J. Dairy Sci. 106:9105–9114
https://doi.org/10.3168/jds.2022-23177


# Repeatabilities of individual measures of feed intake and body weight on in-house commercial dairy cattle using a 3-dimensional camera system

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## ABSTRACT

In this study a 3-dimensional (3D) camera system was set up to measure individual feed intake of dairy cows in a commercial in-house setting. The system was developed to identify the cows while eating, predict body weight based on the curvature of the back of the cow, and quantify the amount of feed eaten by the cow at each visit of eating. The identification of the cow was based on recognizing the patterns, colors, and curvatures of the back from a reference database obtained in a corridor after milking, where images were taken of all cows with a simultaneous reading of the electronic ear tag. Body weight is predicted using the curvatures of the back of the cow. Feed intake is quantified as the difference in surface of the feed a cow can reach before and after a visit is initiated. This estimate is in liters but converted to kilograms, using the density of the feed in the specific herd. A total of 9,142 cows were measured in 19 herds across 3 breeds: Jersey (2,513 cows), Red Dairy Cattle (2,813 cows), and Holstein (3,816 cows). Mean daily feed intake was higher for Red Dairy Cattle (61.72 kg) and Holstein (64.59 kg) than for Jersey (55.74 kg). Repeatability estimates for daily feed intake as a weekly average was 0.62, 0.65, and 0.63 for Jersey, Red Dairy, and Holstein cattle, respectively. Mean body weight was higher for Red Dairy (647.9 kg) and Holstein (683.8 kg) than for Jersey (469.6 kg). Repeatability estimates for body weight as a weekly average was 0.83, 0.85, and 0.88 for Jersey, Red Dairy, and Holstein, respectively. The perspectives in having such records available is huge both for the farmer and for the dairy industry. The records can both be used for improving management in farms on an individual cow level and herd level, but also for genetic evaluation and selection as well as testing feeding regimens. Feed intake can be measured on an individual level using a 3D camera system.
**Key words:** feed intake, body weight, 3D camera, repeatability

Received December 21, 2022.
Accepted July 17, 2023.
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## INTRODUCTION

Feed cost is up to 70% of the running cost for a farmer, so saving even a marginal amount of feed will make a huge impact on the return on a farm. A part of the variation in feed intake and efficiency is heritable, which make selection for improved feed efficiency possible (Løvendahl et al., 2018). A limitation to implement this is lack of data on the individual cow level recorded in commercial settings throughout the lactation. So far, equipment for registering individual feed intake has primarily been on research farms and based on scale system that are expensive and time consuming to manage (Seymour et al., 2019). This includes the HOKO-system (Insentec B.V.) and GrowSafe automated feeding system (GrowSafe Systems Ltd., Airdrie, Alberta, Canada). Feed intake measured in research farms is repeatable (0.66) as well as heritable (0.34; Berry et al., 2014), so selection can be performed to change the trait in the preferred direction. The Insentec monitoring system permits loose-housed cows to freely access several feeding and drinking stations, which allows researchers to collect continuous feeding and drinking behavioral data. The basis of this system is radio frequency identification (**RFID**) ear tags coupled with an automated barrier between the cow and the feed and water. The Insentec monitoring system performs well in several studies including Chapinal et al. (2007). A scale-based system with a physical barrier placed between the cow and the feed still is expected to influence the natural feeding behaviors of the cow. The ideal system measures, controls, and monitors individual feed intake of the free-housed cow, whereas not interfering with feeding habits and not introducing additional work or inhibiting workflow on the farm (Halachmi et al., 1998).

In the last decade several studies have aimed at doing genetic analysis of feed intake on research farm data (Manzanilla Pech et al., 2014; Li et al., 2016). Often such analysis consists of registrations on fewer than 1,000 cows and face challenges on limited amount of data to do proper analysis. Therefore, international collaborations have been set up (Berry et al., 2014; Tempelman et al., 2015; Baes et al., 2022). This has opened up for much more advanced modeling of the complex phenotype. It has also made it possible to make more proper genetic evaluation to be implemented in practical breeding (Li et al., 2020; Khanal et al., 2022). However more data are still needed to make accuracies higher on the breeding values.

New and emerging technologies has always been either implemented to measure new phenotypes or known phenotypes in a new way in dairy cattle production. Also, 3-dimensional (**3D**) cameras can be used for generating data that can be used to improve management in dairy cattle production such as BCS (DeLaval Body Condition Scoring, DeLaval International AB, Tumba, Sweden). The development of 3D cameras has been remarkable over the last decades and is today, for example, installed in gaming consoles and can be purchased for relatively low cost while providing accurate data continuously. This can be used to surveil traits that needs to be recorded and stored throughout the day, such as feed intake and behavior.

A 3D camera system to identify cows, predict BW and make individual feed intake records has been developed (WO 2014/166498, Borchersen, 2014; WO 2017/001538, Borchersen et al., 2017; WO/2020/260631, Lassen and Borchersen, 2020). The system (Cattle Feed Intake System) works without disturbing daily behavior of either the cows or the management of the daily routine in the barn. The cameras records data around the clock and based on image analysis cows are identified at the feeding table (Thomasen et al., 2018) and the amount of feed eaten is quantified (Lassen et al., 2018). In these studies, the data were collected in a limited time period and identification percentage and repeatabilities of the feed intake between days and weeks were reported and showed promising results. Other camera-based systems have been initiated to make individual feed intake records. Bezen et al. (2020) used the convoluted neural network (**CNN**) approach to quantify feed intake and showed a mean squared error of 0.119 $kg^2$ feed per meal based on 63 meals recorded on 6 cows in 36 h. Identification relied on observing digits related to the cow identification on collars on the neck of the cow.

The aim of this study was to analyze individual measures of feed intake and predicted body weight recorded in commercial farms using 3D cameras. This was studied by estimating the repeatability of the phenotypes recorded in 3 different dairy breeds.

## MATERIALS AND METHODS

Because animals were not handled in any way or removed from their normal environment, no ethical approval was required for this study.

### *Cow Identification Unit and Weight Measurement*

The reference unit consists of a single 3D camera using time-of-flight technology (Microsoft Xbox One Kinect v2) to create a 3D image and an RFID reader (Agrident Sensor ASR550). A Dell T630 128 gigabytes random access memory server with 3090 RTX graphics card is used for the data analysis. These were installed in a narrow corridor with a time-based trigger system that allocated all images in 3 s after the RFID read to the specific ear tag, which ensured that one reference image was obtained from each cow when they pass through (Figure 1). The corridor has been narrowed further than a normal exit corridor to ensure that no cows pass in obscure positions, go as 2 cows together, or even turn in the corridor. The 3D camera was placed directly above the passing cows 3.4 m above floor level. At the same position, a homemade walking scale (Eziweight S2) was installed to measure individual BW of the cow that was passing (Gebreyesus et al., 2023).

Before any cows enter the system, the fixed interior in the image of an empty corridor is annotated. In that way, anything that enters an image will be noticed as a change from the annotated picture and considered a cow. Pictures were corrected in all 3 dimensions and stitched live as they were generated between cameras to make an image from one camera informative with the corresponding image from the camera next to it. All images were afterward sent to a central server were the remainder of the within-herd analysis were conducted. Three types of images are recorded from the 3D camera: RGB pictures, infrared (**IR**) pictures, and depth pictures indicating the distance from the camera to the object that is within the range of the camera, both in the lock after milking (Figure 2) and while the cows are eating at the feeding table (Figure 3). Direct sunlight in the image is a known challenge for an RGB camera as the Kinect camera. Therefore, herds were selected where the feed was indoor under a roof and no or limited direct sunlight on the feed were observed during the day.

### *Cow Identification*

The first step in the image processing is to estimate features from the geometric information in the 3D images, which are significant for separating the individuals. A calibration procedure converts the region within the cow circumference to a point cloud, so each pixel in this region of the 3D image is transformed into the corresponding spatial 3D coordinates. The calibration procedure is primarily done to remove distortions due to perspective. Furthermore, the calibration allows a combination of the point clouds information from 2

**Figure 1.** Example of setup of the Cattle Feed Intake System. The cameras are placed 4.5 m in the air, 2.3 m apart. The passage box in the left part of the barn is used for reading ear tags and taking simultaneous image for BW prediction and identification at the feeding table.

neighboring cameras if a cow is placed on the border between the camera's field of view. Additionally, all images are standardized to have the same length and width. Upon this, a corrected depth image of the cow region is created by interpolating the point cloud back from 3D depth image into a 2D depth image.

The process starts by finding the circumference and spine of the cow in the raw uncorrected 3D images (Figure 4). The circumference is defined as the last pixel before the image sees the annotated floor. Across the back of the cow, the highest point is found and named the spine. This is simply the highest point across the whole corridor. The feature generation process starts by finding the points on the corrected depth image lying 3, 5, 10, and 15 cm below the spine level of the cow, so how far left or right, respectively, you should go from the spine to drop 3, 5, 10, or 15 cm. This describes the contour of the back of each cow. Because of the length standardization descripted above, 100 spots are placed for each of the 3, 5, 10, and 15 cm features. In total 900 spots were placed for each image. The variables used to predict BW are the distance between the 3, 5, 10, and 15 cm, respectively, from left to right across the spline of the cow. The height is measured perpendicular

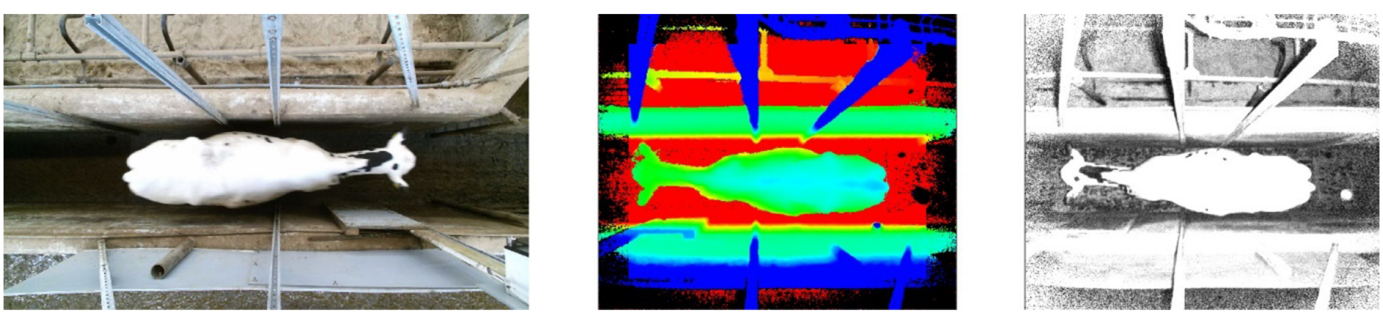

**Figure 2.** Example of images registered for each visit after milking. This includes an RGB image, a depth image, and an infrared (IR) image.

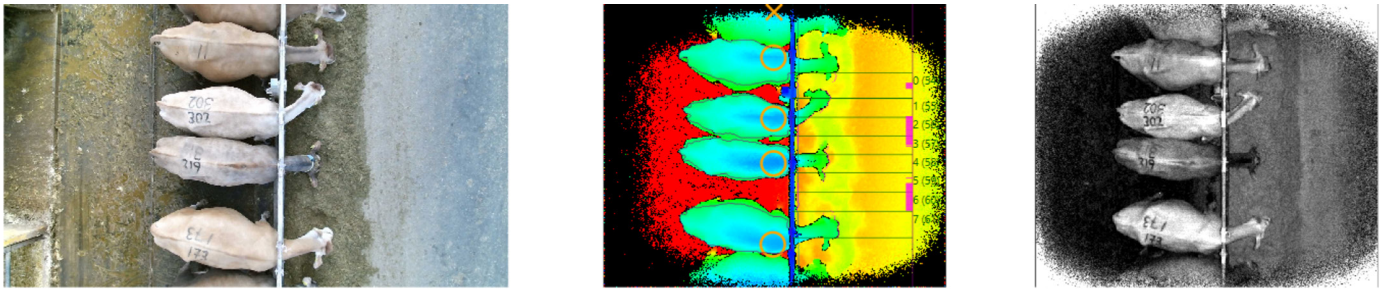

**Figure 3.** Example of the images registered while cows are eating. This includes an RGB image, a depth image, and an infrared (IR) image.

to the spine of the cow to make the features invariant with respect to position and orientation. Cubic smooth splines are fitted to the points corresponding to each distance to reduce noise. An illustration of some of the acquired image and an example of these contours is presented in Figure 4. The raw spine features are generated by measuring distance between the intersection of the spine normal and the splines on each side of the cow. The raw spine features are normalized to correct for anatomical differences.

When cows leave the milking system their electronic ear tag was read, and at the same time, 3D pictures are taken of the back of the cow. A total of 270 pictures in 3 categories (90 RGB, 90 IR, and 90 depth pictures) are taken every 5 s, and the median picture for each category is saved and used later. These pictures were stored and used as a reference to predict the same cow based on the contours, color, and patterns of the back of the cow, when eating at the feeding table based on the Mask CNN algorithm (Borchersen et al., 2017; Thomasen et al., 2018). This approach was tested in 3 validation studies for the individual breeds where the true cow identity was manually annotated to visits at the feeding table over a 14-d period in each study. For the 3 breeds, 6,575 images from 101 cows were used for Holstein, 8,825 images from 129 cows were used for Jersey, and 3,897 images from 155 cows were used for Red Dairy Cattle (**RDC**). The validation was conducted by

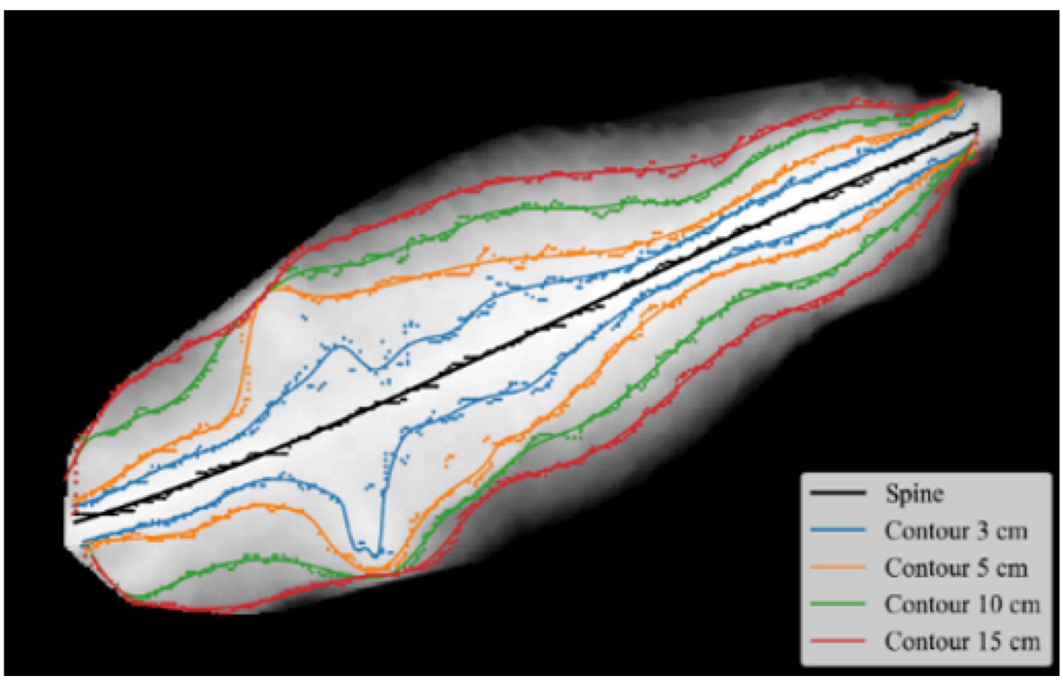


**Figure 4.** Example of quantified contours from an image. The spine is the black line based on 100 dots being distributed after an image has been standardized to the same length and width. The blue, orange, green, and pink dots are predicted based on the distance from the spine to drop 3, 5, 10, and 15 cm, respectively, to the left and right of the spine.

comparing the real ID of the cow with the predicted ID based on the Mask CNN algorithm and performed in all 3 breeds.

## Feed Intake Measures

Each camera is placed 2.5 m apart and 4.5 m from the empty feeding table covering the entire feeding table (Figure 1). In relation to each camera, a NUC computer (Intel) was installed to make preprocessing of the data. This includes a calculated median picture taken over every 5-s interval. When a cow moves its head to the feeding table, the identification procedure initiates, and an identity is predicted at each visit. The feed along the full feeding table is divided into virtual boxes of 30 cm, as it provides a manageable measure for the feed volume (Figure 6; Borchersen, 2014). In addition, the last image of the feeding pile before the cow puts in her head and began eating was stored. When the cow has finished the meal and takes the head out again, the first new image of the feeding pile is stored. The height in each pixel from 2 stored images are now subtracted from each other, and the removed feed is quantified on pixel level (Figure 5). The feed volume is determined continuously to ensure information before and after the cows are eating (Figure 5). In Figure 5, an example of the quantification of a visit is shown. The red part indicates where feed has disappeared, and the blue part indicates where the volume has increased. The feed eaten for a specific visit is the sum of the 2. The blue part where the feed has increased can come from droppings of what a cow has taken in her mouth or from the cow sorting and pushing in the feed. While the individual cow is eating, the feed volume cannot be a direct measurement. However, an estimate of the feed volume is generated by interpolating the feed volume before and after the cow visit. A time base median filter is applied to the dataset to remove short-term noise artifacts. From the interpolated feed volume, the delta feed volume is calculated at every time stamp (t), meaning $\Delta t = t - (t - 1)$. At the end of each day an amount of feed is not distributed to any cow. This feed (less than 3%) is then distributed to all cows during the day dependent on hours and minutes spend eating.

From each specific visit, 5 variables are stored: the ID of the cow, the placement in the barn, time when the meal was initiated, time when the meal was finalized, and the amount of feed eaten. Identification of the cow's head outline is necessary to measure the feed volume measure, as it is not possible while the cow is eating to calculate the feed volume of the virtual boxes it covers. This is visualized in Figure 6. During a meal, feed will be allocated to a specific cow from 5 virtual boxes. The virtual box right below the cow, as well as the 2 virtual boxes to the left and the right. If 2 cows share a virtual box during a feeding visit, they will also share the feed taken from this box during the 2 cow specific visits. If 2 cows share a virtual window and one cow leaves the virtual window before the other, the feed take is distributed according to the time each cow spends in the virtual window. That feed is distributed at the first time point when no cow is covering the virtual window. If a third cow is entering before the first or second cow has left the virtual window, the feed is distributed to the 3 cows according to the time spend at the virtual window. By measuring the height of the feed pile on the floor, the volume of the feed can be calculated. The feed height is determined in every pixel and summing up the pixels within a virtual box leads to a volume in liters for each virtual box. The amount of feed distributed on the feeding table at each feeding to each group of cows from the mixer wagon was translated from liters into kilograms by multiplying the liters of feed with the density of the feed. A total of 3 algorithm version where used. The first was a default model (Borchersen, 2014), the second included an eating rate filter to adjust for unrealistic amount of feed eaten in a limited amount of time, and the third algorithm included an improved version of head detection while eating.

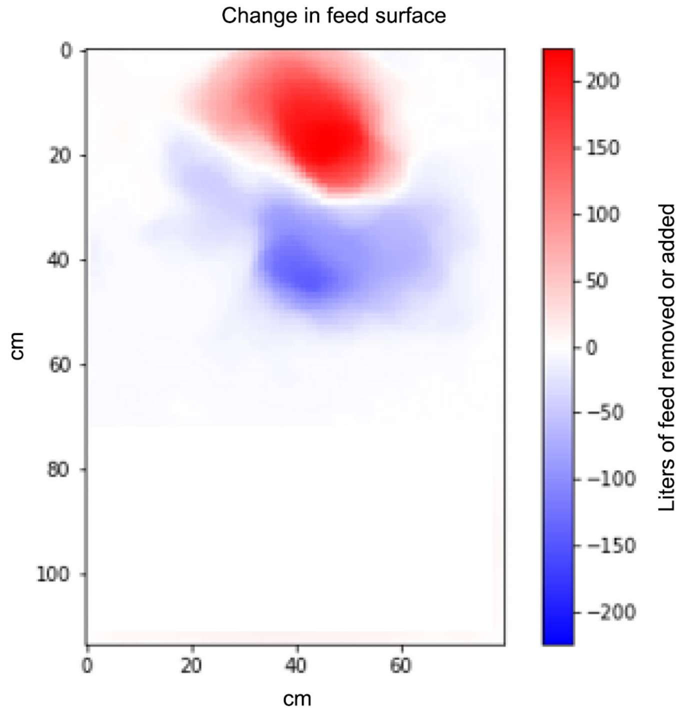


**Figure 5.** An example of the result of a feed visit in which the surface of the feed after the visit is subtracted from the surface of the feed before the visit. The red color in the image indicates feed has been removed, and blue indicates feed has increased. The sum of feed removed for one visit is the sum of the red and blue area.

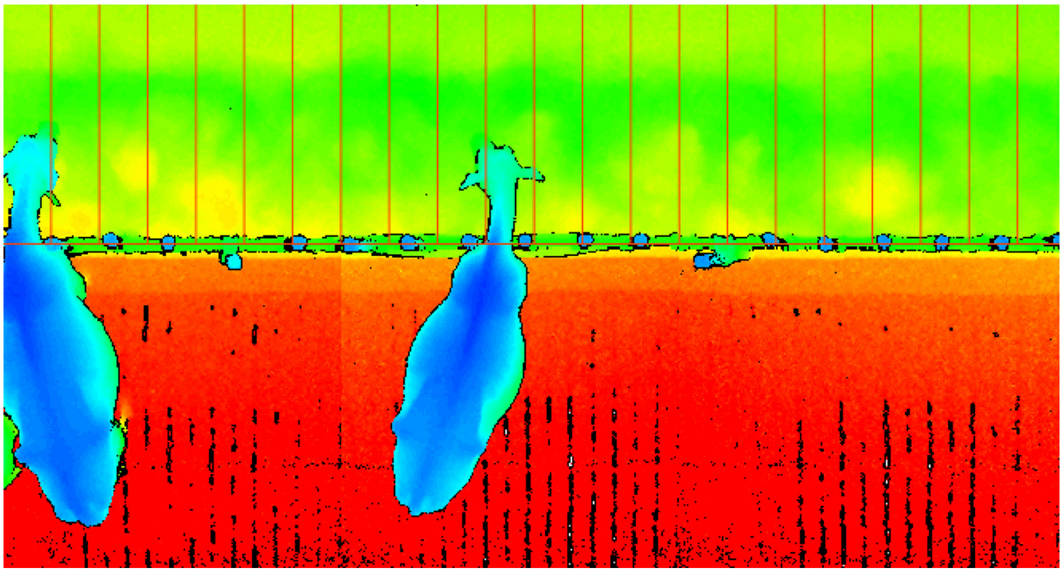

**Figure 6.** Depth images illustrating the virtual boxes marked with red lines. The various colors resemble the height of the object in every pixel.

### Data and Modeling

Data were recorded in 19 commercial dairy herds in Denmark with Jersey, Holstein, and RDC. Data were recorded from February 1, 2019, to August 1, 2022. Jersey cows were present in 6 herds, Holstein cows in 7 herds, and RDC in 6 herds. In all herds, cows were kept indoors all year around. Weekly averages based on daily measures for both feed intake (kg) and BW (kg) was generated and used as phenotype for this study.

To obtain repeatabilities, data were analyzed using the mixed procedure in SAS. The model used to estimate the repeatability was as follows:

$$\text{FI or BW} = \text{h} + \text{w} + \text{y} + \text{wil}^{(\text{wim})} + \text{wim}$$
$$+ \text{lac} + \text{algorithm version} + \text{animal} + \text{res},$$

where FI is feed intake, BW is body weight, h is the fixed class effect of herd, w is the fixed class effect for the week within year, y is the fixed class effect of year, $\text{wil}^{(\text{wim})}$ is a Wilmink regression on weeks in milk, wim is a regression on weeks in milk, lac is a fixed class effect of lactation, algorithm version is a class effect of the algorithm version used in the given time period, animal is the random animal variation, and res is the random residual variation.

## RESULTS AND DISCUSSION

### Algorithm for Identification of Cows

The identification algorithm was tested in a validation study over a 2-wk period for all 3 breeds. Results showed that ID was correct in more than 99% of the visits independent on breed (99.2% for Holstein, 99.4% for Jersey, and 99.1% for RDC). The implementation is dependent on the quality of the ear tags attached to cows, but a farmer always knows which cows are in a specific group, and if the ear tag is not read for a day or 2, it can be replaced. The system is not dependent on freeze-branding the cows, various neck collars, or physical installations in the stable. In another study, a red-green-blue depth (RGB-D) camera was used together with deep learning methods to make individual measures of feed intake (Bezen et al., 2020). An identification algorithm based on numbers in the collar of the neck of the cow was used and tested on 6 cows in a 36-h period based on 63 meals in the time period. Of these visits, 93.65% had the right identification and apparently often the numbers 7 and 1 were confused with each other. There are no results shown on a larger dataset in, for example, a whole herd of more than 100 cows.

### Feed Intake Measures

A total of 9,142 cows were measured. This included 2,513 Jersey cows with 79,036 weekly averages (intake registrations for each day in a corresponding week), 2,813 RDC with 60,015 weekly averages, and 3,816 Holstein cows with 92,767 weekly averages. These cows were distributed in 6 Jersey, 6 RDC, and 7 Holstein herds. Mean daily feed intake in kilograms with corresponding standard deviation and minimum and maximum value is presented in Table 1. This is done both overall for each breed. Mean intake was higher for

**Table 1.** Data description including breed, number of cows, mean feed intake (kg/d), standard deviation, and minimum and maximum observations

| | | | Feed intake (kg/d) | | | |
|---|---|---|---|---|---|---|
| Breed | Number of cows | Weekly measures[1] (kg/d) | Mean | SD | Minimum | Maximum |
| Feed intake | | | | | | |
| Jersey | 2,513 | 79,036 | 55.74 | 11.53 | 21.1 | 87.3 |
| Red Dairy Cattle | 2,813 | 60,015 | 61.72 | 12.41 | 21.5 | 93.6 |
| Holstein | 3,816 | 92,767 | 64.59 | 13.96 | 24.8 | 94.2 |
| BW | | | | | | |
| Jersey | 2,513 | 79,036 | 469.6 | 51.38 | 312 | 712 |
| Red Dairy Cattle | 2,813 | 60,015 | 647.9 | 85.91 | 340 | 943 |
| Holstein | 3,816 | 92,767 | 683.8 | 86.73 | 354 | 989 |

[1]Average daily intake as a mean of measurements taken each day in a week.

RDC (61.72 kg) and Holstein (64.59 kg) than for Jersey (55.74 kg). In other studies, feed intake is mainly shown in kilograms of DM, and therefore, hard to compare. The feed intake is comparable with feed intake measured in a research farm with Jersey cows (Li et al., 2016), RDC (Liinamo et al., 2012; Li et al., 2016), and Holstein cows (Li et al., 2016). The standard deviation of the mean feed intake was also higher in Holstein (13.96 kg) and RDC (12.41 kg) than for Jersey (11.53 kg). This is mainly due to scaling because coefficient of variation is similar for all 3 breeds. This magnitude is also difficult to compare with feed intake measured in kilograms of DM from research farms, though the ranking is similar between these 3 breeds and what is shown from research farm data where other than Holstein data are available. The mean feed intake per week is also shown in Figure 7. This figure shows that feed intake in all 3 breeds are lowest in early lactation and increases to a maximum around wk 7 to 10. This is also in line with results shown from research farm data (Li et al., 2016). In a Latin square design with 24 Holstein cows using 4 different diets (grass silage or maize silage combined with either dried beetroot or cracked barley), this 3D camera-based system has been validated. An $R^2$ of more than 0.90 were found between daily feed intake measured by scale and 3D camera for all 4 diets (G. Giagnoni, J. Lassen, P. Lund, L. Foldager, M. Johansen, and M. R. Weisbjerg, validation of feed intake measures in dairy cows using 3D cameras and image analysis, unpublished results, Aarhus University, Denmark). In this setup, a scale was based below each 3D camera, and one cow would have access to each camera and scale combination. These results indicate that even with diets with large difference in density, there is correspondence between what is measured with camera and scales.

### *Repeatability of Feed Intake*

Repeatability estimates for daily feed intake was 0.62, 0.65, and 0.63 for Jersey, RDC, and Holstein, respectively (Table 2). These estimated were based on animal variances of 30.55, 46.41, and 58.53 kg for Jersey, RDC, and Holstein, respectively. The magnitude of these estimates corresponds to the difference in magnitude seen in the standard deviation of the mean of the feed intake. The measured repeatability was at the same level as several other studies have reported in the past based on research farm data (Berry et al., 2014). Manzanilla Pech et al. (2014) estimated daily $R^2$ for DMI. The study showed that daily $R^2$ for DMI decreased from 0.38 to 0.16 in the first 111 DIM, followed by an increase to 0.60 until the end of lactation. In a study of 755 grazing Holstein cows, repeatability estimates ranged from 0.18 to 0.57 during lactation (Berry et al., 2007).

Most studies on feed intake use DMI rather than kilograms of feed, as in this study. No system to make individual feed intake measures in dairy cattle measures DMI as such. All systems measure feed intake in kilograms and then multiplies by either an assumed or a measured DM percentage. When converting feed intake in kilograms to DMI, several approaches could be applied. One could use a fixed DM% if herds are very

**Table 2.** Breed, animal variance, residual variance, and repeatability for weekly feed intake

| Breed | Animal variance (kg) | Residual variance (kg) | Repeatability |
|---|---|---|---|
| Jersey | 82 | 51 | 0.62 |
| Red Dairy Cattle | 101 | 53 | 0.65 |
| Holstein | 123 | 72 | 0.63 |

**Table 3.** Breed, animal variance and residual variance ($kg^2$), and repeatability for predicted BW

| Breed | Animal variance | Residual variance | Repeatability |
|---|---|---|---|
| Jersey | 2,195 | 445 | 0.83 |
| Red Dairy Cattle | 6,248 | 1,134 | 0.85 |
| Holstein | 6,638 | 885 | 0.88 |

stable with feeding during a year. One could rely on farmers' tests of the feed or when available, the DM% measured by the mixer wagon. In a preliminary study of data from this 3D-based camera system heritability estimates between 0.23 and 0.34 between breeds was found for DMI (Manzanilla Pech et al., 2022)

## Body Weight

Mean BW was higher for RDC (647.9 kg) and Holstein (683.8 kg) than for Jersey (469.6 kg; Table 3). This is in the same magnitude of what is shown in research farm data (Li et al., 2016). Repeatability estimates for BW as a weekly average was 0.83, 0.85, and 0.88 for Jersey, RDC, and Holstein, respectively. This is higher than what has earlier been shown for research farm data (Liinamo et al., 2012; Li et al., 2016). In a study of Holstein cows, daily repeatability was measured for live weight (Manzanilla Pech et al., 2014). Daily repeatability for live weight showed the lowest point at 35 DIM (0.43) and the highest point at 220 DIM (0.69). In a preliminary study of data from this 3D-based camera system heritability estimates between 0.38 and 0.49 between breeds was found for BW (Manzanilla Pech et al., 2022)

Incorrect identifications and distribution of feed will be misleading and make it difficult for a farmer to make correct management decisions based on the data. In addition, neck collars can rotate around the neck, in which case numbers will not be identifiable, whereas the curvature, collars, and patterns of the back will be fixed every day. Many 3D cameras are available on the market using various technologies, such as stereoscopy, structured light, or time-of-flight. Condotta et al. (2020) tested several cameras under controlled environments. In a formal test, the Microsoft Kinect 2 cameras performed best under indoor conditions, which is the environment used in this study. At the same time, the Kinect 2 camera is the cheapest on the market. New, improved, and cheaper cameras will arrive on the market continuously, and the system presented in this study will need to replace the Kinect 2 camera when this can be justified. The effect of direct sunlight on the Kinect camera based on the time-of-flight algorithm was also

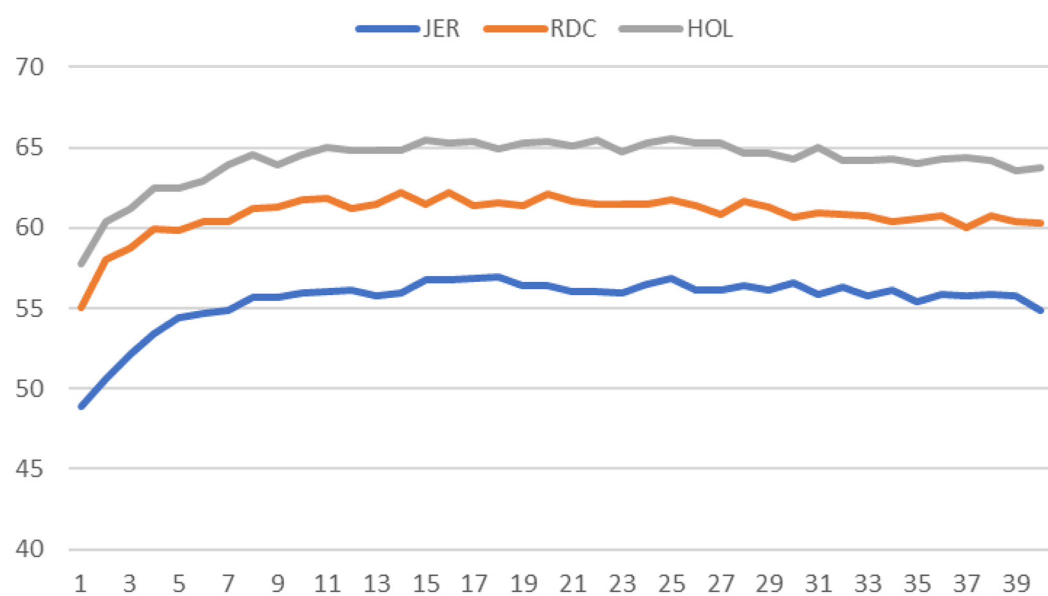


**Figure 7.** Average weekly intake in kilograms, plotted against week in lactation for Jersey (JER), Red Dairy Cattle (RDC), and Holstein (HOL), respectively.

studied by Bloch et al. (2019) when assessing the potential of using cameras to measure feed intake. That study also discussed static versus moving cameras. This was because 2D cameras were used in the study, and therefore, several images were needed to quantify the amount of feed removed from each cow visit. In the current study, static 3D cameras were installed. This was done for practical reasons, to avoid disturbance of the farmer and the cow in everyday day life. Images were stitched together between neighbor cameras to make full use of all images.

### Value of Full Lactation Records

A major priority for developing this system was to obtain data throughout lactation. This is important for both genetic analysis as well as management for the farmer that has the system installed. The way to use this type of data is very different from farm to farm. Some will use single cow data, and others will use group data, such as first lactation cows versus second lactation cows. In relation to genetic analysis, several studies have shown that genetic correlation changes during lactation between feed intake, milk yield, and BW (Manzanilla Pech et al., 2014; Li et al., 2017). Estimates for the genetic correlation between feed intake and milk yield varies from −0.80 in early lactation to 0.8 in mid and late lactation (Manzanilla Pech et al., 2014). Selection for improved efficiency in early lactation, where feed intake specifically needs to be improved based on records obtained in mid lactation, might lead to even lower feed intake in early lactation. From a management perspective, feed intake records are interesting throughout lactation. In early lactation, the majority of health problems occur (Lehmann, 2016), related to mastitis, reproduction, and nutrition. In mid lactation, the farmer wants to know which cows are most efficient in order to optimize a culling strategy, and in late lactation the farmer is interested in feed intake, to optimize strategies in relation to drying off cows. Everything else being equal, the farmer should slaughter the cow with the worst efficiency rather than the one with the lowest yield, when he has the information available. With this 3D-enabled system, feed intake information will be available more efficiently for the farmer in real time.

## CONCLUSIONS

Individual feed intake and BW can be measured using a 3D camera system that identifies the cow, predicts the BW, and quantifies the amount of feed eaten by the individual cow. Repeatability was between 0.62 and 0.65 for daily feed intake and between 0.83 and 0.88 for BW measured as a weekly average.

## ACKNOWLEDGMENTS

This study received no external funding. The authors have not stated any conflicts of interest.

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