Monitoring System to Detect Problems in Broiler Houses Based on Image Processing

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Abstract

Abnormal animal behaviour and reduced growth rate in a broiler house are just a few signs that can indicate an undesired situation, such as diseases, technical malfunctioning in feeding and drinking lines and suboptimal management procedures. It is important that the problems be detected in an early stage to avoid harming the welfare or the production of broilers. In this paper, an automated method to detect problems in a broiler house using cameras and an image analysis software is introduced. Three top view cameras mounted in the ridge of a commercial broiler house with 28000 animals continuously monitored the floor space below and the images taken by the cameras were translated into animal distribution index every 5 minutes by analysis software. Based on the distribution index data, a real-time model was developed to predict the normal animal distribution index as a response to the light input. Using this model, an online prediction could be made in real-time as to generate an alarm whenever animal behaviour abnormally deviated from the prediction. Results showed that this method was able to report 95.24 percent of events in real-time, demonstrating a high potential of using automatic monitor tools for broiler production over a complete growing period.

Keywords: broiler chicken, automatic monitor, real-time model, image analysis, distribution index

Introduction

According to Food and Agriculture Organization (FAO) (Cluff and Jones, 2010), during this decade the annual world poultry production is expected to increase by 2.8%. Modern farmers are confronted with increasing pressure to keep a large number of animals per farm, which will become even more acute in future years. Therefore, intensive farming is unavoidable and effective management in broiler houses is crucial. In this connection technology can offer assistance for real time monitoring of animal production (Cox, 2003). Specifically, continuous automated monitoring of agricultural animals can result in "early warning systems" that improve the management of individual animal needs at any time and improve broiler welfare. Technology of monitoring broilers by camera and image processing has already been practiced by many scientific researchers because it is non-intrusive and cost-effective technology that can be automated to work in real-time. De Wet et al. (2003) employed computer-assisted image analysis to estimate daily body weight changes of broiler chickens. Kristensen et al. (2011) investigated possibility of detecting leg disorders in broiler chickens. Daw-
kins et al. (2009) showed that automated measures of optical flow have the potential to provide continuous 'outcome' measures of the welfare state of the flock. However, what is missing in previous works is an algorithm that can report problems of the broiler house in real-time and can help the farmers to manage keeping their broilers more efficiently.

In this study the index to monitor broiler breeding is distribution. Sudden variations of broiler distribution could be linked to undesired situations, such as thermal discomfort, insufficient feeding, and technical malfunctioning in feeding and drinking lines or many other welfare issues. Using the distribution index of broilers measured by a real-time monitoring and image analysis techniques this study aimed to describe a method for early warning of events in a commercial house.

Materials and methods

1.1 The eYeNamic system

The eYeNamic system is an image pre-processing tool for livestock monitoring (Costa et al., 2009). Three Internet Protocol (IP) cameras (MOBOTIX AG Security-Vision-Systems, Rhine-land-Palatinate, Germany) were installed in the ridge at the height of 5 m and distributed over the length of the house which was 63.5 m long. The top-view images over the floor were captured with a resolution of 1280 by 960 pixels and 0.5 Hz frame rate in MPEG (Moving Picture Experts Group) format. Figure 1 shows an example image of using three cameras in a surface of 19.8 by 63.5 m² with broilers at the age of 27 days.

![Figure 1. Picture of the ground surface in a broiler house equipped with eYeNamic divided to 60 1 by 1 m² zones in one camera’s image.](image)

1.2 Birds and housing

For the experiments, a commercial broiler house in the Netherlands was equipped with an eYeNamic system. The house had dimensions of 19.8 m by 63.5 m and a height of 5.10 m and housed 28,000 Ross 308 broilers. During the experiment, day-old chicks with a weight of 40 ± 5 g were brought to the house and grew up during 42 days. At the beginning there was 28,000 chickens, but around day 35, there was an unloading of chickens, 5000 with a mass of 1800 g, and there was mortality, which was not taken into account. Therefore, until day 35, the stocking density was calculated to 40 kg m⁻², and on day 35, it was 33 kg m⁻². On day 42 as chickens grew up, stocking density was 42 kg m⁻².

The building was equipped with a climate control system (Type Fancom FUP1EA2). Mean air temperature was set as 34°C during day 1 while temperature was decreased gradually until 20°C at the end of the growth period. Light was switched on and off four times a day, so there were 4 light periods for 5 hours each and 4 dark periods for one hour each. The start of the first light period was at 3 AM.

1.3 Distribution index
To calculate the animal distribution index, the image captured by each camera was divided into 60 zones. Occupation density of broilers in each zone was calculated by equation (1) after converting the image into a binary form using the histogram shape-based thresholding explained by Buyse et al. (1996).

\[ ZOD_{ij}(t) = \frac{\sum_{(x,y) \in Z_{ij}} O(x,y,t)}{Z_{ij}} \times 100 \]  

In the above equation, \( O(x, y, t) \) is the occupation (foreground pixels in the binary image) of a zone and \( Z_{ij} \) is the size of the zone in pixels.

There were 180 zones in total because there were three cameras in the house and each camera captured 60 zones. For covering a total of 28000 birds, the average occupation rate of 180 zones was calculated using equation (2).

\[ ZOD(t) = \frac{\sum_{i=1}^{C} \sum_{j=1}^{M} \sum_{l=1}^{N} ZOD_{ij}(t)}{C \times M \times N} \]  

In the above equation, \( M \) and \( N \) are the number of rows and columns of zones respectively and \( C \) is the number of cameras.

Using \( ZOD(i, j)(t) \) of each of the cameras the distribution index is calculated from the three matrices. All values, i.e. 180 values, are checked to see how many of them are out of the range of 20 % from \( ZOD(t) \) by equation (3).

\[ U_{ij}(t) = \begin{cases} 1 & \text{if } |ZOD_{ij}(t) - ZOD(t)| < \alpha \times ZOD(t) \\ 0 & \text{else} \end{cases} \]  

\( U_{ij}(t) \) is the distribution index in zone \((i, j)\), \( ZOD_{ij} \) is the zone occupation density in zone \((i, j)\), \( ZOD(t) \) is the average occupation rate of all zones calculated by equation (2), and \( \alpha \) is a fixed coefficient, 0.25 or 25% in this study.

Finally the distribution index for a total of 28000 birds is yields by equation (4).

\[ UI(t) = \frac{\sum_{i=1}^{C} \sum_{j=1}^{M} \sum_{l=1}^{N} U_{ij}(t)}{C \times M \times N} \]  

### 1.4 Development of the adaptive real-time model

The distribution index of the animals and abnormal behaviour was visible by top-view images. Abnormal behaviour was defined as a sudden drop in the distribution of animal assumed as more than 25% from expected distribution which was dependent on growth rate.

The study was comprised of two experiments, each continuously recording video of the broilers in the house for 42 days which correspond to the whole growth period. The first experimental data were used for development of image analysis techniques and the second for validation.

In short intervals, distribution index of broilers in a broiler house increases linearly although indeed it follows a non-linear trend. This trend can be affected by several factors including problems in feeding or drinking system and light intensity. These events could be detected using a model-based algorithm developed and presented in this work.

As mentioned earlier, the data of the first experiment was used to develop a linear real-time model and test the distribution index of the birds as a response to the light input. Since distribution index can be assumed to vary linearly within a few light periods, this model is designed to predict the data of next light periods using the average slope of the previous periods. Therefore, linear model was more practical for this application and it has advantage of simple and fast implementation for real-time applications.

Linear real-time model can be used to fit a predictive model to an observed data set and the least squares approach was used to fit parameters of the linear model. In figure 2, \( b \) is the final distribution index value of the previous light periods and \( K \) is the average slope of distri-
bution index change in the last three light periods. K and b were adapted for each light period and this process was repeated for each light period recursively. It means the moving prediction window (figure 2 (b)) was shifted for one light period each time and next light period data were predicted.

When the measured values deviate from the predicted standard values, an event could be occurring in the house. In figure 2 (b), when the measured values were out of 25% range of the predicted value as marked in thick dark grey line, the prediction was lost. If the faulty (thick dark grey line) region continued for more than 15 minutes, an alarm was generated. Figure 3 shows an example of applying the prediction model on several light periods of distribution index data. In general chickens are well distributed as shown in the left picture of Figure 3. However as a problem occurred with the feeder line, broiler could not access to food on that feeder line and spread over the regions close to other feeder lines as shown in the right picture of Figure 3. This caused a drop in distribution index and we could detect the problem by the prediction model.

In the second experiment, the alarm regions predicted by the real-time model were compared a logbook filled by the farmer whenever he knew there was a problem or when he was observing abnormal behaviour of broilers.

\[
d = b + K \cdot t
\]

(Slope) \( K = \frac{\Delta d}{\Delta t} \)

Figure 2. A linear real-time model used to predict distribution index. (a) \( b \) is the final distribution index value in the previous light period, \( K \) is the average slope of distribution index change in the last three light periods. (b) Prediction window consisting of three light periods to predict the next light period data.

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Figure 3. Detection of an event of feeder line disorder by predicting distribution index in a broiler house.

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Results and discussion

In this paper an algorithm was described to detect occurrences in a broiler house using image interpretation and analysing the distribution index of broilers in captured images. Figure 4 demonstrates the predicted and the measured values that align to a precise extent. In this phase a linear real-time model was used. Subsequently, alarms generated by the algorithm were compared with the events logbook filled in by the farmer.

The results of applying the algorithm on the data of the commercial broiler farm for a complete fattening period are presented in Figure 4. Taking events logbook of the farmer as reference, the EDI algorithm managed to successfully detect 20 out of 21 (95.24 %) of the events happening in the house.

There are many parameters that should be carefully monitored to ensure broilers are in a good welfare status. Problems with facilities, such as water and food supply systems, environment control equipment or external disturbances, such as regular inspections might affect them (Manning et al., 2007). Detection of problems in a broiler house using image analysis and real time calculations is a possible step towards automatizing monitoring broiler chickens and has numerous applications. Some of the possible applications in monitoring broilers are detecting problems with feeder and drinker lines, malfunctioning of the heater or ventilator and vaccination effects.

Currently parameters such as temperature are constantly measured in conventional broiler houses. In addition, alarm systems using water intake monitoring have also been investigated (Pluk et al., 2010). However, detection of events based on animal behaviour using automated image analysis in a commercial farm, has never been reported in literature.

To evaluate the performance of the algorithm presented in this work, the results of the algorithm for detecting the events of data were compared with the method proposed by Pluk et al. (2010). While Pluk et al. (2010) analysed the water use pattern of broilers, the presented method in this work analysed distribution index of broilers which were highly dependent on broilers’ behaviours. This promises automatic detection of abnormal behaviours in broilers. Figure 5 compares the results obtained by each method and shows that the method implemented in this work could detect 95.24 % of the events correctly while raised no false alarms. The reference method though provoked 6 false alarms and failed to detect 2 of the events.

This method offers many potential applications to improve animal husbandry management. Although events such as vaccination that have long-term effects on broilers are more difficult to be detected, the algorithm still managed to detect 1 out of 2 of these events (the last right columns in Figure 5).

Finally, the results show that the presented algorithm together with the eYeNamic system can be used as a reliable early warning system for the farmer to manage his farm more feasibly and more economically.
Figure 4. Distribution index of the commercial farm over a growth period (42 days); Mean Percentage Error (MPE) for this example was 4.2%.

Figure 5. Categorization of events and comparison of performance of EDI algorithm with the algorithm presented by Pluk et al. (2010). True positive cases using EDI were 20 (95.24%) vs. 13 (61.9%) using [14], False negative cases were 1 (4.76%) vs. 2 (9.5%) and False positive cases using EDI were 0 (0%) vs. 2 (28.6%)

Conclusions

A technique has been introduced that offers fully automated identification of problems in a broiler house. This became possible by performing real-time camera vision-based monitoring through top-view video processing and linear real-time prediction models. The results show that by real time prediction of distribution index of broilers, it is possible to detect problems in feeding, drinking, heating and ventilation systems and vaccination effects. So far, the system is able to detect these problems with an accuracy of 95.24 % while no unwanted alarm was provoked. In conclusion, the introduced method is an important economic factor for the livestock sector since food and water intake, health, welfare, performance and farm profitability are all variables that are important to be monitored. Finally, developing this method can help farmers to monitor their animals' behaviours and health in a more efficient way.

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