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Weight prediction of broiler chickens using 3D computer vision

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ABSTRACT

In modern broiler houses, the broilers are traditionally weighed using automatic electronic platform weighers that the broilers have to visit voluntarily. Heavy broilers may avoid the weigher. Camera-based weighing systems have the potential of weighing a wider variety of broilers that would avoid a platform weigher which may also include ill birds. In the current study, a fully-automatic 3D camera-based weighing system for broilers have been developed and evaluated in a commercial production environment. Specifically, a low-cost 3D camera (Kinect) that directly returned a depth image was employed. The camera was robust to the changing light conditions of the broiler house as it contained its own infrared light source.

A newly developed image processing algorithm is proposed. The algorithm first segmented the image with a range-based watershed algorithm, then extracted twelve different weight descriptors and, finally, predicted the individual broiler weights using a Bayesian Artificial Neural Network. Four other models for weight prediction were also evaluated.

The system were tested in a commercial broiler house with 48,000 broilers (Ross 308) during the last 20 days of the breeding period. A traditional platform weigher was used to estimate the reference weights. An average relative mean error of 7.8% between the predicted weights and the reference weights is achieved on a separate test set with 83 broilers in approximately 13,000 manually annotated images. The errors were generally larger in the end of the rearing period as the broiler density increased. The absolute errors were in the range of 20–100 g in the first half of the period and 50–250 g in the last half. The system could be the stepping stone for a wide variety of additional camera-based measurements in the commercial broiler pen, such as activity analysis and health alerts.

1. Introduction

In 2025 the world population is expected to exceed 8 billion people, and by 2050 it is expected to hit 9.6 billion (Malik, 2013). This 35% increase in world population over the next 35 years necessitates effective livestock production methods. The current study focuses on broiler chickens which is one of the main food sources with an estimated annual global production of more than 90 million tonnes of meat (Faostat, 2012). The weight of the broilers throughout the rearing period is one of the key metrics in assessing the effectiveness of the production by comparing consumed feed with measured broiler weight. The daily mean weight is used as metric in common practice. A deviation from the expected weight can further indicate ill thrift, diseases and vitality issues (Lott et al., 1982; Flood et al., 1992). Currently, the farm manager can choose to weigh a sample of the broilers manually or use an automatic platform weighing system. Manual weighing generally requires a lot of manual labor and is therefore time consuming and it is also stressful for the birds (Turner et al., 1983; Doyle and Leeson, 1989). With the automatic platform weighing systems, the birds that stand or sit on the platform will be weighed to give daily mean weights automatically. These systems are less stressful for the broilers, since there are no intruders chasing and constraining them. However, there is the tendency that the heavier broilers will visit the weigher less frequently than others in the final weeks and, hence, underestimate the true weight (Newberry et al., 1985; Chedad et al., 2003; Blokhuis et al., 1988).

In the current study, a non-intrusive camera-based system is investigated. The system does not require the broilers to voluntarily step onto the weigher and therefore weighed all birds in the field of view of the camera. Besides, the camera may cover a larger area of the floor than a traditional platform weigher. With an area of 1 m^2 the weight of several birds may be estimated to get more accurate mean weight estimates and weight distributions. Potentially, it may also weigh birds that would avoid a platform weigher due to e.g. illness or large weight. Camera-based systems

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are not commercially available for broiler weighing, but do exist for e.g. pig weighing (AgroFarm, 2015). Camera-based pig weighing has received a lot of attention (Schofield, 1990; Kashiha et al., 2014), but also e.g. cows and sheep have been measured and weighed using cameras (Tasdemir et al., 2011; Menesatti et al., 2014). The basic assumption of camera-based weighing is a close relation between animal volume and weight which may often be realistic in production scenarios. Further, many studies assume that the weight is directly related to the visible occupied area of the animal as seen from the camera (Kashiha et al., 2014; Mollah et al., 2010). Other approaches use specific biometric measures such as head–tail length or shoulder-shoulder distance (Wang et al., 2008).

One of the few examples of camera-based broiler weighing is De Wet et al. (2003) which investigated surface area and periphery of the broilers as weight descriptors. They achieved an average relative error on the predicted weights of 11% from the surface area. Mollah et al. (2010) used the contour area to predict weight during the 42 day rearing period with comparable precision. These proof-of-concept studies suggest that camera-based weighing of broilers is indeed feasible.

There has been other uses of camera-based techniques than weight prediction on poultry. For instance, segmentation and tracking algorithms were developed by Sergeant et al. (1998) and Leroy et al. (2006) with the purpose of analyzing the behavior of broilers and laying hens, respectively. In the recent work by Nakarmi et al. (2014), algorithms were developed for a 3D camera together with RFID tags to track laying hens. Dawkins et al. (2013) investigated optical flow algorithms for automatic irregularity detection in the broiler flock and Kristensen and Cornou (2011) explored motion detection algorithms for activity pattern analysis.

In the current work, an automatic camera-based system for use in commercial production scenarios with free-ranging broilers in the pen was developed. Due to heavily controlled day and night cycles, the vision system was designed to perform equally well under varying light conditions. The approach was to use the low-cost Kinect 3D camera which satisfied these criteria. A weighing system that use this 3D information to estimate the weight of free-ranging broilers was developed and the system performance was evaluated against a commercial platform weigher.

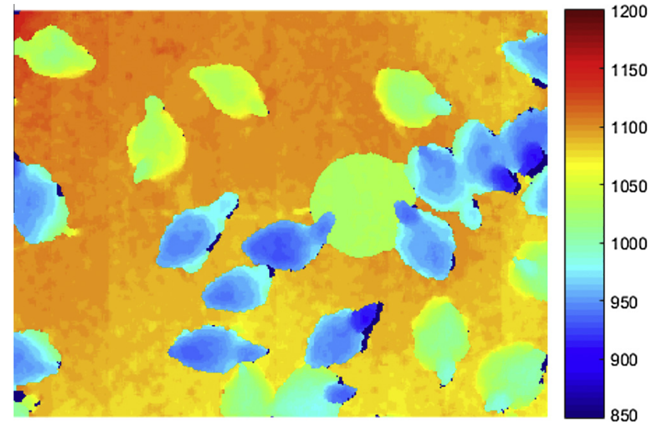


Fig. 1. Depth image taken with the Kinect camera. The different colors directly show the distance from the camera to a position in the image and can therefore be seen as a 3D representation. The scale bar shows the distance in milimeters from the Kinect camera to an object. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

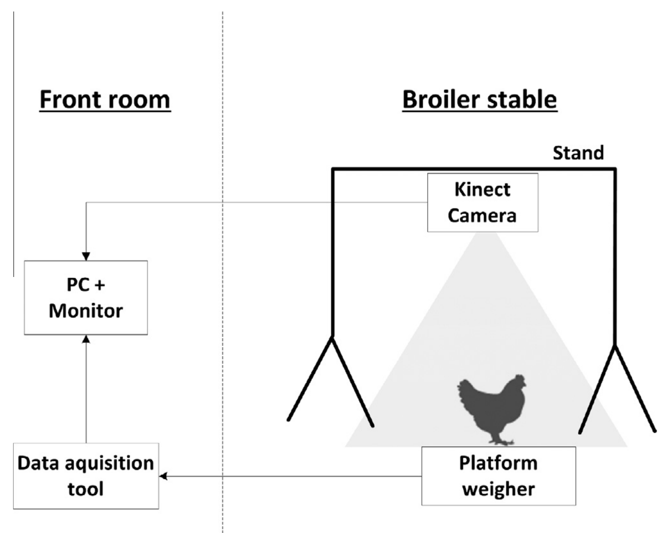


Fig. 2. Overview of the experimental arrangement which consists of a Kinect camera and platform weigher inside the broiler stable and data acquisition in the front room.

2. Experimental setup and data set

2.1. Experimental arrangement and equipment

The current study focused on 3D range cameras and in particular the Kinect camera which is a low-cost consumer product that could realistically be used in commercial automatic weighing systems. The Kinect camera directly records a depth image (640×480 px) as seen in Fig. 1. It has been used in many computer vision systems previously due to the its ability to record 3D information, but also its robustness to visible lighting conditions and ease of image segmentation (Andersen et al., 2012). The Kinect itself emits an infrared pattern to estimate depth which means that it is not disturbed by the changes in the visible light that can happen in a broiler house and will work even in complete darkness. The infrared pattern is generated using a laser with a wavelength of 830 nm, which is located well above the spectral sensitivity of the broilers (350–750 nm) (OpenKinect, 2015; Lewis and Gous, 2009). This left the broilers unaffected by the IR pattern emitted by the Kinect and it did therefore not disturb their day and night cycles.

A overview of the experimental arrangement is illustrated in Fig. 2. It consisted of the Kinect camera together with a traditional platform weigher (DOL 94-10 from SKOV A/S) that was used to give a reference weight. Besides, a data acquisition tool (Analog Discovery from Digilent Inc.) and a standard PC were located in the front room. The Kinect camera was mounted in an aluminum box to protect it from the dust within the rearing house and attached to a metal stand 110 cm above the floor covering an area of 1.20×0.87 m^2 on the ground. The platform weigher was glued to the floor below the camera. The frame rate of the Kinect camera was 15 FPS, while the sample rate of the weigher was 25 Hz.

The experiment was carried out in a commercial production-environment in a typical rearing house of the region (Broenderslev, Denmark, March 2014). The fully-isolated house contained approximately 48,000 Ross 308 broiler chickens. The house measured 22×125 m^2 with 50% wood-shavings and 50% sphagnum as litter. The photoperiodic regime consisted of two dark periods from 00:00 to 4:00 and from 12:00 to 14:00. During the light periods, light intensity was approximately 25 lx. The temperature was 34 °C from day 1 and decreased to 18 °C on the final day. The humidity was at 50% at day 1 and increased to 77% at the final day. The ventilation system was a negative pressure system with ventilators in both the ceiling and the rear wall. Fig. 3 illustrates

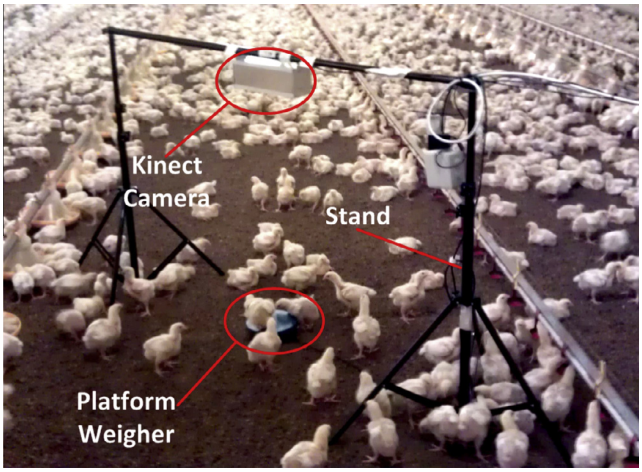


Fig. 3. Photo of the experimental arrangement. The photo was taken the same day the system was set up in the broiler stand – the 14th day of the rearing period. Note that at this photo, the broilers are still avoiding the camera stand where they would normally be standing as closely together as seen in the rest of the stable.

Table 1
Summary of data sets.

Data set	Broilers	Images
Training set	189	31,285
Test set	83	13,667
Full data set	272	44,952

the broiler stable and the experimental arrangement. The data acquisition lasted from day 14 to 33 of the 33-days long rearing period. This part of the rearing period was chosen since the broilers are more cluttered and therefore more challenging for the computer vision algorithm. During the period, the broilers were growing from an approximate weight of 0.4 kg to 2 kg and at any time 10–20 broilers were within the field of view of the camera.

2.2. Data set description and labeling

The data set consists of a subset of the acquired depth images and weighings evenly distributed over the recording period. Each recording has a 40 s duration and was initiated when the platform weigher detected a decrease in weight of more than 200 g. The data set was created by manually clicking on a broiler in the depth image when it was standing on the weigher and then clicking on the same broiler in the following images until it either left the camera field of view or the recorded image sequence ended. A MATLAB script was developed for the manual labeling process (MATLAB, 2013). For each image sequence, a single reference broiler weight was found by averaging the weight samples where the broiler was on top of the platform weigher. Afterwards, the full data set was split up into a training set and a test set with a 70% – 30% split. A summary of the number of broilers and images in the data sets can be seen in Table 1.

3. Methodology

The proposed system first acquired a depth image, then predicted the broiler weight from our new algorithm, and, finally, stored the result in a database from which metrics such as the daily mean flock weight and daily weight distribution could be extracted. The algorithm was composed of 3 steps; (1) segmentation of the broilers, (2) extraction of features from each segmented broiler and (3) weight prediction of each broiler based on the extracted features. The algorithmic flow is illustrated in Fig. 4 and will be described in more detail in the following subsections. The algorithm was developed and executed in the MATLAB environment.

3.1. Broiler segmentation using range-based watershed

Watershed segmentation is widely used in gray scale image processing to partition an image into a number of segments by extracting their contours. Usually, a height function is defined over the image domain to create an artificial depth image with local minima at the objects of interest. Next, a flooding technique is used to incrementally flood regions that surrounds the local minimum until the regions meet. When two flooded regions meet, a watershed line separating the two regions is created (Chen and Georganas, 2006).

Since the intensities in the depth images from the Kinect are directly related to the distance from the camera to the object, the Watershed algorithm can be applied directly to these without applying a height function. The broilers created small valleys with local minima and the floor created plateaus in the image, as seen in Fig. 5b.

To avoid oversegmentation of the broilers, the depth image was smoothed using a Gaussian kernel followed by a morphological opening with a circular structuring element. The morphological opening removed the local minima associated with the broiler heads while preserving the local minima from the broiler bodies. In this work used a 15×15 px zero-mean Gaussian kernel with a standard deviation of 10 and a circular structuring element with a radius of 17–23 px depending on the age of the broilers. To remove potential segmentations of the floor, any segment located less than 2 cm from the floor was discarded. An example of broiler segmentation using the Watershed algorithm can be seen in Fig. 5c.

3.2. Feature extraction

Throughout the litterature, several vision related features are proposed for predicting the weight of livestock such as broilers, pigs and herrings (Mathiassen et al., 2011; Wang et al., 2008; Mollah et al., 2010; De Wet et al., 2003). These features can be categorized as either 1D, 2D or 3D features depending on the underlying space from which they are extracted. E.g. the area is considered a 2D feature, while the volume is considered a 3D feature. The best performance is obtained, when combining multidimensional features (Mathiassen et al., 2011). Thus, a combination of 12 different handcrafted 1D, 2D and 3D features were used for predicting the weight of the broilers.

3.2.1. 1D features

During the rearing period, the food and water supplies as well as the circadian rythm of the broilers were heavily controlled to ensure the broilers followed the optimal growth pattern and reached their target weight at the end of the rearing period. Hence, the age of the broiler is closely related to the weight of the broiler (Mollah et al., 2010) and was used as a feature.

3.2.2. 2D features

Projected area, width of the broiler, perimeter, radius of largest inscribed circle and eccentricity were used as 2D features.

The projected area is a widely used feature for weight estimation (Mathiassen et al., 2011; Wang et al., 2008; Mollah et al., 2010; De Wet et al., 2003). It is simply the area, which the broiler takes up when projected onto the image plane.

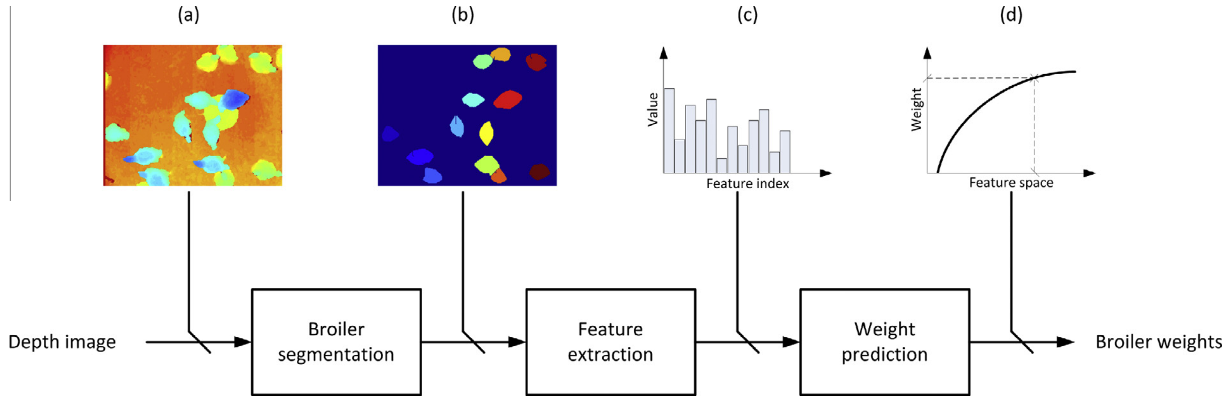


Fig. 4. Algorithmic flow of proposed method for weighing broilers: (a) original depth image; (b) broilers separated from the background; (c) calculated weighing parameters from an individual; and (d) predicted weight of an individual.

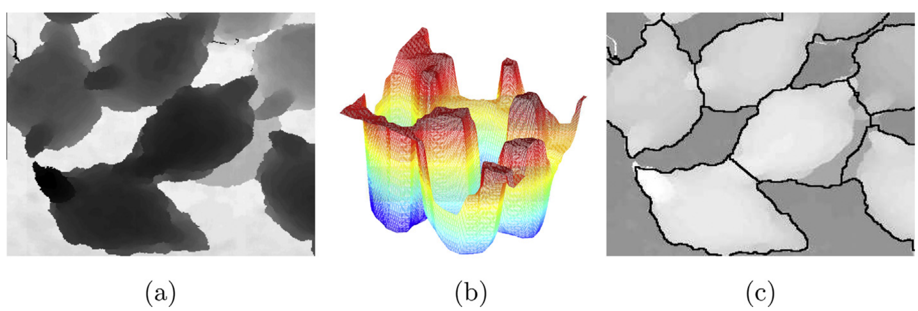


Fig. 5. Watershed algorithm used on the depth image. (a) A cropped depth image with six broilers standing close to each other. (b) Mesh plot of a blurred depth image, which illustrates the valleys created by the broilers. (c) Subdivision lines (black) created by using the watershed algorithm.

As a broiler grows, it increases in both length and width. However, due to the movement of the head when it walks and pecks, the width of the broiler was expected to be the more stable feature of the two. Although, the width was affected by the broiler flapping its wings, it was experienced less often than the bobbing of the head. Because of a broiler's elongated shape, the minor axis of the segmented broiler was used as the width of the broiler.

The perimeter has been used with great success as a weight predictor for broiler chickens and pigs (De Wet et al., 2003; Wang et al., 2008). The perimeter was calculated by simply counting the number of pixels in the contour (Fig. 6a).

The largest inscribed circle is the largest circle, which can be drawn inside the contour of the broiler (Fig. 6b). Compared to the perimeter, this feature was more robust against flapping of the broilers wings. The radius of largest inscribed circle was approximated using a distance transform of the broiler contour (Xia et al., 2007).

It was observed that the younger broilers tend to have a more elongated body, while the older broilers had a more round shape. This lead to a high eccentricity in small broilers while a low eccentricity in large broilers. Thus, the eccentricity was included as a feature.

3.2.3. 3D features

The depth images from the Kinect can be used for features that relate to the three dimensional shape of the broiler, and not just flat two dimensional features. The 3D features were generally related to the volume of the broiler. The volume, convex volume, surface area, convex surface area, back width and back height were used as 3D features (Mathiassen et al., 2011).

Due to the placement of the camera, a full 3D model of the broilers were not available. Therefore, the volume of a broiler "shell" was approximated as seen in Fig. 6c. Two different approaches were used for estimating the volume: numerical integration and convex hull. The volume using numerical integration of the depth pixels was estimated by:

$$V = \sum_{i=1}^{N} (p - d_i) \cdot A_i$$

where V is the estimated volume, N is the total number of pixels, p is the average contour depth of the broiler, and d_i and A_i are the depth value and approximated pixel area of the ith pixel in the segmented broiler, respectively.

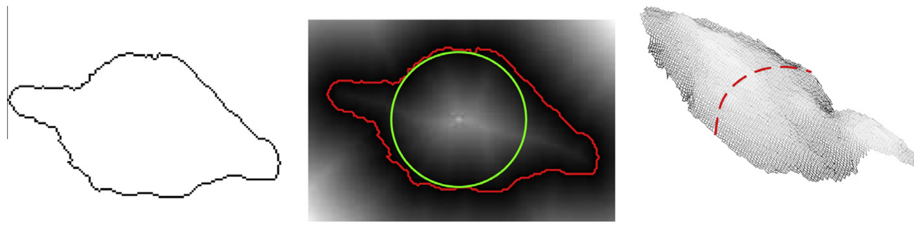
The estimated volume using convex hull was approximated from points that represent the facets of the convex hull of the total point cloud, that were part of the segmented broiler. It was assumed that the broiler's body was a convex object. However, this assumption was not met if the broiler's head and neck was included in the model.

As the broiler volume increased, their surface area must also increase. Two different approximations to the surface area were used; 3D Delaunay triangulation and convex hull. The Delaunay triangulation (Delaunay, 1934) was applied to the point cloud that represents a segmented broiler. This creates a set of triangles in the 3D space. The total surface area were approximated by summing all areas of the triangles:

$$S = \sum_{i=1}^{T} \frac{1}{2} |\mathbf{u}_i \times \mathbf{v}_i|$$

where, S is the surface area, T is the total number of triangles, while $\mathbf{u}_i$ and $\mathbf{v}_i$ are the two vectors that span the ith triangle.

The convex surface area was based on the convex hull of the point cloud from the segmented broiler, and it was computed in



(a) (b) (c)

Fig. 6. (a) Broiler contour. (b) Largest inscribed circle. The red line shows the contour of the broiler. The green circle is the largest inscribed circle. The background represents the distance transform of the contour image. Black and white represent a point that is close and far from to the contour, respectively. The white peak of the distance transform represents the center of the incribed circle. (c) Back width illustrated with a red dashed line across the 3D mesh grid of a broiler. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the same way as in the Delauney surface area, although the triangles were now facets of the convex hull of the total point cloud.

The back width of the broiler was similar to the 2D feature "width". However, in contrast to the width, the back width used the depth information and traversed across the back of the broiler instead of just the direct distance from side to side (Fig. 6c). Because of the elliptical shape of the broilers, the minor axis was used to define the cross section where the width was calculated. The back width was found by numerical integration of the cross section:

$$W = \sum_{i=1}^{L-1} \sqrt{l_i^2 + |x_{i+1} - x_i|^2}$$

where W is the back width, x_i and x_{i+1} are depth values on the cross section with index i and $i+1, l$ is the length between the points with index i and $i+1$ and L is the total number of points on the cross section.

The last feature included in the proposed model was the back height. The back height was defined as the difference between the average depth value on the contour of the segmented broiler and the depth value on top of its back. It was assumed that the top of the back of the broiler was located approximately at its center of mass.

To ensure scale invariance, all features were converted from points in a three dimensional coordinate system to metric units.

3.2.4. Feature stability

Most of the features that were used were geometrical features, where the geometry of the broiler's body was used to derive the features. As already mentioned, features were affected by the motions of head and tail. In Wang et al. (2008), the authors use morphological opening applied to a thresholded image to remove such variations of a pig before weight prediction. The same method was applied to remove the head and tail from the broiler as illustrated in Fig. 7. A sphere was used as a three dimensional structuring element to remove the head and tail in the depth image by performing a morphological closing. This effectively removed the head and tail of the broiler while keeping the rest of the body almost unaffected (Fig. 7b). This preprocessing increased the feature stability.

3.3. Weight prediction using regression models

To predict the weight of the broilers based on the extracted features, 5 different regression models were explored. These models were selected for further evaluation from an initial cross-validation-based model parameter search on training data. Experiments were made with both multivariate linear regression, (feed-forward) Artificial Neural Networks (ANN) and Bayesian Artificial Neural Networks. The Bayesian ANN is a probabilistic method that returns the posterior probability of the weight, given the features, but using a regression function of similar form as the traditional ANN (Bishop, 2006).

The explored models were:

1. Multivariate linear regression model with all 12 features.
2. Artificial neural network with a (12-3-1) topology.
3. Artificial neural network with a (12-10-1) topology, trained with early stopping.
4. Artificial neural network with a (12-10-1) topology, trained with weight decay.
5. Bayesian artificial neural network with a (12-10-1) topology.

3.4. Evaluation metric

During the rearing period, the broilers experienced an exponential growth in weight, which made the absolute error a poor metric for comparing broilers across different ages. Therefore, the mean relative error and its standard deviation was used as metrics. The mean relative error and its standard deviation are given by:

$$e_R = \frac{1}{N}\sum_{n=1}^{N} \frac{|\hat{w}_n - w_n|}{w_n} \tag{1}$$

$$\sigma_R = \sqrt{\frac{1}{N}\sum\nolimits_{n=1}^{N} \left(\frac{|\hat{w}_n - w_n|}{w_n} - e_R\right)^2} \tag{2}$$

The mean relative error can be interpreted as the relative accuracy of the weight predictions and the standard deviation as the variation in the relative accuracy.

4. Results

4.1. Evaluation of regression models for weight prediction

All regression models for weight prediction was trained and evaluated on a separate training set to identify an optimum set of parameters for each model. The mean relative error were used as a training metric in all cases. The training of the neural networks was performed using 10-fold crossvalidation. For each fold, the training of the network was repeated 10 times to avoid local minima. Fig. 8 shows the relative error per day for each of the five regression models. All five regressions models had very similar performance.

The Bayesian ANN was chosen as the regression model, because it gives a principled approach to outlier detection. The outlier detection was used to remove broilers from the set of weight predictions. It was found that these broilers generally had erroneous

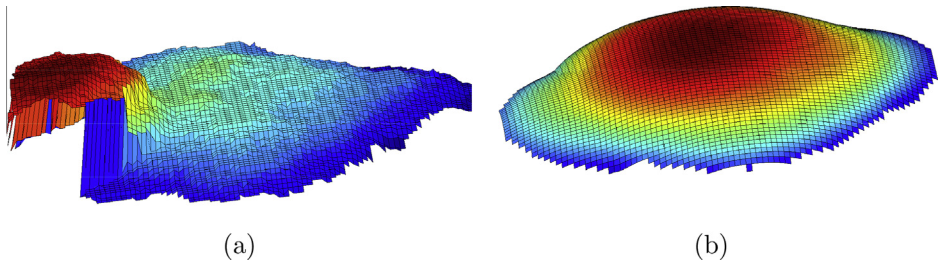


Fig. 7. Example of the morphological broiler head and tail removal. The head and tail were both removed in 3D structure using a morphologial opening with a spherical disk. (a) The original 3D mesh structure of the broiler. (b) Mesh structure after the morphological head and tail removal.

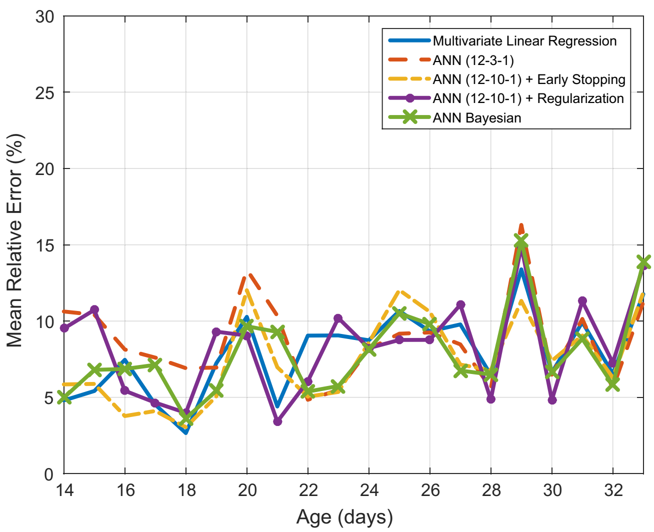


Fig. 8. Weight prediction results for different regression models based on the training set. The results show a very similar performance for all five regression models.

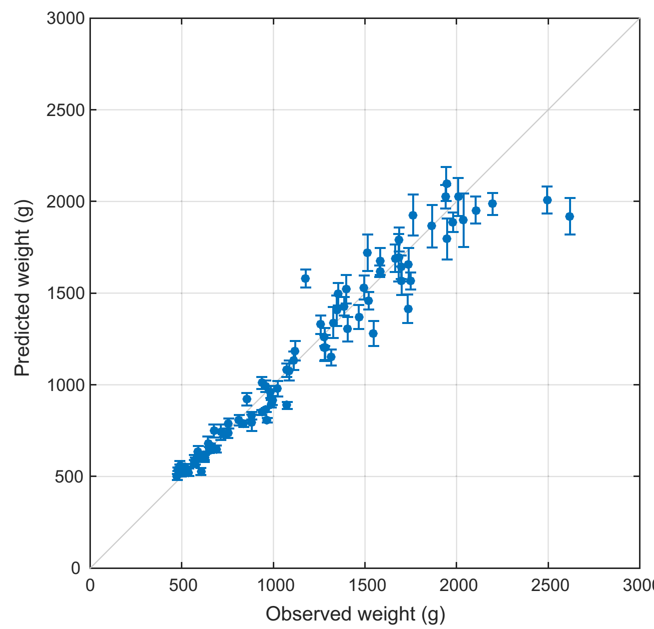


Fig. 9. Correlation plot for each broiler in the test set. The dot shows the average predicted broiler weight of a given broiler, and the error bars correspond to one standard deviation.

segmentations, severe occlusion problems or the broilers were spreading their wings.

4.2. Evaluation on test data set

The algorithm with the Bayesian ANN was evaluated on the test set. A correlation plot relating the observed weight with the predicted weight can be seen on Fig. 9. In the correlation plot, several predicted weights for a single broiler were averaged into a single point. The error bars correspond to one standard deviation. The points were grouped very closely to the ideal diagonal line, although the heavier broilers had an increased spread and standard deviation. Across all broilers and ages, a relative mean error of 7.8% with a relative standard deviation of 6.6% was achieved.

On Fig. 10, the observed and the predicted daily mean broiler weight based on the test set are seen. Each point corresponds to the daily mean based on all samples on a given day and the error bars correspond to one standard deviation. The observed daily mean broiler weight was within one standard deviation of the predicted daily mean broiler weight on most days. As expected, the standard deviation increased with the age of the broilers. On the test data set, an average daily error of 4.5% from day 14 to 33 was achieved. This corresponded to an average daily absolute error of 55 g.

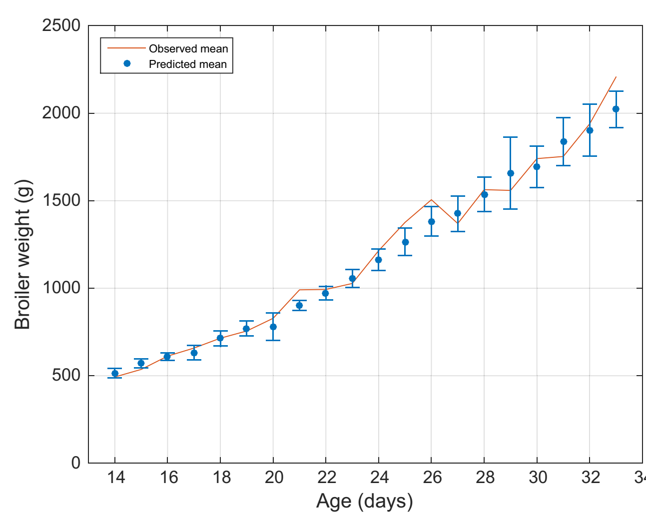


Fig. 10. The observed and predicted daily mean broiler weight for the test set. The error bars correspond to 1 standard deviation.

5. Discussion

The proposed system had a precision that was comparable to previous research (De Wet et al., 2003; Mollah et al., 2010). Additionally, the results were obtained under commercial production settings and as a fully automatic system without human intervention. However, there were still situations that challenged the system, as illustrated in Fig. 11. As seen on Fig. 11a, the broiler

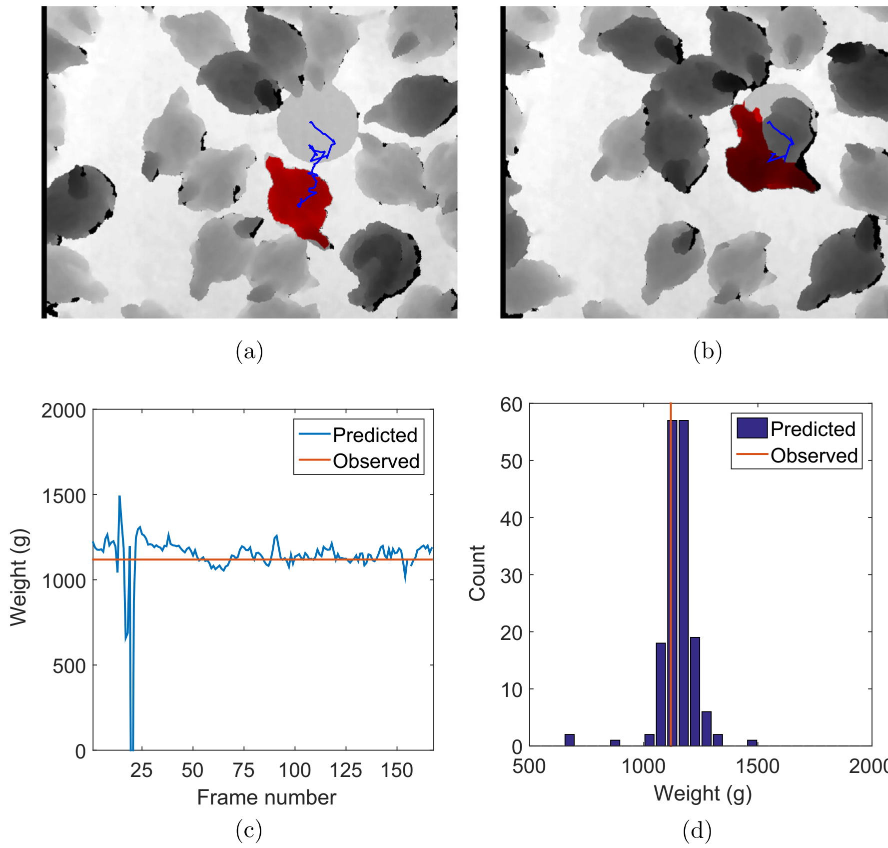


Fig. 11. Example of weight predictions of a single broiler. (a) The depth image (frame 160) with the broiler being weighed and several other broilers. The segmentation of the broiler being weighed is highlighted with red. The blue line shows the observed path, which the broiler had taken up until this frame. (b) Same as (a), but for frame 20. (c) Weight prediction of the broiler as a function of the image number (blue line). No outliers were removed in this example. The red line shows the observed weight. (d) Histogram of all the predicted weights of the broiler. The red line shows the observed weight. A single negative weight estimate is not shown. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

started on top of the circular platform weigher. Here, it flapped its wings (Fig. 11b) before it hopped off the weigher and moved a little away from the weigher and sat down. The flapping of the wings were seen as large fluctuations in the weight estimations in Fig. 11c (frame 10–30). Smaller fluctuations (frame 80–100) was also seen when the broiler hopped off the weigher and when it sat down (frame 140–160). Even smaller fluctuations was seen even when the broiler was not moving or flapping its wings. The fluctuations in the weight estimations were a result of the change of shape of the broiler and imperfect segmentation of the broiler body (Fig. 11b). Fig. 11d shows a histogram of all the predicted weights for the broiler during the image sequence. It was seen that the system overestimated the weight of the broiler. This tended to happen when the broilers were either partly occluded or are standing very close to each other. It was expected that the segmentation would be difficult when the broilers were standing close together, and unfortunately this would often be the period with the highest relevance for measuring broiler weight. To address these issues, experiments with tracking methods following each individual broiler through the image stream was made. Ideally, these methods could filter out images where the broiler had irregular behavior (e.g. flapping wings or stretching) or segmentation issues (e.g. broiler occlusion) and give more precise weight estimates. Unfortunately, the experiments were not very successful as the tracking methods were also sensitive to the high density of broilers and target swapping and lost tracks often occurred.

There were also other observations during the experimentation. For instance, one could argue that simply using the age of the broilers as a feature by itself, could give fairly good weight estimations. This is in fact the traditional reference weight curve that farm managers frequently employ. While this is partly true, the proposed system gave better weight predictions with all 13 features than simply using the Age feature alone. Besides, using only the Age feature will not allow the system to return the weight histogram which could be a useful management tool or identify ill birds.

The proposed vision system was supposed to be used by farm managers to quantify broiler health and growth. However, further investigation is necessary to verify whether or not the current system has sufficient precision for this use and how the system will generalize to e.g. another flock of birds or production scenario. It is also unclear how well it could quantify ill birds, but vision systems certainly have this potential in contrast to traditional platform weighers.

6. Conclusions

This paper proposed a non-intrusive voluntary 3D camera-based weighing system for broiler chickens. The system was developed and evaluated under commercial production settings. The system proved to be robust towards the varying light conditions during the night and day cycles due to its own infrared light source.

The camera-based system has a clear advantage over the traditional platform weigher in its ability to weigh several broilers at once. However, further development in the segmentation of the broilers is required as a poor segmentation lead to poor weight prediction. A better segmentation will also pave the way for tracking of the broilers, which could also lead to a better weight prediction of the individual broiler by gradually refining the weight estimates over several images.

The camera based weighing system could be a first step in bringing vision technology into the broiler pen. When the first vision system has been implemented in the pen, additional applications could easily be added to the existing system to increase its value to the farmer. The additional applications could focus on attributes that are currently not easy to monitor automatically, such as feeding and drinking patterns, activity analysis and spatial use.

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