128. Automated estimation of pose features in broilers using computer vision

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Abstract
The importance of sensor-based phenotyping is increasing in the broiler industry, aiming at improved animal health and welfare, and lower economic losses. We analysed 11 pose features of 87 individual chickens at three ages (day 14, 21, and 33) using video recordings filmed from behind while the broilers walked through a corridor one by one. A pre-trained deep learning model was trained on a limited number of frames (n=181) to adapt it to a new environment for accurate keypoint detection. Extraction of the three poses of interest (double support, left and right steps) was fully automated. Significant ($P<0.05$) differences were observed among ages in hock joint angles, shank versus horizontal line angles, normalized drumstick and shank lengths, and hock/knee distance ratio. Recording walking broilers from behind proved to be useful in obtaining relevant pose features in an automated way.

Introduction
Poor leg health is a significant welfare and economic issue in the broiler industry (Knowles *et al.*, 2008). Sensor-based phenotypes collected at large scale can support the improvement of genetic gain of locomotion if incorporated in the breeding strategy. In a study of 51,000 broilers from 176 flocks, 27.6% of the birds showed poor locomotion (defined by gait score ≥3 on a 0-5 scale), and 3.3% were almost unable to walk (gait score ≥4; Knowles *et al.*, 2008). Several approaches have been proposed to monitor locomotion in poultry, including inertial measurement units (Bouwman *et al.*, 2020) and cameras (Aydin, 2017; Caplen *et al.*, 2012). In a study, broilers were filmed from above while walking through a corridor, and broilers with higher (≥3 on a 0-4 scale) gait scores had shorter steps, lower speed, and more pronounced lateral body oscillation (Aydin, 2017). In another study, the pose of standing broilers was compared to their gait using photogrammetry from 21 to 42 days of age (Mendes *et al.*, 2016). The aim of our study was to analyse the pose of individual broilers across ages using video images under semi-practical circumstances.

Materials & methods
Experimental setup and video recording. Individually tagged male broilers (n=109) from the same cross were filmed three times (at 14, 21, and 33 days of age) at a Cobb test facility in the Netherlands. During testing, birds had to walk one by one through a corridor created within their pen with dimensions 3 m (length) × 0.4 m (width). An Intel® RealSense™ Depth Camera D415 (Intel Corp., Santa Clara, CA, USA) camera was placed at the start of the corridor, which recorded the chickens from behind during walking. Some birds were removed from the experimental groups for other purposes or due to mortality, therefore, 87 birds remained for video recording by 33 days of age. The RGB video recordings of the camera were converted to .mp4 format with 12 FPS and 1,280×720 pixels resolution for further analysis using a custom Python code.

Keypoint detection. Eight keypoints (head, neck, left and right knees, hocks, and feet) were detected using a pre-trained broiler pose estimation deep learning model developed in DeepLabCut (Mathis *et al.*, 2018). Details of the pre-trained broiler pose estimation model are described in detail elsewhere (Doornweerd *et al.*, 2021). However, this pre-trained model struggled with accurately detecting the keypoints of the chickens in the new environment (e.g. different illumination, red drinkers above the head of the chickens,

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other chickens at the end of the corridor). Therefore, video frames of some birds that had been removed from the current setup between day 14 and 33 were used for retraining of this model. Altogether, 181 frames were used for retraining (day 14: five birds, day 21: eight birds), whereas 40 frames (day 14: two birds, day 21: two birds) were used for testing the retrained model, which resulted in a 82/18 train-test split. This model was then used for the analysis of the newly acquired videos, along with a spline filter and dynamic cropping (the latter in day 14 videos only) to reduce noise in the keypoint estimates. Coordinates and likelihoods of the estimated keypoints were used for pose extraction and calculating the features.

Automated pose extraction. Birds that did not walk during the test (n_{D21}=1, n_{D33}=3) were excluded from further analyses. Briefly, the first and last 10% of the frames of each video were discarded. Then, maximum leg lift and feet being on the ground were detected, based on the local maxima and minima in the longitudinal data of keypoint coordinates. Based on these two distinct feet positions, pose proposals were generated for the three specific poses of interest: double support stance, left and right steps with maximum leg lift. Pose proposals were then sorted based on the normalized vertical difference between the left and right feet, using the vertical difference between the highest knee and lowest foot in the given frame for normalization. Frames with double support phase were selected by minimizing the vertical difference between the left and right foot. On the contrary, steps were selected based on maximizing the vertical difference between feet. For each bird-age-pose combination, the three best frames (based on the vertical differences as sorting criteria) were chosen to calculate pose features. The quality of automatically detected poses was checked visually by extracting the respective frames of 10 randomly selected birds from each age.

Pose features. Altogether, 11 features were defined, where the left and right sides of the same attribute counted as two separate features: normalized step height (%), hock joint lateral angles (degrees), medial angle of the shank and the horizontal line (degrees), normalized drumstick length, normalized shank length, and the ratio between the horizontal distance of hocks and that of the knees (Figure 1). The same normalization was performed as with pose proposals described above. Pose features of the three extracted best frames were averaged to represent the given feature of the bird at that specific pose at a given age.

Statistical analysis. Birds alive on day 33 were included in the analyses. Extracted features were analysed in R version 4.0.2 (R Core Team, 2020). Differences by age were tested using a linear mixed model with age as a categorical variable and chicken as a random factor, using the lme4 package in R (Bates *et al.*, 2015). Pairwise post hoc comparison of age groups was performed using Tukey contrasts. The level of significance was set to 0.05.

Results

Based on the visual check of the labelled keypoints using the original pre-trained model, label jumps between the bird of interest and birds in the background were more common at younger ages. However, label jumps between the drinker and the head occurred quite frequently irrespective of age. Further training

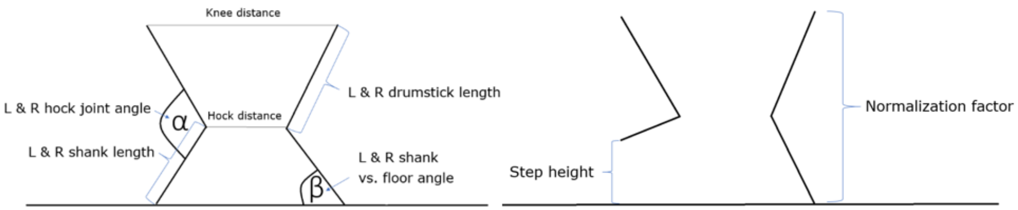

Figure 1. Schematic representation of the analysed features at double support (left) and steps (right).

of the pre-trained broiler pose estimation model substantially reduced the occurrence of these errors. The training and test errors of the final model were 2.11 pixels and 4.02 pixels, respectively, at 100,000 iterations.

The automated pose extraction algorithm correctly identified and selected the relevant poses. Examples of automatically extracted double support stance, left and right steps from day 14 are shown in Figure 2.

Sharper hock joint angles (*P*<0.01) and shank vs horizontal line angles (*P*<0.05) were observed on day 33 than on day 21 (Table 1). Normalized drumstick lengths were shorter (*P*<0.0001), whereas normalized shank lengths were longer (*P*<0.05) on day 21 and 33 than on day 14. The hock/knee distance ratio was larger (*P*<0.01) on day 21 and day 33 compared to day 14. No clear trends were observed regarding step height by age.

Figure 2. Automatically extracted double support stance, left and right steps on day 14 (images cropped and enlarged).

Table 1. Descriptive statistics of pose features by age.

Feature	D14		D21		D33	
	Mean	SD	Mean	SD	Mean	SD
Left hock angle (°)	153.7	7.1	153.6	6.6	150.1	8.2
Right hock angle (°)	154.5	5.8	157.2	5.5	154.0	6.6
Left shank vs horizontal line angle (°)	84.24	4.76	85.38	6.47	82.93	6.65
Right shank vs horizontal line angle (°)	83.06	5.94	83.58	4.55	81.18	6.33
Left drumstick rel. length	0.583	0.048	0.542	0.047	0.535	0.046
Right drumstick rel. length	0.601	0.047	0.564	0.046	0.572	0.037
Left shank rel. length	0.423	0.033	0.443	0.061	0.454	0.051
Right shank rel. length	0.411	0.037	0.449	0.047	0.439	0.040
Hock/knee distance ratio	0.586	0.094	0.625	0.058	0.644	0.066
Left step height (%)	36.47	6.53	39.08	6.79	39.20	8.71
Right step height (%)	39.20	7.08	36.00	7.36	32.08	9.59

Discussion

We demonstrated the usability of recording walking broilers from behind for monitoring certain locomotion features. Further training of a pre-trained pose estimation model with a limited number of frames improved its performance in the new environment. The automated pose extraction algorithm proved to be useful for high-throughput pose extraction. Although, further improvements could be made to this algorithm, because in some instances the double support stance was somewhat asymmetric, and not the highest leg lift was captured during some steps.

In contrast with the photogrammetry method used by Mendes *et al.* (2016), video recordings have the potential to be upscaled to practical circumstances. Using a top view of the chickens, Aydin (2017) calculated features such as speed, step frequency and length, and lateral body oscillation. In our setup, angles, hock-knee distance ratio, and step height were the most informative features, whereas relative drumstick and shank lengths were more heavily influenced by perspective. Further work could focus on the relationship of these video-derived features with gait.

Ethical statement

Data were collected under control of Cobb Europe. Cobb Europe complies with Dutch legislation on animal welfare.

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References

Aydin A. (2017) Comput. Electron. Agr. 136:140-146. https://doi.org/10.1016/j.compag.2017.02.019

Bates D., Maechler M., Bolker B., Walker S. (2015) J. Stat. Softw. 67(1):1-48. https://doi.org/10.18637/jss.v067.i01

Bouwman A., Savchuk A., Abbaspourghomi A. and Visser B. (2020) Front. Genet. 11:207. https://doi.org/10.3389/fgene.2020.00207

Caplen G., Hothersall B., Murrell J.C., Nicol C.J., Waterman-Pearson A.E., *et al.* (2012) PLoS ONE 7(7): e40800. https://doi.org/10.1371/journal.pone.0040800

Doornweerd J.E., Kootstra G., Veerkamp, R. F., Ellen E.D., van der Eijk J.A.J., *et al.* (2021) Front. Anim. Sci. 2:791290. https://doi.org/10.3389/fanim.2021.791290

Knowles T.G., Kestin S.C., Haslam S.M., Brown S.N., Green L.E., *et al.* (2008) PLoS ONE 3(2): e1545. https://doi.org/10.1371/journal.pone.0001545

Mathis A., Mamidanna, P., Cury K.M., Abe T., Murthy V.N., *et al.* (2018) Nat. Neurosci. 21, 1281–1289. https://doi.org/10.1038/s41593-018-0209-y

Mendes A.S., Paixão S.J., Sikorski R.R., Bonamigo D.V., Morello M.G., *et al.* (2016) Braz. J. Poult. Sci. 18(4):573-580. https://doi.org/10.1590/1806-9061-2015-0079

R Core Team (2020) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.