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Individuality of a group: detailed walking ability analysis of broiler flocks using optical flow approach

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ABSTRACT

Impaired walking ability is one of the most important factors affecting broiler welfare. Routine monitoring of walking ability provides insights in the welfare status of a flock and assists farmers in taking remedial measures at an early stage. Several computer vision techniques have been developed for automated assessment of walking ability, providing an objective and biosecure alternative to the currently more subjective and time-consuming manual assessment of walking ability. However, these techniques mainly focus on assessment of averages at flock level using pixel movement. Therefore, the aim of this study was to investigate the potential of optical flow algorithms to identify flock activity, distribution and walking ability in a commercial setting on levels close to individual monitoring. We used a combination of chicken segmentation and optical flow methods, where chicken contours were first detected and were then used to identify activity, spatial distribution, and gait score distribution (i.e. walking ability) of the flock via optical flow. This is a step towards focusing more on individual chickens in an image and its pixel representation. In addition, we predicted the gait score distribution of the flock, which is a more detailed assessment of broiler walking ability compared to average gait score of the flock, as slight changes in walking ability are more likely to be detected when using the distribution compared to the average score. We found a strong correlation between predicted and observed gait scores ($R^2 = 0.97$), with separate gait scores all having $R^2 > 0.85$. Thus, the algorithm used in this study is a first step to measure broiler walking ability automatically in a commercial setting on a levels close to individual monitoring. These validation results of the developed automatic monitoring of flock activity, distribution and gait score are promising, but further validation is required (e.g. for chickens at a younger age, with very low and very high gait scores).

Introduction

Impaired walking ability is one of the most important factors affecting broiler chicken welfare [33], as it can cause broilers to have difficulties to perform natural behaviors, to access feed and water, and may further cause pain and discomfort [9,11,14,23,31,45]. Routine monitoring of walking ability gives insights into the actual welfare status of a flock and assists farmers in taking remedial measures at an early stage [20]. Walking ability is often assessed via the gait score method [27,46]. However, this method is mostly used for research purposes, as it is time consuming, assessors need to be trained, outcomes may still be subjective and depend on the quality of the assessor, and biosecurity may be at risk [7].

Recently, several computer vision techniques have been developed for automated assessment of walking ability, mainly in relation to broiler activity and distribution. Most studies have focused on assessing walking ability via computer vision in an experimental setting [1–5,32] and some in a commercial setting [15,16,40,44]. Activity and distribution by themselves are also important early warning signs in relation to broiler welfare, for example distribution has been linked to heat stress [34,48] and both activity and distribution have been related to prevalence of hock burn and footpad dermatitis [17,18,21,24] and disease

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[13]. These computer vision techniques provide more objective alternatives to the current subjective and time-consuming methods to assess welfare in commercial flocks. With modern broiler houses including thousands of chickens, the use of cameras and computer vision is a promising method to monitor animal welfare remotely and continuously. In addition, computer vision techniques provide a non-invasive and biosecure method for assessing broiler chicken walking ability.

The optical flow approach has been used to assess broiler walking ability via changes in activity and distribution [4,15,16,40,44]. Optical flow is defined as the distribution of apparent velocities of movement of brightness in an image [22]. The estimation of motion based on optical flow techniques and its applications within the poultry industry is still one of the most active research domains in Precision Livestock Farming. This is because the optical flow approach allows crowd motion dynamics to be measured on levels close to individual tracking, without the need to maintain the identity of the monitored individuals. With recent studies [18] underlying the need to build flock monitoring algorithms which provide more detailed information on a group level, the potential of the optical flow quality on such analysis needs further investigation. In fact, different production scales, housing alternatives, and a broad range of different production environment parameters need to be tested on real farms to create a solid basis for future commercialization of robust vision-based solutions.

Another challenge that needs to be addressed at flock level is precise motion estimation of numerous small objects, including self-occluding objects due to high stocking density and individuals with erratic movement patterns. In addition, such an estimation needs to be performed with high consistency over time to include the biological and environmental variability. Furthermore, it is important to identify ways of assessing broiler welfare in more detail than flock average scores only and at high stocking densities. Therefore, the aim of this study was to investigate the potential of optical flow algorithms to identify flock activity, spatial distribution and gait score distribution in a commercial setting on levels close to individual monitoring.

Materials and Methods

Ethical approval

The housing and management and the experimental procedures were conducted in accordance with the national legislation on animal welfare and animal experiments, and approved by the institutional Animal Welfare Body. This study was not considered to be an animal experiment under the Law on Animal Experiments, as confirmed by the institutional Animal Welfare Body (25th of February 2020, Wageningen, The Netherlands).

Animals and housing

Approximately 28.000 day-old broilers (Ross 308, as-hatched) from a commercial hatchery were housed in a concrete-floored commercial broiler house of 1530m^2 (length: 85m × width: 18m) with roof windows (3% of floor area) located in the Netherlands. Crushed straw pellets were provided as litter material. Management was according to commercial practice with *ad libitum* access to feed (a standard 3-phase commercial diet) and water. Standard temperature, relative humidity, lighting (4D:8L:2D:10L) and vaccination schedules were applied. Five cycles of 43 days were run between August 2020 and July 2021 at this commercial poultry farm and management was similar for all cycles.

Image collection

Four overview cameras (10MP color camera with 1.3mm fisheye optics, IDS Imaging, Germany) were mounted under the ceiling at 4-m height, providing a top-down overview of the production environment, and recorded 10 hours per day from 7:00 till 17:00. These recording hours were chosen due to the presence of human observers responsible for the gait scoring as well as to include the dark period into video material (from 12:00 till 14:00). Each camera covered an area of approximately 20 × 15m (approximately 20% of the floor area) with a complete view of the operational width of the house. Cameras were installed across the length of the house but did not cover the front and back area (approximately 80% of floor area was covered in total). The video frames had a resolution of 3840 × 2748 pixels and were recorded at a framerate of 0.5 Frames Per Second (FPS). During the last two cycles, the framerate for the recordings was set at 2 FPS, with frame resolution being reduced to 1920 × 1374 pixels. In total, 2150 hours of recordings were collected and approximately 5-10% of the video material was used for the algorithm development and validation.

Walking ability

Walking ability was assessed via the gait score protocol according to Welfare Quality [46] using a catching pen and with birds being released one-by-one for scoring, with the gait score ranging between 0 (normal, dexterous and agile) and 5 (incapable of walking). In the first cycle, gait score was not assessed in the flock, as the recordings from the first cycle were mainly used to optimize parameters of the optical flow algorithm. In the second cycle, gait score was assessed at five ages: 16, 23, 28, 36 and 39 days of age. Per age category, six locations spread across the house were sampled: one near the wall, one underneath each overview camera (4 in total, see Fig. 1) and one other random location to cover other regions in the house not necessarily near the wall or underneath an overview camera. The positions under the overview camera were initially chosen to train the algorithm for gait scoring on the same chickens that were graded by the assessors. In the third cycle, gait score was assessed at eight ages: 15, 17, 21, 24, 28, 31, 36 and 38 days of age. Per age category, seven locations were sampled: two near the wall, one underneath each overview camera (4 in total) and one in the middle. In the fourth cycle, gait score was assessed at five ages: 14, 22, 28, 34 and 40 days of age. Per age category, seven locations were sampled similar to those of the third cycle. In this cycle, a catching pen was used only at two locations, for the remaining locations (underneath the overview cameras) no catching pen was used. Birds were habituated to the presence of the observer for at least 5 min and were then assessed for their walking ability. To make sure birds were not scored twice, the observer walked to a different area in the direction opposite to where scored birds had walked previously. In the fifth cycle, gait score was assessed at nine ages:

Fig. 1. Gait scoring performed by the observer underneath an overview camera using a catching pen. The red box indicates the area where chickens were walking through and gait scored.

13, 16, 19, 23, 29, 33, 37 and 40 days of age. Per age category, seven locations were sampled: two near the wall, one underneath each overview camera (4 in total), one other random location. Walking ability was assessed by two trained assessors (index of concordance: 0.72). For all cycles and days included into final analysis, an average of 30 broilers were assessed for their gait per location with a total average of 205 broilers being assessed per assessment day.

Optical flow algorithm development

Optical flow algorithm implementation

To compute the optical flow between the images in our recorded sequences, the optical_flow_mg operator from the Halcon software suite (MvTec) was used. This operator computes the optical flow between the consecutive images *ImageT1* and *ImageT2* and returns the *VectorField* dictionary containing movement vectors from the image plane between *ImageT1* and *ImageT2.*

The optical flow operator has three different options for calculating the movement vectors. For this study, *fdrig* parameter was used, which stands for flow-driven, robust, isotropic, and one using gradient constancy term [10].

The choice of the operator was based on the specifics of the research question: highly dense scenery with variable illumination and rapidly moving objects of varying size. The FDRIG algorithm is implemented in such a way to address the following assumptions:

- Constancy of the grey values in the image
- Constancy of the spatial grey value derivatives
- Large displacements (e.g. occurrence of displacements larger than one pixel)
- Statistical robustness in the data operator (to address the potential influence of the outlying value on final movement vectors)
- Preservation of discontinuities in the flow field (to assure the smoothness of movement in the calculated vector fields)

The parameter used for optical flow calculation within the Halcon library is the variational approach which computes the optical flow values as the minimizer of a suitable energy functional:

$$E(w) = E_D(w) + \alpha E_S(w)$$

where w=(u,v,1) is the optical flow vector field to be calculated with a time step of 1 in the third coordinate. The image sequence with *ImageT1* and *ImageT-n* is regarded as a continuous function f(x), with x=(r,c,t) where *r* and *c* denote the position, and *t* – time attribute. Furthermore, $E_D(w)$ is the data operator and $E_S(w)$ – smoothness operator, while α is regarded as a regularization parameter guaranteeing the smoothness of the solution relative to the data operator.

Since the calculation of the optical flow is very computationally intensive, the resolution of the color images was reduced to one third from the original size, which reduced the inference time from 6 seconds to 400 ms on a i7-4790k CPU (4 cores). The resulting vector field image was transformed into an image which shows the length of each vector field. In the next step the values from VectorFieldLengthImage operator were normalized with the average expected chicken size at the day of life. The expected chicken size prediction was estimated by the average single chicken size using the segmentation of chickens from 4 different ages (15, 23, 28 and 38 days of age).

From these NormalizedVectorFieldLength-Image values, four optical flow statistical values were derived: Average, Variance, Skewness and Kurtosis. These values were averaged up over a time window of 5 seconds, as a trained assessor takes about 5 seconds to assess gait score of one chicken. Additionally, heatmaps were created by adding the NormalizedVectorFieldLength-Images to one Heatmap-Image for the same time window (Fig. 2). As shown in Fig. 3 each camera image was divided into a grid of 9 × 7 regions. In each grid the four optical flow statistic values are calculated.

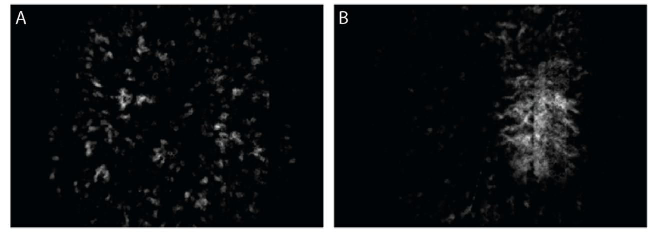

Fig. 2. Heatmaps created with the NormalizedVectorFieldLength operator where brighter areas indicate more movement and dark areas indicate less/no movement, a) image of regular undisturbed chicken movement and b) movement of chickens when someone was walking through the flock.

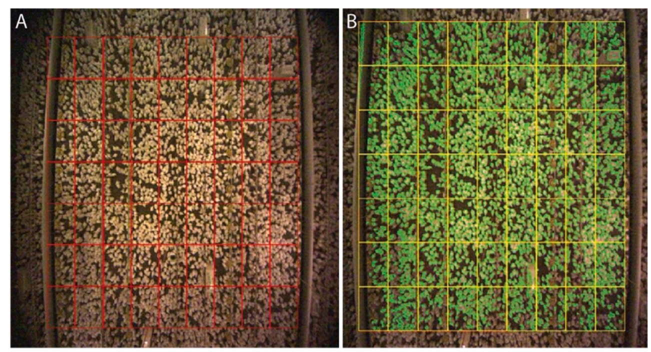

Fig. 3. Images of one overview camera with a) Grids (red lines) for flock activity measurements; b) segmented chickens (green contours) detected in grids (yellow lines).

Optical flow algorithm optimization

The recordings from the first cycle were mainly used to optimize parameters of the optical flow algorithm, to make it robust to (1) changes in lighting conditions and (2) broiler ages (young and old). This was tested at 15, 23, 30 and 38 days of age. From each of these days images from a five-minute period were selected to check if resulting movement intensities were plausible, for both slow- and fast-moving chickens. To address the variability in lighting conditions, pre-selected image sequences with examples of different lighting conditions were used. These sequences included, for instance, an example of a bright ray of sunlight that was suddenly visible in the images. Without the fine-tuning of the optical flow algorithm, such sudden changes in the scene illumination will result in very high average moving intensity values. Therefore, the hyperparameters of the optical flow algorithm were tuned until there was no reaction to the sudden changes in the scene illumination anymore. For the second problem potentially affecting the algorithm performance and related to varying broiler sizes, two types of image sequences were used. The first type was from the early ages (day 15), where the chickens were small and had much space to move around (low spatial density). The second type was taken from the end of the fattening period, where the chickens were almost fully grown and did not have much space to move around (high spatial density). In both types of sequences were examples of a group of chickens moving synchronously in a certain direction. Therefore, the directions and intensity of movement vectors derived from the optical flow algorithm for each type of sequence were analyzed. The fine-tuning continued until there were no pseudo-movements anymore and every significant movement vector was correctly detected.

Optical flow-based gait score measurement

To create a ground truth or a baseline for gait score measurements, gait score was assessed by a trained observer. The number of broilers for each gait score class per location was noted. From this distribution the percentage distribution of the gait score classes per area unit was calculated.

To get a good ground truth, we focused on days where manual gait scoring was performed. We assumed that the average of 205 broilers that were manually scored in each cycle were representative for the whole flock, as it is indicated by [46] a minimum of 150 broilers should be sampled for a reliable gait score. We selected a time period of 10 minutes early in the morning, before anyone entered the house, where the chickens were undisturbed. The input data for the gait score classifier is shown in Table 1.

Instead of training a model that only gives one average gait score per areal unit of assessment, a gait classifier was trained to determine the gait score distribution, which provides a better representation of changes in the walking ability of a flock than one average gait score. In practice, gait score distribution means a regression model for each gait score and a separate grade for each gait category.

Two different approaches were tested during the implementation of the gait score classifier:

Machine Learning Approach based on the usage of feature vectors derived from optical flow as well as additional region and grey value features.

Deep Learning: where the classifier was trained on heatmap images (five second sequences)

A regression model for each gait score was trained with a 'Random Forest Regressor' that uses the majority vote of 100 decision trees. The input data was divided into 65% training and 35% test data and each regressor got the input from the created feature vector and returned the proportion of the corresponding gait score.

To measure the quality of the classifier the coefficient of determination (R^2-metric) for each regressor was calculated.

Optical flow algorithm activity and distribution

Three features were calculated to identify flock activity and distribution: Distribution Index, Activity Index and Activity/Distribution Index. The basis for these calculations is a subdivision of an image from the overview camera into a 9 × 7 grid and independent feature calculations per grid segment.

Distribution Index

Initially chickens were segmented on the whole image simultaneously (green regions/instances; Fig. 3b). Chicken segmentation was performed via the operator "dyn_threshold" from Halcon to detect 'light' regions. This operator uses the original image and a smoothed version of this image, to detect object borders. These chicken regions/instances were intersected with their corresponding grids. Then for each grid the *Zone Occupation Density (ZOD)* value was calculated by dividing the size of the segmented chickens with the size of the grid. The Distribution Index was then derived by summing up values from all zones that were inside the range of 25% from the average zone occupation, divided by the total number of zones. It resulted in value between 0 and 100. The higher the value, the more uniform the flock distribution is.

Table 1
Input data for classifier. OF = optical flow.

Variable name	Description
MeanOF, VarianceOF, SkewnessOF, Kurtosis, HarmonicMeanOF	The average length, variance, skewness, kurtosis and harmonic mean of the calculated OF vector fields (from all grid points)
MeanOFFiltered, VarianceOFFiltered, SkewnessOOFFiltered, KurtosisOOFFiltered, HarmonicMeanOFFiltered	The average length, variance, skewness, kurtosis and harmonic mean of the calculated OF vector fields (only from grids with value > 0)
DistributionIndex	Value of the measured DistributionIndex
ActivityIndex	Value of the measured ActivityIndex
Score 0, 1, 2, 3, 4, 5	Percentage of manual measured corresponding Score proportion

Activity Index

For calculation of the Activity Index, the segmented chickens and the corresponding regions from optical flow were used. Since the optical flow algorithm uses two subsequent images, the chicken regions from both images were merged. To make sure that the regions from optical flow output belong to the chickens, these regions were intersected. The Activity Index was calculated by dividing the area of the moving chicken obtained through the optical flow movement vector with the area of the segmented chicken. The Activity Index is a value between 0 and 100. The higher the value, the more chickens are moving.

Activity/Distribution Index

When the Activity Index calculation is applied on every grid, the additional calculation on how the activity is distributed in the whole image could be performed. Similar to the Distribution Index, all zones that are inside the range of 25% from the average flock activity are summed up and divided by the number of zones. The Activity/Distribution Index is a value between 0 and 100, the higher the value, the more uniformly the activity is distributed.

Results

Flock activity and distribution

For an impression, Fig. 4 shows a situation where an observer walks into the field of view of one camera, places a catching pen and leaves the field of view.

In the first minutes the flock behaved normally (Fig. 5a), the measured values stayed on a constant level. At around 08:11:20 (first red line in Fig. 4), the observer walked into the camera field of view (Fig. 5b). The chickens were running away and a free space around and behind the observer was visible in the plots, the Activity Index increased, while the Distribution and Activity/Distribution Index decreased.

When the observer was placing the catching pen (Fig. 5c) there was a lot of activity around. After the observer leaves the camera view (second red line in Fig. 4), the chickens filled the free floor space again. The Distribution Index increased, thus the distribution got more uniform. The Activity Index was still high while the Activity/Distribution Index increased gradually. The explanation for this could relate to the fact that the activity was not only in one area, but nearly in the complete image.

In the supplementary files, videos of these sequences are included that are overlayed with a heatmap showing the moving average of the Activity- and Distribution Index calculation on the grids (Supplementary file 1 and 2, respectively). In addition, we included plots for activity measurements of 4 different days (14, 19, 27 and 35 days of age), from 7:00 in the morning till approximately 17:00 in the afternoon (Supplementary file 3).

Flock walking ability

Two gait classifiers were used within the Machine Learning implementation: (1) camera-based gait score, and (2) daily averaged gait score averaging scores for each camera. For the camera-based gait score the input features of one camera were linked to the manual measured gait scores of that camera. For the daily averaged gait score, the gait scores manually measured under the four overview cameras were averaged and linked to the data from every camera. Table 2 presents the correlations for each gait score using different models (camera-based or

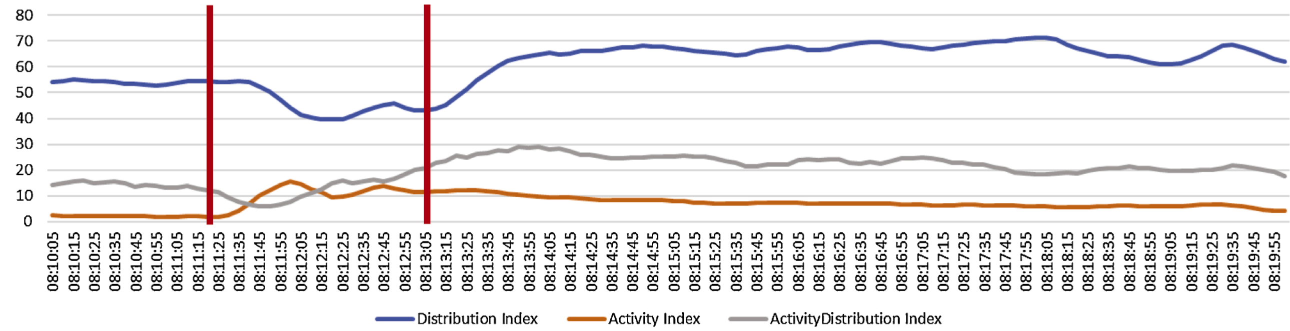

Fig. 4. Plot for activity measurements over a time period of 10 min, showing the Distribution index (blue line), the Activity index (orange line) and the ActivityDistribution index (grey line). The red lines indicate the period where the observer walks into the field of view of the camera.

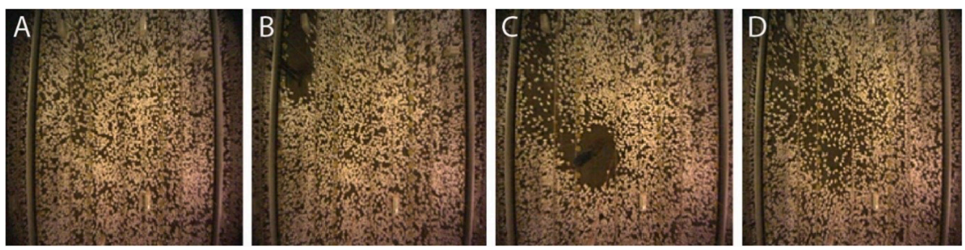

Fig. 5. Image Sequence of the observer walking into the field of view of the camera from a) undisturbed flock, b) observer walks into the field of view in top left corner, c) observer crosses some drinker and feeder lines to the center and d) just after the observer has left the field of view.

Table 2
Correlations (R^2) for the regression model for each score trained on cycles 3 to 5 using the camera-based or daily averaged classifiers.

	Score 0	Score 1	Score 2	Score 3	Score 4	Score 5	Aggregated gait score[1]
Camera-based gait score	0.73	0.81	0.72	0.90	0.63	0.52	0.87
Daily averaged gait score	0.69	0.85	0.73	0.92	0.81	0.62	0.87

[1] The aggregated gait score was derived using this formula: $Gaitscore = 0 * Score0\% + 1 * Score1\% + 2 * Score2\% + 3 * Score3\% + 4 * Score4\% + 5 * Score5\%$

daily averaged gait score) for data from three cycles (cycle 3-5). We first analyzed the measured movement intensity and variances, and then selected a period where variance and movement intensity were on a low level for at least ten minutes. These images where used as input for algorithm training and testing. In total 10,932 samples were used. The correlations shown are calculated on each prediction, which were 5-sec long and were based on individual feature input vectors.

The observed and predicted gait score distribution for all measurement days of cycles 3 to 5 is shown in Fig. 6. Score 0 is hardly observed and the proportion of broilers with score 1 declined with age, while score 2 and 3 were most frequently observed and the proportion of broilers with score 4 and 5 was very low. Fig. 7 shows the average observed and predicted gait score for all measurement days of cycles 3 to 5.

The correlations calculated in Table 3 are higher than the correlations calculated in Table 2, because those in Table 2 are calculated on a

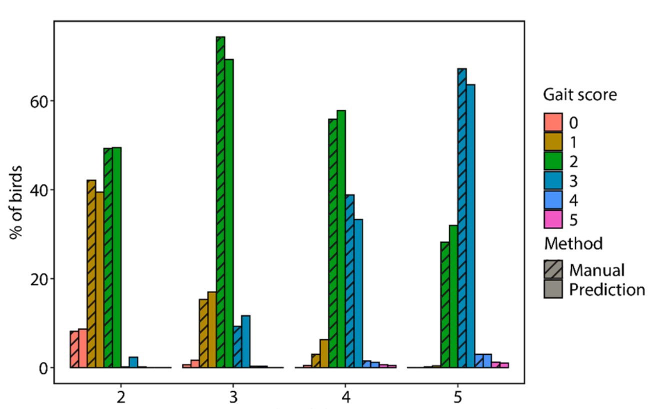

Fig. 6. Observed percentages of birds for each gait score via manual measurements (lined fill) and predicted (full fill) percentages for each gait score (colors) grouped over cycles 3-5 and shown per week of age.

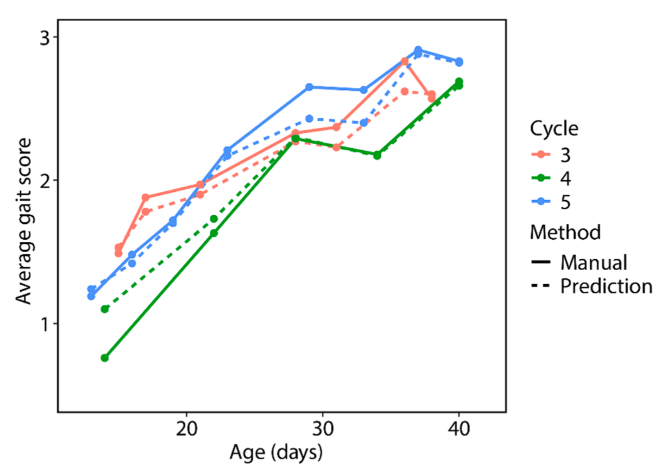

Fig. 7. Observed average gait score via manual measurements (solid lines) and predicted (dashed lines) for each sampling age in days for three production cycles (colors).

Table 3
Correlations (R^2) between average gait score prediction (using the daily averaged model) and manual measurements for each score based on cycles 3 to 5.

Score 0	Score 1	Score 2	Score 3	Score 4	Score 5	Aggregated Gait score[1]
0.90	0.98	0.92	0.97	0.91	0.83	0.97

[1] The aggregated gait score was derived using this formula: $Gaitscore = 0 * Score0\% + 1 * Score1\% + 2 * Score2\% + 3 * Score3\% + 4 * Score4\% + 5 * Score5\%$

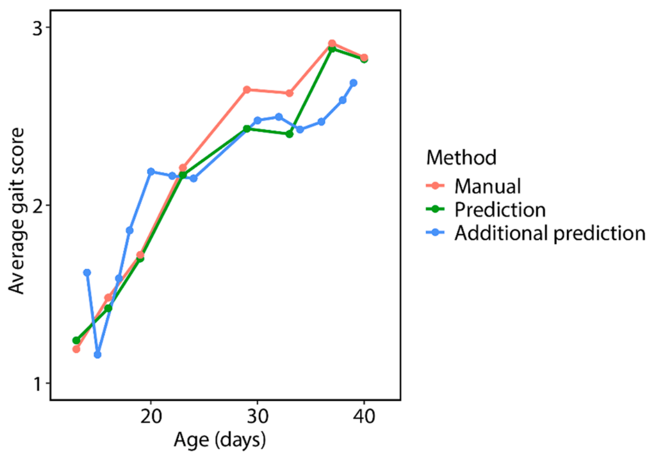

Fig. 8. Comparison of average gait scores (based on gait score distribution) between methods using gait score prediction of additional days (red line), gait score prediction (blue line) and manual gait score of cycle 5 only (green line).

sample base, with a 70/30% split on 3.644 samples. In these samples there is a certain variation in the measured feature values even of consecutive samples. Thus, predicted values were not averaged but the comparison was made sample vs. sample with the observed value on the same day. Correlations in Table 3 are based on thousands of predictions of one day averaged into one value. Thus, predictions were first averaged over each day leading to one prediction per day, which was then compared to the observed value on the same day.

In order to test the gait score prediction model on additional days where no gait scoring was performed, we used the days before and after the measurement was done (Fig. 8).

In all these tests we used 70/30% split for training and testing. If we add the additional days to our training set, one could argue that the prediction model is overfitted. So, we also tested a 90/10% split. That means we train only on 10% of the data and test on 90%, which is a very unusual way of training an AI. With a 90/10% split the correlations between manual scoring and predictions are high, as shown in Table 4.

Discussion

The aim of this study was to develop optical flow algorithms to identify flock activity, distribution and gait score in a commercial setting on levels close to individual monitoring. The first illustrative validation results of the developed automatic monitoring of flock activity, distribution and gait score in a commercial setting are promising, but further validation is required. To allow an easier comparison with other optical flow models trained on a similar type of data, the R-squared was chosen as a unified relative performance metric. Since there is an ongoing trend of moving from research environment settings to a commercial one, further development of optical flow algorithms is impossible without the deeper understanding of individual variance occurring within the observed groups. As Chicco et al. [12] stated, the use of reliable and standardized regression analysis evaluation metric such as R-squared (R^2) is more informative and transparent when it comes to large scale studies with living subjects. A strong correlation between predicted and observed gait scores was found for the aggregated gait score ($R^2 = 0.97$), with separate scores ranging between 0.85 and 0.97. Previous studies found significant correlations between optical flow measures and average gait score in commercial setting [15,16]. One study further developed a predictive equation for average gait score based on significant correlations with the difference in peak and baseline activity and age [40], although evaluation of the predicted gait scores was not performed. Similar to our study, van Hertem et al. [44] used optical flow methods for prediction of gait score and found a correlation of 0.915 between predicted and observed gait scores in a commercial setting, which is in line with the high correlations found in the present study.

Our algorithm is different from previously developed algorithms in four ways. First, some previously developed equations included additional information to predict gait score, such as age or body weight, or used methods where it was necessary for someone to walk through the flock [40,44]. Our prediction does not need additional information from the flock or for someone to walk through the flock. This makes our model simpler and there is a smaller biosecurity risk, although it can be argued that a farmer could walk through the flock, which would then not have an impact on biosecurity perse. Second, previous studies assessed gait score from 3 weeks of age onwards, with some only assessing at one age [15,16] and others at three ages [40,44]. Dawkins et al. [15] indicated that optical flow measures (i.e., skew and kurtosis) from 20 days of age onwards were already significantly correlated with gait score at 28 days of age. In our study, prediction of gait score was possible from around 2 weeks of age until the end of the fattening period around 38 days of age. We focused on assessing from 2 weeks of age onwards, as walking ability is often good and starts to become poorer when birds grow quicker and gain more weight [26,28,35,37–39,47]. Gait score increased with age, similar to previous findings [26,35,41]. It would be interesting to assess and predict gait score at younger ages and to see whether changes in gait score distribution at these young ages could already be used as an early-warning signal for impaired flock health, enabling early intervention by the farmer. Third, previous studies predicted average gait score for commercial flocks, while here we predicted the gait score distribution. Although average gait score is often used as welfare indicator [46], the gait score distribution gives a more detailed view of broiler welfare regarding walking ability. When a flock has 50% broilers with score 1 and 50% with score 5, this would result in an average gait score of 3. An average gait score of 3 would also be the result of 20% broilers with gait score 1, 2, 3, 4 or 5. Although the average is the same, the distributions over scores differ greatly. Slight changes in walking ability of a flock are more likely detected when using the gait score distribution compared to average gait score. Finally, previous

Table 4
Comparison of correlations (R^2) between average gait score prediction (using the daily averaged model) and manual measurements for each score using standard training (70/30) versus extreme training (90/10).

	Score 0	Score 1	Score 2	Score 3	Score 4	Score 5	Aggregated gait score[1]
Split (70/30)	0.85	0.97	0.93	0.97	0.93	0.86	0.97
Split (90/10)	0.72	0.94	0.88	0.95	0.92	0.81	0.94

[1] The aggregated gait score was derived using this formula: $Gaitscore = 0 * Score0\% + 1 * Score1\% + 2 * Score2\% + 3 * Score3\% + 4 * Score4\% + 5 * Score5\%$

studies used optical flow to assess flock activity but did not include individual chicken segmentation. In the current study we moved a step towards focusing more on the pixel representation of individual chickens. Chicken segmentation was not 100% accurate, with other types of objects sometimes being included such as bales, feeder or drinker lines. This might have caused other types of movement or areas to be included, which can lead to over or underestimation of the amount of movement or provide inaccurate information about individual chicken areas in the processed images.

Further development and testing of the algorithm are needed. Young birds often have lower gait score (gait score 0 and 1) as they have a lower body weight, but the gait score increases with age as birds get heavier [26,28,35,37,39]. In flocks with fast-growing broilers most broilers have a gait score 2 or 3, while gait score 4 and 5 are also not very common [6,28,39], which might be because severely lame birds are culled. This supports our findings from manual observations, where score 0 was hardly observed and the proportion of broilers with score 1 declined with age, while score 2 and 3 were most frequently observed and the proportion of broilers with score 4 and 5 was very low. The relatively low occurrences of these scores makes it difficult to train models on these scores. This might lead to over or underestimation of average gait score and indeed we found predicted average gait scores to be lower compared to manual assessment, especially for cycle 3 and 5. Training models more on scores 0-1 and 4-5 and including more variation (i.e. cycles) will improve predictions, but still these scores will have a lower occurrence compared to scores 2-3, meaning predictions will always be less accurate compared to scores 2 and 3. In addition, cameras were installed so that the complete width of the house could be viewed, however the peripheral sites (i.e. close to the wall) were not included as the visibility was not optimal because of the fish eye optics. Manual gait scoring was performed close to the wall, but these observations were not included for training the algorithm. This might cause predictions to be lower compared to manual assessment as broilers with poor gait score might rest close to the walls to minimise disturbance by other birds, although they might also stay close to feeders or drinkers for longer periods [45]. The algorithm was able to show good performance and gait score distribution was quite similar for wall vs. other locations, indicating that inclusion of birds near the wall might not be needed. It would be interesting to further test whether including wall areas results in an even better prediction of gait score.

Continuous recording of gait score allows to gather a much larger number of birds and therefore more meaningful sample size in comparison to manual assessment, which is labor intensive and can cause biosecurity issues [7]. Drawbacks of using cameras for automated assessment may be related to high densities, especially at older ages, or partly occluded birds. In addition, the cameras used in the current set-up needed to be cleaned regularly to get a good image. However, using cameras is a better option compared to wearable sensors (i.e. RFID or UWB) as those are labor intensive to set-up and maintain, can further disrupt birds behavior, and may influence walking ability [29].

The ultimate aim is to detect animal welfare problems and provide farmers with a valuable, objective management tool. Automated monitoring of the gait score distribution, flock activity, and spatial distribution can potentially provide farmers with valuable information that they can use to make decisions on how to manage their flocks for better health and welfare. For example, disease often results in animals being less active [30] and ill broilers could also show worse gait scores because of this reduced activity [8,36] or because of a direct relation between the disease and lameness [19]. In cycle 5, the flock had an *Enterococcus* outbreak, mortality was higher and the gait score was worse (higher). Indeed, previous studies show that *Enterococcus* infection was related to increased mortality and lameness [19,25,42]. The activity and distribution indexes should be compared to a reference value and farmers can then receive a warning message if values deviate above a certain threshold. However, this still needs to be implemented and tested. To make our system more viable, we are looking into integrating several systems to automatically detect and monitor resource use of broilers [43] and combine this with automatic flock activity, distribution, and gait assessment. Long-term applications could include complete integration of all systems in a poultry house, where computer vision algorithms are integrated with existing climate control, feed, water and light systems. Then, a farmer can for example identify in detail whether deviations in the gait score are linked to specific management aspects.

Conclusions

This study developed optical flow algorithms to identify flock activity, spatial distribution and gait score distribution in a commercial setting on levels close to individual monitoring. The validation results of the developed system are promising, but further validation is required (e.g. for chickens at a younger age, with very low and very high gait scores). The algorithm used in this study is a first step to measure broiler walking ability automatically in commercial settings on a level close to individual monitoring. Furthermore, the algorithm predicted the gait score distribution of the flock which is a more detailed assessment of broiler chicken walking ability compared to average gait score of the flock.

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Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jan Schulte-Landwehr is employed by CLK GmbH Bildverarbeitung & Robotik. The remaining authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The authors do not have permission to share data.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2023.100298.

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