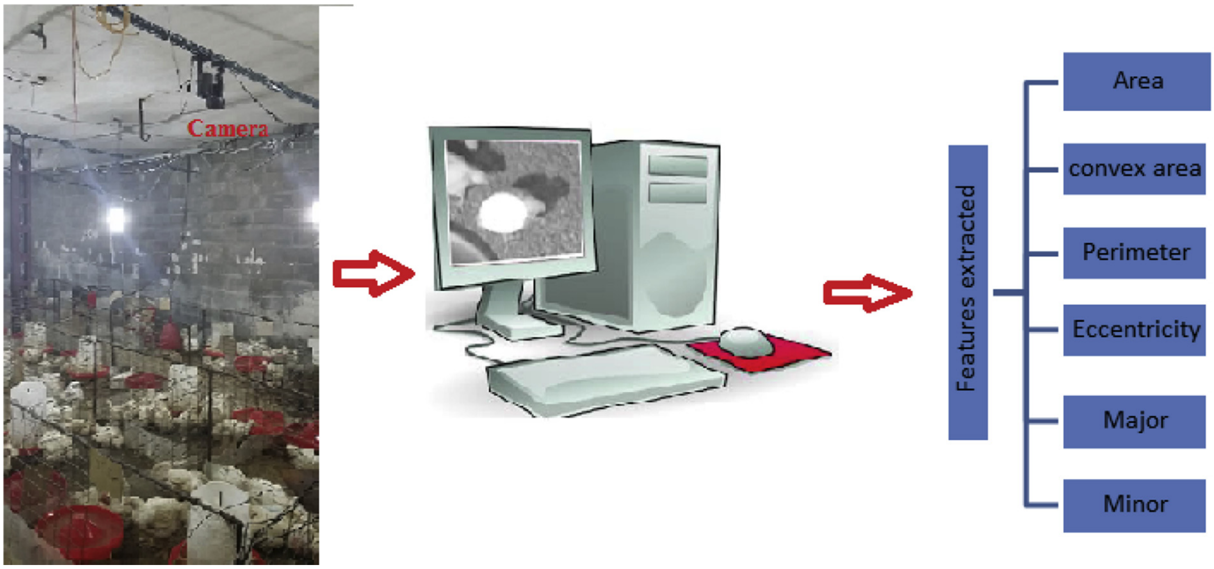

Fig. 1. Schematic representation of imaging and feature extraction.

$$s.t.\begin{cases} y_i - (\langle w, \phi(x_i)\rangle + b) \le \varepsilon + \xi_i \\ (\langle w, \phi(x_i)\rangle + b) - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0, i = 1, \dots, n \end{cases}$$

where C is referred to as the regularization constant and ε is the tube size of SVR. ξ_i and ξ_i^* are slack variables for exceeding the target value by more than ε and for being below the target value by more than ε, respectively. The quality of estimation is measured by the loss function L(y, f (x, ω)). SVR uses a new type of loss function called ε-insensitive loss function proposed by Vapnik (1995):

$$L_\varepsilon(y, f(x,\omega)) = \begin{cases} 0 & if |y - f(x,\omega)| \le \varepsilon \\ |y - f(x,\omega)| - \varepsilon & otherwise \end{cases} \tag{5}$$

The empirical risk is (Smola and Scholkopf, 2004):

$$R_{emp}(\omega) = \frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(y_i, f(x,\omega)) \tag{6}$$

In the optimization formulation, the parameter C determines the tradeoff between the model complexity and the degree to which deviations larger than ε are tolerated in the optimization formulation. In this research the proposed approach by Cherkassky and Ma (2004) was used for the selection of the optimal values for the parameters C and ε. Their suggested method was based the basic analytical form of dependencies for parameter selection. Parameters C and ε were calculated based on equations (7) and (8), respectively (for detailed derivation the reader is referred to the publication Cherkassky and Ma, 2004).

$$C = \max(|\bar{y} + 3\sigma_y|, |\bar{y} - 3\sigma_y|) \tag{7}$$

$$\varepsilon = \tau\sigma\sqrt{\frac{\ln n}{n}} \tag{8}$$

where $\bar{y}$ is the mean of the training responses (outputs), and σ is the standard deviation of the training response values (Cherkassky and Mulier, 1998; Kwok and Ivor, 2003; Smola et al., 1998; Vapnik, 1998) According to empirical tuning, the constant value $\tau = 3$ gives good performance for a variety of dataset sizes, noise levels, and target functions for SVR.By introducing Lagrange multipliers and applying the optimality constraints, the decision function has the following explicit form (Paniagua-Tineo et al., 2011):

$$f(x) = \sum_{i=1}^{nsv}(\alpha_i - \alpha_i^*)K(x_i, x) \quad s.t. \quad 0 \le \alpha_i^* \le C, \quad 0 \le \alpha_i \le C, \tag{9}$$

$$K(x_i, x) = \sum_{j=1}^{m} \varphi_j(x)\varphi_j(x_i) \tag{10}$$

where n_{SV} is the number of Support Vectors, $K(x_i, x)$ is the kernel function of support vector and α_i are the so-called Lagrange multipliers. There some fixed (nonlinear) mapping kernel function, such as the polynomial kernel function $K(x_i, x) = [(x \cdot x_i) + 1]$, the RBF (radial basis function) kernel $K(x_i, x) = \exp\left(\frac{-|x - x_i|^2}{2\sigma^2}\right)$, and the sigmoid kernel function $K(x_i, x) = \tanh(v(x \cdot x_i) + c)$ (Vapnik, 2000; Drucker et al., 1997). A particular kernel type and kernel function parameters selection are generally based on application domain knowledge and also should reflect distribution of input (x) values of the training data (Vapnik, 1998). The RBF kernel that contains a free parameter, γ which is the Parzen window width for this kernel was used. Choosing γ is typically not critical, because the model quality is stable for commonly a reasonably broad range for this parameter. To implement the SVR LIBSVM software was utilized (Chang and Lin, 2001).

3. Results and discussion

To find the location of the broiler chickens, first images was segmented. To remove the background and image binarization the adaptive thresholding method was used (Yang, 1994). After that, an ellipse fitting algorithm using generalized Hough transform was performed to localize chickens within the pen, (Davies, 1989). Afterward the chick's body was taken out as an ellipse (McFarlane and Schofield, 1995) (Fig. 2). According to the literature, measuring the animal body dimensions with head included would bring in an additional error, due to repeated shifts of the head position

Please cite this article in press as: Amraei, S., et al., Application of computer vision and support vector regression for weight prediction of live broiler chicken, Engineering in Agriculture, Environment and Food (2017), http://dx.doi.org/10.1016/j.eaef.2017.04.003

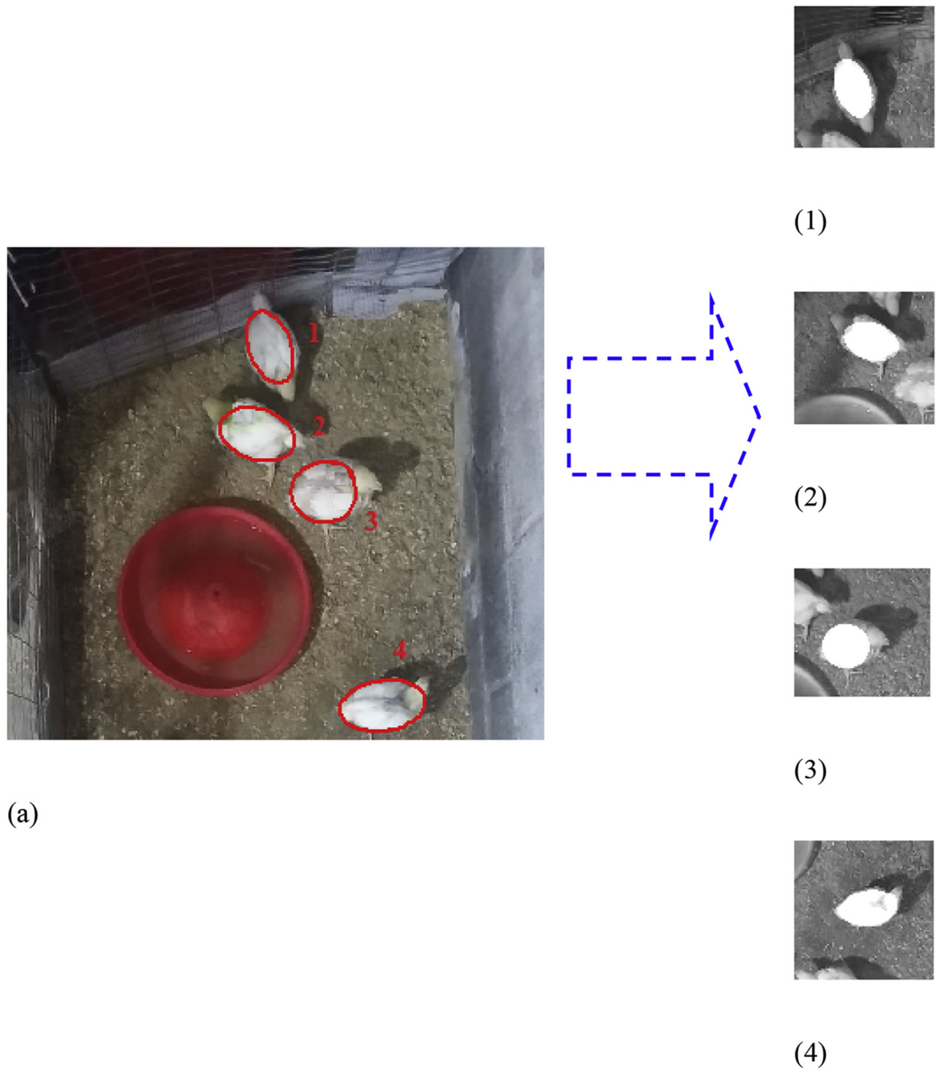

Fig. 2. (a) Ellipses fitted to chickens" body; segmented images.

(Schofield, 1990; De Wet et al., 2003). Therefore, head and tail of chickens was removed using Chan-Vese method (Chen et al., 2002).

The comparison results of weight estimation of SVR and manual weight measurement of twenty birds up to 42 days every seven days were shown Tables 1 and 2.

According to Tables 2 and 3 at days 7, 14, 21, 28, 35 and 42 of broiler breading, weight of 40%, 35%, 55%, 65%, 50% and 85% of broiler were overestimated, respectively. Therefore, machine vision system along with SVR mostly has estimated higher weight than manual measurement. It is also worth noting that the maximum absolute difference between real and predicted values in corresponding rearing days were 5.2, 22.9, 31, 58.5, 127, and 178.3 g respectively. Mollah et al. (2010) were randomly selected 20 birds at 7, 14, 21, 28, 35 and 42 days of breading and developed a machine vision system to predict weight of live broiler chickens. The weights of 50%, 60%, 70%, 55%, 4% and 20% of broiler were estimated higher than real weight, in each respective day of rearing days. Furthermore, according to their report the estimated body weights differed significantly ($P < 0.05$) from manually measured body weights at age of 42 day. Wang et al. (2008) used the artificial neural network technique to correlate a multitude of physical features extracted from the walk-through images to pig live weight in an attempt to improve the accuracy of live weight approximation. The results of their study showed that the average relative error of the walk-through weighing system was around 3%.

According to Table 3 body weights were similar to body weights recorded manually ($P > 0.05$). Doyle and Leeson (1989) developed an automatic weighing system for poultry reared on a litter floor. According to the reported results, the body weights obtained automatically were similar to body weights recorded manually ($P > 0.05$) with broilers weighing up to 2 kg and turkeys up to 2.5 kg. However, some researchers obtained poor agreement between automatic and manual mean weightings (Newberry et al., 1985; Blokhuis et al., 1988).

The estimated body weight and manually measured body weight was shown in Fig. 3. The RMSE, MAPE and the R^2 value of SVR algorithm were 67.88, 8.63% and 0.98, respectively. The coefficient of determination for pig based on artificial neural network reported by Wang et al. (2008) was 0.99. The reason of having higher accuracy in Wang et al. (2008) study compare to this study could be the existence of feather as well as birds perching. These might be increased the birds' dimensions and lead to errors in weight prediction.

Table 1
Comparison between the manual and the estimated body weights at 7, 14 and 21 days of age (individual basis).

Bird ID	7 days				14 days				21 days			
	Manual weight(g)	Estimated weight (g)	Difference (g)	Error(%)	Manual weight (g)	Estimated weight (g)	Difference (g)	Error(%)	Manual weight (g)	Estimated weight (g)	Difference (g)	Error(%)
1	128.2	126.2	−2	0.015601	342.6	340	−2.6	0.007589	670.3	696	25.7	−0.03834
2	124.6	126.2	1.6	−0.01284	371.1	371.1	−0.6	0.001614	737.6	724.1	−13.5	−0.018303
3	111.1	108.3	−2.8	0.025203	309.8	309.2	−0.6	0.001937	646.7	640.7	−6	−0.009278
4	116.4	119.7	3.3	−0.02835	309.8	309.2	−0.6	0.001937	718.4	721.9	3.5	−0.00487
5	129	131.7	2.7	-0.02093	333.1	341	7.9	−0.02372	700	714.1	14.1	−0.02014
6	130.8	128.4	−2.4	0.018349	288.1	275	−13.1	0.04547	524.2	520.8	−3.4	−0.006486
7	110.1	105.9	−4.2	0.038147	323	318.5	−4.5	0.013932	640.2	634	−6.2	−0.009684
8	161.2	156	−5.2	0.032258	339.1	329	−10.1	0.029785	605.2	627	21.8	−0.03602
9	109	108.2	−0.8	0.007339	440.6	452	11.4	−0.02587	842	832	−10	−0.011876
10	102.3	99.1	−3.2	0.031281	320.8	320	−0.8	0.002494	660	674.9	14.9	−0.02258
11	149.4	147.4	−2	0.013387	372.3	368.1	−4.2	0.011281	744	720	−24	−0.032258
12	109.1	110.5	1.4	−0.01283	318.8	330	11.2	−0.03513	680.3	678.3	−2	−0.00294
13	166.3	162.9	−3.4	−0.02044	268.8	268	−0.8	0.002976	719.9	710	−9.9	−0.013752
14	79.2	81.7	2.5	−0.03157	346.5	332	−14.5	0.041847	579	568.3	−10.7	−0.01848
15	126.4	124.6	−1.8	0.014241	394.9	402	7.1	−0.01798	732.2	732	4.8	−0.00656
16	127	124.2	−2.8	0.022047	356.9	369	12.1	−0.0339	683.2	705	21.8	−0.03191
17	149.3	145	−4.3	0.028801	278.4	272	−6.4	0.022989	564.5	570	5.5	−0.00974
18	112.6	114.3	1.7	0.0151	310.6	302	−8.6	0.027688	629.1	615	−14.1	−0.022413
19	136.4	139.3	2.9	−0.02126	384.1	407	22.9	−0.05962	702	733	31	−0.04416
20	154.5	156.7	2.2	−0.01424	372.5	372	−0.5	0.001342	699.7	725	25.3	−0.03616

Table 2
Comparison between the manual and the estimated body weights at 28, 35 and 42 days of age (individual basis).

Bird ID	28 days				35 days				42 days			
	Manual weight(g)	Estimated weight(g)	Difference (g)	Error(%)	Manual weight(g)	Estimated weight(g)	Difference (g)	Error(%)	Manual weight(g)	Estimated weight(g)	Difference (g)	Error(%)
1	1122.3	1151	28.7	−0.02557	1494	1434	−60	0.040161	2242	2310.1	68.1	−0.03037
2	1244.3	1260	15.7	−0.01262	1921	1911.8	−9.2	0.004789	2674	2790.1	116.1	−0.04342
3	1083.2	1115	31.8	−0.02936	1616	1502	−114	0.070545	2181	2300	119	−0.05456
4	1238.1	1289	50.9	−0.04111	1754	1880	126	−0.07184	2322	2470	148	−0.06374
5	1041.8	1030.2	−11.6	0.011135	1614	1660	46	−0.0285	2227	2330	103	−0.04625
6	817.5	876	58.5	−0.07156	1217	1320	103	−0.08463	1712	1770	58	−0.03388
7	1091	1040	−51	0.046746	1556	1558.2	2.2	−0.00141	2045	2120	75	−0.03667
8	989.2	976.5	−12.7	0.012839	1506	1450.3	−55.7	0.036985	1991	2120	129	−0.06479
9	1417.3	1448	30.7	−0.02166	2172	2140.3	−31.7	0.014595	2916	3010	94	−0.03224
10	1111.2	1144	32.8	0.02952	1736	1820	84	−0.04839	2300	2230.3	−69.7	0.030304
11	1179.7	1137	−42.7	0.036196	1775	1790	15	−0.00845	2443	2609.8	166.8	−0.06828
12	1060.4	1021	−39.4	0.037156	1690	1630	−60	0.035503	2224	2330	106	−0.04766
13	1289	1320	31	−0.02405	1950	2000	50	−0.02564	2451	2300.2	−150.8	0.061526
14	990.1	1004	13.9	−0.01404	1565	1601	36	−0.023	2172	2300	128	−0.05893
15	1310.8	1289.2	−21.6	0.016478	2029	2020	−9	0.004436	2838	2950	112	−0.03946
16	1153.5	1205.8	52.3	−0.04534	1556	1500	−56	0.03599	2046	2140	94	−0.04594
17	867.7	898	30.3	−0.03492	1303	1190.8	−112.2	0.040064	1711	1850	139	−0.08124
18	1009.2	977	−32.2	0.031906	1501	1440	−61	−0.07923	1852	2030.3	178.3	−0.09627
19	1121.4	1160	38.6	−0.03442	1603	1730	127	−0.0395	1924	1820	−104	0.054054
20	1040.6	1080	39.4	−0.03786	1443	1500	57	−0.0395	1777	1950	173	−0.09736

Table 3
Differences between the manual and the estimated body weights (weekly basis).

Age (days)	Manual weight	Estimated weight	Difference	p-Value[a]
7	126.645	125.815	0.83	0.90291
14	339.12	339.355	−0.235	0.986908
21	673.925	677.355	−3.43	0.881682
28	1108.915	1121.085	−12.17	0.79584
35	1650.05	1653.92	−3.87	0.960302
42	2200.316	2285.3	−84.9842	0.465161

[a] Paired *t*-test was performed to know whether there was any statistically significant difference between the manual and the estimated body weights.

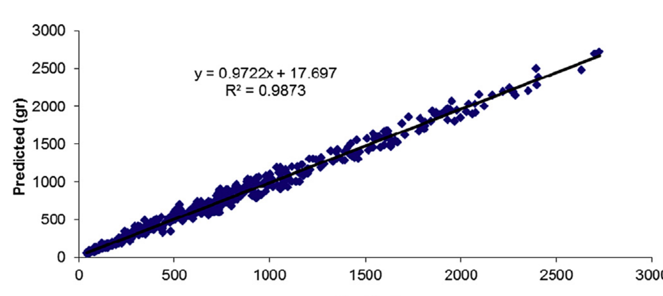

Fig. 3. Scatter plot of manual and estimated body weight of broiler with SVR.

Please cite this article in press as: Amraei, S., et al., Application of computer vision and support vector regression for weight prediction of live broiler chicken, Engineering in Agriculture, Environment and Food (2017), http://dx.doi.org/10.1016/j.eaef.2017.04.003

4. Conclusion

Collecting frequent and accurate body weights of broiler is of great importance for breeder. Therefore, in this paper image processing and support vector regression were used to predict live body weight of boiler chicken. To localize chickens within the pen ellipse fitting algorithm using generalized Hough transform was performed and head and tail of chickens using Chan-Vese method were removed. The comparison results of weight estimation of SVR and manual weight measurement of twenty birds up to 42 days every seven days showed that predicted body weights were similar to body weights recorded manually ($P > 0.05$). The RMSE, MAPE and R^2 values were 67.88, 8.63%. And 0.98, respectively.

Acknowledgments

The authors acknowledge the financial support provided by the Ramin Agriculture and Natural Resources University of Khuzestan.

References

Alonso, J., Villa, A., Bahamonde, A., 2015. Improved estimation of bovine weight trajectories using support vector machine classification. Comput. Electron. Agric. 110, 36–41.
Alonso, J., Castañón, Á.R., Bahamonde, A., 2013. Support Vector Regression to predict carcass weight in beef cattle in advance of the slaughter. Comput. Electron. Agric. 91, 116–120.
Blokhuis, H.J., Van der Haar, J.W., Fuchs, J.M.M., 1988. Do weighing figures represent the flock average. Poult. Int. 4 (5), 17–19.
Brandl, N., Jørgensen, E., 1996. Determination of live weight of pigs from dimensions measured using image analysis. Comput. Electron. Agric. 15 (1), 57–72.
Chang, C., Lin, C., 2001. {LIBSVM}: a Library for Support Vector Machines (Version 2.3).
Chen, Y.R., Chao, K., Kim, M.S., 2002. Machine vision technology for agricultural applications. Comput. Electron. Agric. 36 (2), 173–191.
Cherkassky, E., Mulier, F., 1998. Learning from Data: Concepts, Theory, and Methods. John Wiley and Sons.
Cherkassky, V., Ma, Y., 2004. Practical selection of SVM parameters and noise estimation for SVM regression. Neural Netw. 17 (2), 113–126.
Cortes, C., Vapnik, V., 1995. Support-vector network. Mach. Learn. 20 (3), 273–297.
Davies, E.R., 1989. Finding ellipses using the generalised Hough transform. Pattern Recognit. Lett. 9 (2), 87–96.
De Wet, L., Vranken, E., Chedad, A., Aerts, J.M., Ceunen, J., Berckmans, D., 2003. Computer-assisted image analysis to quantify daily growth rates of broiler chickens. Br. Poult. Sci. 44 (4), 524–532.
DeShazer, J.A., Moran, P., Onyango, C.M., Randall, J.M., Schofield, C.P., 1988. Imaging Systems to Improve Stockmanship in Pig Production. AFRC Institute of Engineering Research, p. 24.
Doyle, I., Leeson, S., 1989. Automatic weighing of poultry reared on a litter floor. Can. J. Anim. Sci. 69, 1075–1081.
Drucker, H., Burges, C.J.C., Kaufman, L., Smola, A., Vapnik, V., 1997. Support vector regression machines. Adv. Neural Inf. Process. Syst. 9, 155–161.
FAO (Food and Agriculture Organization), 2013. In FAO Year Book. Food and Agriculture Organization of United Nations.
Gao, X., Du, J.X., Wang, J., Zhai, C.M., 2014. Shape and color based segmentation using level set framework. In: Intelligent Computing Methodologies. Springer International Publishing, pp. 265–270.
Gonzalez, R.C., Woods, R.E., Eddins, S.L., 2004. Digital Image Processing Using MATLAB. Pearson Education India.
HSUS, 2010. The Welfare of Animals in the Pig Industry. The Humane Society of the United States (HSUS).
Kwok, J.T., Ivor, W.T., 2003. Linear dependency between ε and the input noise in ε-support vector regression. IEEE Trans. Neural Netw. 14 (3), 544–553.
Lokhorst, C., 1996. Automatic weighing of individual laying hens in aviary housing systems. Br. Poult. Sci. 37, 485–499.
McFarlane, N.J., Schofield, C.P., 1995. Segmentation and tracking of piglets in images. Mach. Vis. Appl. 8 (3), 187–193.
Mehdizadeh, S.A., Sandell, G., Golpour, A., Torshizi, M.A.K., 2014. Early determination of pharaoh quail sex after hatching using machine vision. Bull. Env. Pharmacol. Life Sci. 3, 05–11.
Mollah, M.B.R., Hasan, M.A., Salam, M.A., Ali, M.A., 2010. Digital image analysis to estimate the live weight of broiler. Comput. Electron. Agric. 72 (1), 48–52.
Newberry, R.C., Hunt, J.R., Garriner, E.E., 1985. Behaviour of roaster chickens towards an automatic weighing perch. Br. Poult. Sci. 26, 229–237.
NRC, 1994. National Research Council. National Requirements of Poultry, 9^{th} Rev. Edn. National Academy Press, Washigton, DC.USA.
Otsu, N., 1979. A threshold selection method from gray-level histograms. IEEE Trans. Syst. Man. Cybern. 9 (1), 62–66.
Paniagua-Tineo, A., Salcedo-Sanz, S., Casanova-Mateo, C., Ortiz-García, E.G., Cony, M.A., Hernández-Martín, E., 2011. Prediction of daily maximum temperature using a support vector regression algorithm. Renew. energy 36 (11), 3054–3060.
Schofield, C.P., 1990. Evaluation of image analysis as a means of estimating the weight of pigs. J. Agric. Eng. Res. 47, 287–296.
Schofield, C.P., Marchant, J.A., White, R.P., Brandle, N., Wilson, M., 1996. Monitoring pig growth using a prototype imaging system. J. Agric. Eng. Res. 72, 205–210.
Sherrier, R.H., Johnson, G.A., 1987. Regionally adaptive histogram equalization of the chest. Med. Imaging, IEEE Trans 6 (1), 1–7.
Smola, A.J., Scholkopf, B., 2004. A Tutorial on Support Vector Regression. Statistics and Computing, pp. 199–222, 0.1023/B: STCO.0000035301.49549.88.
Smola, A.J., Murata, N., Schölkopf, B., Müller, K.R., 1998. Asymptotically optimal choice of ε-loss for support vector machines. In: ICANN, vol. 98. Springer, London, pp. 105–110.
Turner, M.J.B., Gurney, P., Belyavin, C.G., 1983. Automatic weighing of layer-replacement pullets housed on litter or in cages. Br. Poult. Sci. 24 (1), 33–45.
Turner, M.J.B., 1981. Performance Monitoring of Livestock Using On-line Computers. British Society for Animal Production (Occasional Symposium on Computers in Animal Production, Harrogate).
Turner, M.J.B., Gurney, P., Crowther, J.S.W., Sharp, J.R., 1984. An automatic weighing system for poultry. J. Agric. Eng. Res. 29, 17–24.
Vapnik, V., 1995. The Nature of Statistical Learning Theory. Springer Verlag, New York.
Vapnik, V., 1998. Statistical Learning Theory. John Wiley and Sons, New York.
Vapnik, V., 2000. The Nature of Statistical Learning Theory. Springer-Verlag, New York.
Wang, Y., Yang, W., Winter, P., Walker, L., 2008. Walk-through weighing of pigs using machine vision and an artificial neural network. Biosyst. Eng. 100, 117–125.
Yang, Q., 1994. An approach to apple surface feature detection by machine vision. Comput. Electron. Agric. 11 (2–3), 249–264.

Please cite this article in press as: Amraei, S., et al., Application of computer vision and support vector regression for weight prediction of live broiler chicken, Engineering in Agriculture, Environment and Food (2017), http://dx.doi.org/10.1016/j.eaef.2017.04.003