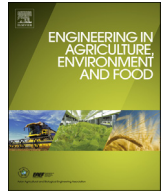




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Application of computer vision and support vector regression for weight prediction of live broiler chicken

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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.

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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.

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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/m²). 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 pixels² 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 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:

$$S = \{(x_1, y_1), \dots, (x_n, y_n)\} \quad (1)$$

Where x_i and y_i are input and the output vector values for i th 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 f will be measured by MAPE and RMSE defined as follows (Alonso et al., 2015):

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

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

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):

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

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