

Development of imaging tracking algorithms for the automatic recording of welfare indicators of broiler on farm

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Abstract

Guaranteeing consumers broiler production that respects animal welfare is the basis of the farmer's profession, but civil society wants more transparency on farming practices. On farm welfare assessment methods require time and the presence of a trained observer. Image analysis is an opportunity to perform continuous and real-time measurements without disturbing animals. The objective of this paper is to review the performance of an image-based broiler detection algorithm, using artificial intelligence to monitor individual broiler mobility. Most of the train and test database of images used reflect commercial broiler stocking density. The test database represents the different stages of broiler production. The overall accuracy of right detection is 91%. The sensitivity of the algorithms varies with age and broiler density per m². It decreases with age of broilers, from 66% for 0-day-old broilers to 90% for 40-day-old broilers. Overall, the model achieves a detection rate of 80% across all age groups. Broiler detection is strongly linked to the number of pixels that define the animal and bird activity. The quality of the tracking depends very strongly on the ability of the system to detect the animals correctly, but also on their activity. Regarding these promising results, the data generated will be used for the early detection of health and welfare problems in broilers and the calculation of welfare and health indicators in commercial broiler farms.

Keywords: broiler, computer vision, mobility

Introduction

Growing public awareness of the way in which animals are reared is prompting the poultry industry to introduce ways of reporting welfare and health of poultry. Methods exist for assessing animal welfare on farms. They involve the application of welfare measurement protocols, based on occasional observation of the animals by trained people. Many researchers are interested in the possibility of using new technologies to assess and report animal welfare on farms. The advantage of these tools is to allow data to be collected in real time, without causing stress to animals and in a more objective and less time-consuming way than the methods traditionally used by a human observer (Créach et al. 2019). It is already possible to use image analysis to monitor changes in poultry activity and their distribution in the barn, at group or individual level. A first approach is based on the percentage of pixels whose colour changes over successive images of a video. This is used to assess the activity of a group of broilers (Fraess et al., 2016; M. Dawkins et al. 2021). The data generated has been correlated, for example, with broilers'

carriage of *Campylobacter* bacteria (Colles et al., 2016), the occurrence of Footpad dermatitis, hockburns (Dawkins et al., 2017; Peña Fernández et al. 2018) and gait score of broilers (Silvera et al. 2017). This list of articles is far from exhaustive. One company has released the EyeNamic solution, based on this approach (De Montis et al., 2013). The disadvantage of this method is that it is based on the analysis of pixel colour change and not on the direct analysis of animal behaviour. A second approach to image analysis involves tracking individual birds. Some researchers, such as Collins in 2008, have monitored individual birds in groups of 20 for a limited period (10 minutes). A French company has recently launched a solution based on this approach (Copeeks), but no publication is available on the methodology used or the performance of the proposed solution. The videos available are only of very short duration (30 seconds). The approach involving animals wearing RFID tags (Siegford et al., 2016; Sales et al. 2015; Feiyang et al. 2016; Li et al. 2020; Oliveira et al., 2019), like with visual tracking, makes it possible to collect individual animal activity (speed, acceleration, time spent near specific equipment, etc.). Although the reliability of this solution is interesting for assessing welfare, it is not feasible to use it in commercial barns. Removing the device requires handling the RFID-tags on each animal, which is time-consuming and laborious for farmers.

Developments in image analysis to assess poultry activity show that tools developed can still be perfected and are still at the prototype stage. Although systems are being developed, there is currently no system adapted to commercial stocking densities that allows individual data to be collected to calculate welfare indicators for broilers. The individual data collected using this analysis algorithm could be used to calculate poultry welfare and health indicators. This would make it possible to automate the assessment of welfare of broilers, with more regular and more detailed information than these obtained on an ad hoc basis using conventional methods (such as the EBENE® method; Bignon et al., 2017), so that the farmer could take corrective action if necessary during the flock. The aim of this article is to report on the current performance of a new image-based detection algorithm, using artificial intelligence and enabling individual monitoring of broilers on commercial farms. These algorithms have been developed as part of the EBroilerTrack project, led by ITAVI with INRAE INTHERES.

Material and methods

Individual broiler detection and tracking algorithms developed

Before processing, rough images are previously deformed using distortion corrections with a dedicated algorithm because the camera's wide angle distorts the image in the field. The objective is to calculate effective and real distance and speed done per animal. Highly deformed zones, at the edge of the field, are particularly impacted by this procedure.

The tracking method developed consists of two independent parts. The first involves the individual detection of each broiler in the field of view of the camera. A convolutional neural network (YOLO V8) is used for this detection. It has been trained on a database containing almost 1 854 images (with and without distortion corrections), i.e. 13 1915 broilers (71 broilers per image on average). A portion of the images was manually annotated, while another portion comes from open-source datasets found online.

Additionally, data augmentation techniques have been performed to increase dataset variability. This type of detection model is less sensitive to lighting conditions in the poultry barn and variations in the contrast between broiler and litter. As a result, the algorithms are able to separate crowded broilers more easily, compared with a traditional detection method (not based on learning and without artificial intelligence) (O'Mahony N. et al., 2019). At the end of this detection stage, the position and size of each broiler is available (see section 1.3).

The second step consists of following each detected broiler from one image to the next (tracking step). To do this, the BoT-SORT tracking model is used. It uses a Kalman filter to anticipate the future position of the objects, and then uses an association by optimization (Hungarian optimization) to match the objects detected in the new image to those whose estimated positions are closest. In this way, a unique identifier is assigned to each animal as soon as it arrives in the camera field and from one image to the next. If a bird goes out of the field and comes back later, a new identifier is applied. There is no continuous monitoring of individual along time on farm because there is no possibility to monitor the whole area of the poultry barn with one camera.

Kind of data that can be generate by the model

Areas of interest, such as feeders and troughs, are identified in the camera field of view in order to find out how often these areas are used (number and duration of passages through the area) (see Figure 1). To do this, we use the previously trained YOLOv8 detection model. The feeding zone is defined by a circle around each feeder and the drinking zone by a rectangle around the pipette line (see Figure 1). The areas of interest are automatically traced several times during the batch using a dedicated algorithm. It is also possible to define a zone around an enrichment to find out how often it is used, in the same way as for other zones. A rectangle is automatically drawn around each broiler identified, and the length and width of each rectangle are recorded.

Figure 1 : Example of feeder and drinking zone (in blue) [photo credit ITAVI].



Examples of the data generated by these tracking algorithms are listed in Table 1 below. The area available per animal corresponds to the area of the Voronoi cells or the

maximum area of the polygon in Figure 2, containing a broiler without crossing another cell. An animal that moves or its neighbours modifies its Voronoi cell.

Figure 2: Example of Voronoi cells, one cell containing a broiler [photo credit ITAVI].



Table 1: Results of the proposed algorithm per age

Indicators generated	Unit/broiler
Distance travelled	Cm
Movement speed	Cm/s
Duration of activity period	S
Time spent in zone of interest	S
Surface area of broilers seen for above (= surface area of the rectangle representing each broiler)	Cm ²
Surface area available / animal	Cm ²

Variables used to evaluate detection performance of the model

The images were acquired on commercial poultry barns, providing an environment representative of real field conditions. This is to ensure that the model is tested in conditions similar to those in which it will be deployed.

Each image in our sample has been carefully annotated to mark the position of the broilers with an individual bounding box. The test sample consists of 10 images representing different age groups of broilers, ranging from 0 to 40 days. More specifically, the age ranges represented are: 0, 4, 7, 10, 15, 25, 30, 35 and 40 days. Those 10 images were

previously deformed using distortion corrections with a specific algorithm. This sample reflects the different stages of development of the broilers.

The metrics used to evaluate the performance of the detection model developed to track broilers on farm are:

The Precision (P) measures the proportion of broilers detected that are actually positive. It reflects the number of items detected that are really in the class of object of interest, here broiler. It is expressed in % broilers detected.

$$Precision = \frac{\text{Number of true positives}}{\text{Number of true positives} + \text{Number of false positives}}$$

The Recall (R) measures the proportion of relevant instances that have been correctly detected by the model. It shows the number of elements of the class of interest (broiler) that have been detected out of all those that exist. It is expressed in % of broilers detected.

$$Recall = \frac{\text{Number of true positives}}{\text{Number of true positives} + \text{Number of false negatives}}$$

The Intersection to Union ratio (IoU) is used as a threshold to determine whether a predicted result is a true positive or a false positive. The ratio is the size of the overlap between the delimitation zone (or bounding box) around a predicted object and the delimitation zone around the field reference data. The threshold used for validation is set arbitrarily at 50 %.

IoU

$$= \frac{\text{Area of intersection between the predicted bounding box and the ground truth}}{\text{Total area covered by the predicted bounding box and the ground truth}}$$

The Average Precision (AP) is a performance measure that combines both precision and recall. It is calculated by plotting the PR (precision-recall) curve, which shows the relationship between model precision and recall as a function of different confidence thresholds. The AP is simply the area under this PR curve (varying between 0 and 1). This quantifies the average precision of the model and the overview of model performance.

The mean Average Precision (mAP) is an average of the mean accuracies over several IoU thresholds. For example, mAP 50-95 corresponds to the average accuracy of IoU ratio values between 0.5 and 0.95, in increments of 0.05.

Results and Discussion

The detection model has an overall precision of 91%, indicating that 91% of the detections made are correct. This level of precision remains relatively stable across different age groups of broilers. However, the recall rate varies, reaching a minimum of 66% for 0-day-old broilers and a maximum of 90% for 40-day-old broilers. Overall, the model achieves a detection rate of 80% across all age groups. This accuracy shows that the model is robust, and recall remains satisfactory. The poorer performance for young broilers can be linked to the colour of chicks which is close to that of the litter and reduces the contrast and complicates detection. A clear improvement would be to enrich the training dataset

with more images of young chicks. Given that the images have undergone deformation corrections, the image quality at the edges is poor. This low quality affects the detection of broilers in these areas. In general, in the training sample there is an average of 71 broilers per image, which is far from representative of experimental conditions where up to 700 broilers per image can be found. This highlights the need to collect data that better reflects the reality of field conditions.

Table 2: Results of the proposed algorithm per age

Age	Number of broilers	P (IoU=0.5)	R (IoU=0.5)	mAP 50	mAP 50-95
0	622	0.87	0.66	0.78	0.34
4	669	0.89	0.75	0.84	0.36
7	536	0.94	0.81	0.89	0.41
10	651	0.95	0.86	0.93	0.53
15	655	0.94	0.86	0.92	0.46
20	637	0.94	0.86	0.92	0.55
25	653	0.90	0.73	0.83	0.45
30	639	0.92	0.79	0.87	0.50
35	322	0.96	0.88	0.93	0.58
40	383	0.95	0.90	0.95	0.61
All age together	5767	0.91	0.81	0.88	0.47

Conclusions

The overall precision of detection is 91%. The overall recall is 81%, it decreases with age of broilers, from 66% for 0-day-old broilers to 90% for 40-day-old broilers. Publications on similar developments do not allow a strict comparison with the results presented in this article, since the trials are only carried out on small groups of birds, where 100% of the birds are detected, and the objectives and methods for evaluating the quality of detection and tracking are not the same. The quality of detection depends on a number of parameters, including the definition of the camera, the size (also linked with the height of the camera) and age of the animal, the stocking density and activity of the animals. The detection model has been improved through dataset enrichment with more images of chicks. More generally, images have been included in the model with a large number of broilers in the field of view and a deformation correction applied. Tracking performance is intrinsically linked to detection performance. If the detection model fails to locate the broilers accurately, the tracking will have difficulty keeping track of these objects. This is particularly true when the broilers move towards the image's edges, where the image quality is often poorer due to the distortion corrections applied. In addition, the presence of obstacles such as feeders and drinkers can obscure the broilers and complicate the tracking process. Another factor to consider is that in consecutive frames, due to their non-independence, a chicken detected in an image at time t has a high probability of being detected again at time $t+1$. Conversely, if it is not detected at time t , for instance, because it is partially obscured behind a feeder, then it is likely to remain hidden at time $t+1$ and thus not detected again. Therefore, unlike scenarios where each image is independent and detection errors could propagate, this approach leverages temporal dependencies between

frames, ensuring a more stable performance for the tracker. Finally, the camera only covers part of the barn. Broilers may therefore leave the camera's field of vision.

With the tracking algorithm in place, the potential applications of the generated data can be thoroughly explored. The dimensions of the bounding boxes around each detected chicken are proportional to their weight, enabling accurate estimation of the weight distribution within a flock and identification of potential growth issues. This method offers a significant advantage over automatic weighing systems by targeting a larger number of chickens and providing a more precise view of weight variability within the flock. Access to resources such as food and water is crucial for the welfare of chickens. Studying attendance at feeders and drinkers allows for assessment of resource competition and equipment functionality. High competition around these resources could indicate an insufficient number, while no attendance could signal faulty equipment. This system enables real-time monitoring to ensure chickens are feeding properly. Additionally, tracking individual trajectories provides valuable information about the health status of each chicken. By analysing mobility, it becomes possible to detect lameness and other anomalies in locomotor behaviours. These welfare indicators allow for continuous monitoring of overall health and early detection of potential diseases. Subtle changes in movement habits could reveal underlying conditions before visible symptoms appear, enabling rapid and effective intervention to preserve the flock's health. Furthermore, individual trajectories can determine whether a chicken is immobile, feeding, drinking, or dust-bathing. This analysis enables the establishment of a time-use profile for each individual, quantifying time spent on each specific activity. By setting benchmarks for these time-use profiles, deviations from the norm can be detected, indicating potential welfare issues. These insights pave the way for significant improvements in the management and welfare of chickens.

In conclusion, the detection and tracking model provides valuable information on group dynamics, allowing us to measure the collective behaviour of broilers. Although limited in terms of detailed tracking of individuals, it provides a useful perspective on population trends and behaviours. The next step will be to determine alert thresholds for the early detection of animal health and welfare disorders to help farmers in using preventive measures to limit the problem spreading the whole flock. By integrating these methods into agricultural practices, it would be possible not only to optimize production but also to ensure a healthier and more suitable environment for the animals.

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