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Body measurements of dairy calf using a 3-D camera in an automatic feeding system

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Abstract

The objectives of this study were to find potential health and welfare indicators derived with 3-D vision techniques and to validate the automated measuring system to continuously monitoring calf growth. The visual system was designed to estimate dairy calf body weight and hip height automatically to allow individual growth monitoring. Sixty-eight Holstein Friesian calves were selected at seven farms in the Netherlands. All calves were kept in group-housing systems and could voluntarily visit an automatic calf feeder. A 3-D Time of Flight camera was placed above the feeder to record the calf body shape in three dimensions. The body weights and hip heights were manually measured to serve as references. After image processing, the hip bones and tail head were determined to define the two regions of interest in the 3-D body surface images. Three features (*i.e.*, body volume, average hip height and standard deviation of the height distribution) were extracted from these regions. The 3-D visual average hip height measurements had an accuracy of 0.028 m (the animal heights varied from 0.73 to 0.96 m) compared with manual measurements. A multiple linear regression model with all image variables was built to estimate calf body weights. The model had mean relative error of 6.50% with a root-mean-square deviation of 6.20 kg. In conclusion, the calf growth and subsequent health and welfare indicators showed similar results for the automated and manual techniques. The quality of this vision system is adequate to replace current labour-intensive methods. Hence, the automation allows continuous calf growth monitoring. Furthermore, the combination of automatic feeding and body measuring not only offers information about animal health, but will also facilitate better informed breeding selections.

Keywords: dairy calf, body measurement, 3-D vision

1 Introduction

In the Netherlands, most dairy farmers rear their own calves as dairy herd replacements (Mohd Nor et al., 2012). Calf health and longevity are critical to future herd production capabilities (Swali et al., 2008), as well as the economic profit (Campbell et al., 2007). In their first few months of life, young cattle develop their immune systems and metabolic functions to adapt to physical and environmental challenges (Heinrichs et al., 1995). A good start of life is essential for subsequent rearing (Murray & Leslie, 2013). However, in this process, challenges from diseases (*e.g.*, diarrhoea) and management decisions (*e.g.*, weaning and dehorning) can reduce animal growth (Windeyer et al., 2014). Therefore, frequently monitoring calf body development can enable early detection of deviations/aberrations, and consequently will minimise losses caused by disease, infertility and death (Frizzo et al., 2011). Body measurements as an indicator to monitor body development have been replaced by the live Body Weight (BW) (Swanson, 1960). The most direct way to weigh animals individually is to use a traditional or electronic scale (Dingwell et al., 2006). However, manual body measurements are time consuming and costly for farmers. Moreover manual measurements require animal handling and introduce high levels of stress to young cows (Heinrichs et al., 1992).

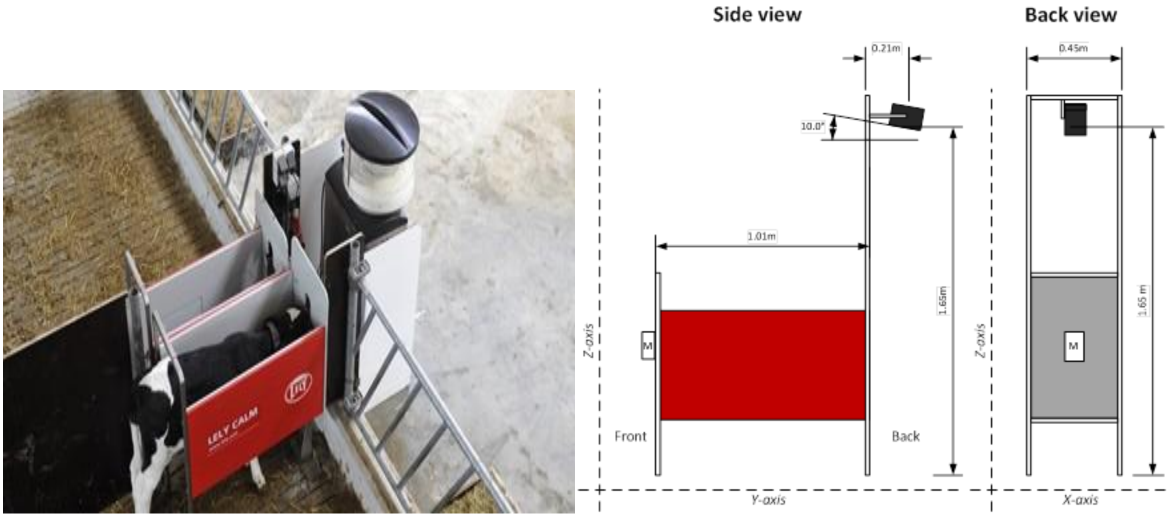
To overcome the limitations of conventional measurement systems, machine vision has been used extensively as a non-intrusive approach for animal body measurements (Mollah et al., 2010). Machine vision can reduce distress caused by manual measurements and offers frequent automatic data acquisition (Wang et al., 2008). Two-dimensional (2-D) image analysis has been applied to estimate the BW of livestock, such as broilers (Mollah et al., 2010), pigs (Wang et al., 2008), and cows (Tasdemir et al., 2011). In most studies, the BW was calculated by applying a prediction model that shows the linear correlation between body image variables and the live BWs (Brandl & Jørgensen, 1996). 2-D images only offer two dimensional projection of the animal. The lack of the third dimension in vision limits applications utilizing depth information (Stajnko et al., 2008). Photogrammetry stereo techniques have been introduced to measure farm animals in three dimensions (3-D). One such successful example is a stereo vision system with six 2-D cameras and three flash units used to capture the 3-D shapes of pigs (Wu et al., 2004). However, these photogrammetric systems are difficult to implement.

Novel 3-D systems can solve the problems posed by conventional vision systems, including photogrammetry stereo techniques. As a result, there has been increasing demand for these techniques in livestock farming (Weber et al., 2014). Currently, one of the most common methods to obtain 3-D information is Time of Flight (ToF) technology (Verdú et al., 2013). ToF systems are based on visible or near-infrared (NIR) light, which illuminates the object to be imaged. Smart pixel sensors receive the reflected light and measure its return time (Lindner et al., 2010). Compared with other vision technologies, ToF is more often applied in robotic systems and in measurements of the dimensions and volume of a target (Hoegg et al., 2013). Insufficient research has been done to measure body development of calves using vision techniques. The objectives of this study were to find potential health and welfare indicators derived with 3-D vision techniques and to validate the automated measuring system to continuously monitoring calf growth.

2 Materials and methods

2.1 Animals and experiment design

The experiments were performed in May, 2013 at seven commercial dairy farms in the Netherlands. Sixty-eight Holstein-Friesian calves ranging in age from 6 to 110 days were recorded. The heights of these animals were between 0.73 and 0.96 meters (m), while their weights varied from 34 to 125 kilograms (kg). All calves were fed by a Lely Calm^{TM} (*Lely Industries N.V., Maassluis, the Netherlands*) Automatic Calf Feeder (ACF) three days after birth (Figure 1 a). They could visit the ACF voluntarily and would be identified automatically by their Radio-Frequency Identification (RFID) tag. During feeding, small portions of milk powder and hot water (39 °C) were mixed and passed to an artificial teat. The calves were observed to be calm and stable during feeding.



(a) *(b)*

Figure 1. (a) A Calf drinking in a double box Lely Calm^{TM} ACF;

(b) Schematic drawing of an IFM 3-D ToF camera mounted on the ACF (M is the artificial teat).

For image collection, a PMD^{TM} 3-D ToF camera (*IFM Electronic GmbH, Essen, Germany*) was used for each ACF. The resolution of the sensor was 64x50 pixels with a distance measuring inaccuracy of 1 cm. The camera was mounted on top of the ACF, 1.65 m (H) above the ground in the middle of two side fences. It was aimed down on the animal back with a 10° angle (β) up to the horizontal plane (Figure 1 b). 3D images of the calf back were recorded with a speed of 8 frames per second (fps). Meanwhile, the animal identification was logged in the ACF. After image collection, animals were weighed by a VS 300^{TM} (*All Scales Europe, Veen, the Netherlands*) mobile weighing platform with an inaccuracy of 1 kg and a maximum capacity of 300 kg. Additionally, the individual calf Hip Height (HH) was measured manually during weighing.

Two experiments were performed during this study: 1. Calf HH measurement and 2. Calf live BW estimation. In the first experiment, data from all sixty-eight animals (n=68) were processed to calculate the accuracy of the automated HH measurements. In the second experiment, forty-nine samples were used to develop a BW estimation model (n=49), while data from the other nineteen animals were used for validation. Summaries of the training and validation datasets are shown in Table 1.

Table 1. Summary of the training and validation datasets used for the BW estimation model.

	Training set	Validation set
No. of measurements	49	19
Weight range (kg)	34-125	40-105
Height range (m)	0.73-0.96	0.79-0.96

2.2 Image processing and analyses

2.2.1 Real world transformation

The recorded raw data in each frame consisted of three matrices (64x50 pixels) in the X, Y and Z directions. From the camera view, X is the width, Y is the length, and Z is the vertical distance from the object to the camera (Figure 2 a). Before processing the image, all three matrices were transformed from image-world to real-world coordinates in Matlab ^{TM}. The 3-D image (Z) was rotated 10° (β) along the x-axis (Equation 1) to the mounting angle. Afterwards, the Z matrix was transformed to the height from the ground (Equation 2).

$$Rot_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\beta) & -\sin(\beta) \\ 0 & \sin(\beta) & \cos(\beta) \end{bmatrix} \qquad \text{Equation 1}$$

$$Z_{real\ world} = H - Z_{image} \qquad \text{Equation 2}$$

2.2.2 Image segmentation and morphological process

First, the pixels in the Z matrix with negative height values were removed as image noise. In addition, all points with heights lower than 0.8 m were labelled as points not belonging to animal's body. Second, in the background image (Figure 2 b), in which the ACF was empty, the positions of the fences on each side of the ACF were measured as the boundaries in the X plane. The pixels outside these boundaries were removed. Pixels with heights lower than the threshold (*i.e.,* the average height minus the standard deviation of the height in the Z plane) were excluded (Figure 2 c). After segmentation, a binary image (Figure 2 d) was built in which irrelevant pixels were given values of zero, while the pixels belonging to the calf body were given values of one. To obtain a clear body contour, a 5x5 square image opening was applied (*i.e.,* erosion followed by dilation). In the next step, this processed binary image was duplicated in all three matrices. Last, by performing image interpolation, an image with a resolution of 0.02 m in both the X and Y directions was reconstructed.

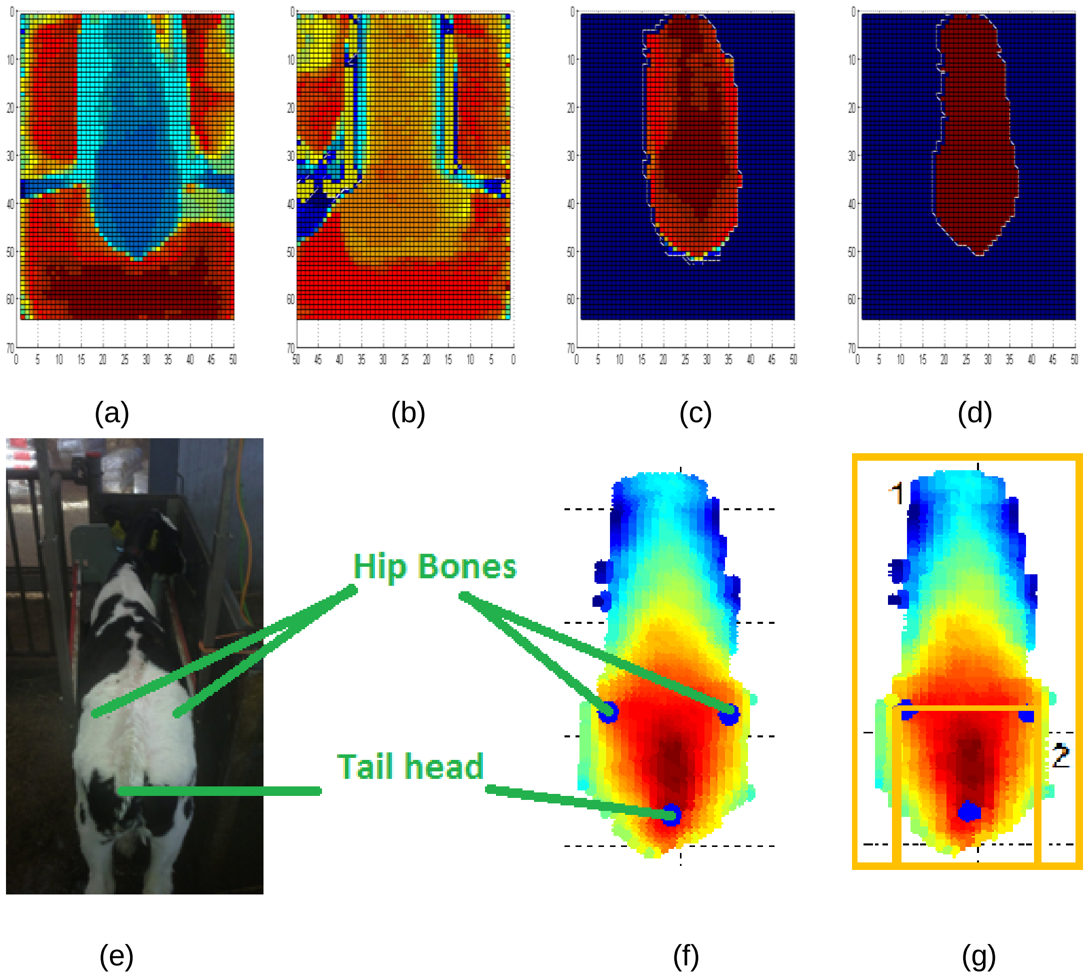


Figure 2. (a) background image; (b) raw image with calf; (c) after image segmentation; (d) morphological process; (e) and (f) body bone marker after interpolation; (g) defined RoIs.

2.2.3 Body markers and image variables

Three anatomical markers were automatically detected on the back of the calf based on its body shape. The first point matched the tail head, while the other two points corresponded to the hip bones on each side (Figure 2 f). These body markers represented protruding anatomical structures relative to the surrounding body parts. Automatic extraction was performed by searching for peaks in height from pre-defined regions. The whole calf body was selected as Region of Interest (RoI) 1, and the region between the hip bones and the tail head was defined as RoI 2 (Figure 2 g). Three Image Variables (IV) representing the dairy calf body shape characteristics were extracted from the processed 3-D images. IV1 was the accumulated value of all heights in RoI1, which indicates the total body volume. IV2 was the median height in RoI2, and IV3 was the Standard Deviation (SD) of all pixel heights above IV2.

2.3 Statistical analyses

2.3.1 BW estimation model

The BW, as the output, was estimated by applying a multiple linear regression model (Equation 3) with three IVs (*i.e.*, inputs). To determine the independence of all IVs to estimate the BW, the inter-correlations between the IVs were calculated according to Equation 4. In addition, the Variance Inflation Factor (VIF) was calculated for each IV to quantify the multicollinearity in the BW estimation model.

$$y_i = \beta_0 + \beta_1 IV1_i + \beta_2 IV2_i + \beta_3 IV3_i + \varepsilon_i \quad i = 1,2 \cdots, N \qquad \text{Equation 3}$$

y_i : BW (kg); IV: Image Variables; β: regression coefficient; i: number of independent measurements; ε: error.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{(n-1)s_x s_y} \qquad \text{Equation 4}$$

r_{xy}: correlation; n: number of measurements; x, y: value of two variables; $\bar{x}, \bar{y}$: average value of two variables; s_x, s_y: SDs of two variables.

2.3.2 Model validation

3-D images from nineteen calves were used to validate the BW estimation model with references from the mobile weighing platform. To quantify the accuracy of the model, the relative error in one specific observation (Equation 5) and in the average of all observations (Equation 6) were calculated. Moreover, the root-mean-square deviation (RMSD) (Equation 7) was calculated to describe the difference between the model-predicted BWs and the manually measured ones (*i.e.*, reference).

$$Relative\ error = \frac{|y_i - \hat{y}_i|}{y_i} * 100\% \qquad \text{Equation 5}$$

$$Mean\ relative\ error\ = \frac{1}{n}\sum_{i}^{n} Relative\ error \qquad \text{Equation 6}$$

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \qquad \text{Equation 7}$$

y_i: measured reference weight (kg); $\hat{y}_i$: weight predicted by the regression model (kg); n: total number of observations.

3 Results and Discussion

3.1 Calf hip height measurement

IV2 is the median value of all heights in RoI2, which encompasses the body region between the hip bones and the tail head. As a comparison, the hip heights of individual animals were measured manually. The height measurements made using the 3-D ToF camera had an accuracy of 0.028 m (the animal heights varied from 0.73 to 0.96 m). Normally, the HH is determined by averaging the heights of both hip bones. However, the consistency of locating these anatomical markers was not high in our research due to the unclearness of the bone structure in young cattle (Figure 2 e). Therefore, in this experiment, we used the hip bones and the tail head to predefine the region of interest only. Further, the median height value of all pixels in RoI 2 was calculated to serve as the HH value. In this way, the measurements were more consistent and robust to noise from surrounding illumination. During manual height measurement, a cow hip ruler was placed on both hip bones. This measurement caused a great amount of distress to the calves, which moved constantly. The test had to be performed several times on each animal due to its low repeatability, demonstrating the need for a non-invasive method. Such a method could replace the current manual method performed by farmers, which is time consuming and causes extreme distress to the animal (Staněk et al., 2014).

3.2 Calf body weight estimation

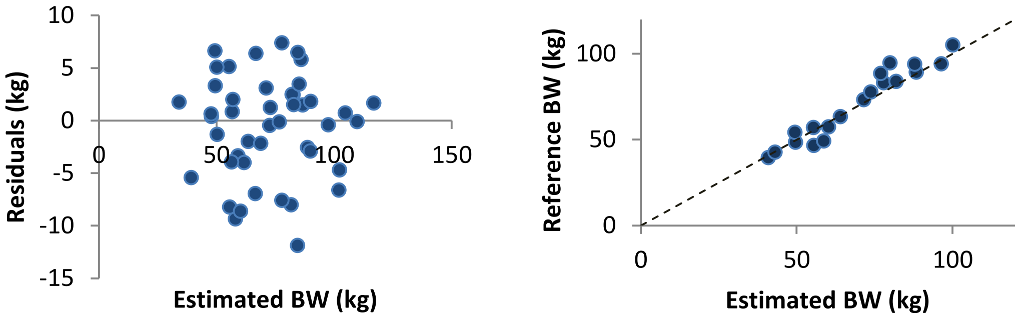
The inter-correlation of IVs (Table 3) showed that the total body volume (IV1) and the mean height in the rear area were highly correlated, whereas the SD of the height distribution (VI3) had small negative correlations with both VI1 and VI2. Furthermore, the VIFs of the first two IVs were both greater than 5 and smaller than 10. Thus the multicollinearities of these two IVs were high but still acceptable. The multiple linear regression model for BW estimation, which was developed using 49 samples, is shown in Equation 8 (P<0.01). The residuals for this test against the predicted BW are shown in Figure 3 a. The results reveal that the residuals were randomly dispersed, with no clear trend in the model outputs. In validation (Figure 3 b), the R-square value of the estimation was 0.91, and the mean relative error was 6.50% with a RMSD of 6.20 kg.

Table 3 inter-correlations and VIFs of all three IVs, which served as inputs for the multiple linear regression model for calf BW estimation.

	IV1	IV2	IV3	VIF
IV1	1			7.9
IV2	0.908	1		5.8
IV3	-0.205	-0.300	1	1.1

$$BW = -59.06 + 0.013 * IV1 + 99.29 * IV2 + 444.68 * IV3 \qquad \text{Equation 8}$$

Currently, a common indirect way to estimate live BW is by measuring the circumference of the Heart Girth (HG). The BW is derived from linear regression analysis of measured HGs (Wilson et al., 1997). Furthermore, BW development, which is the BW deviation per day (*i.e.*, kg/day), has been widely used as a measure of calf growth rate (Koenen & Groen, 1996). In our study, both body volume and average height had a strong, highly positive linear correlation with the reference BWs. On the other hand, the correlation between BW and body development might vary depending on the calf growth stage (Heinrichs et al., 1992). Therefore, we measured the HH as an independent variable for body development. However, as the other component of body measurements, the skeletal measurement should not be greatly influenced by the BW (Enevoldsen & Kristensen, 1997). IV3, which represents the body shape deviations at different height levels, was only weakly correlated with IV1 and IV2 and could be used as an indicator of body condition or skeletal development. Among all body dimension measurements, the BW and HH are still the most commonly used variables to describe individual calf growth (Windeyer et al., 2014).



(a) *(b)*

Figure 3. (a) Residual plot versus predicted BWs as the outputs of the model of the test dataset (n=49); (b) The relationship between reference and estimated BW for the validation dataset (n=19).

4 Conclusions

In this study, a 3-D ToF camera was installed in a Lely Calm™ ACF to perform non-invasive body measurements of 68 young animals. The total body volume, the average hip height and the SD of the height distribution in the body rear part were extracted from the 3-D images. Compared to manual hip height measurements, the average hip height measured by 3-D vision had an accuracy of 0.028 m (the animal heights varied from 0.73 to 0.96 m). All IVs were used in a multiple linear regression model to estimate the calf BWs. The model had mean relative error of 6.50%, with a RMSD of 6.20 kg. In conclusion, the calf growth and subsequent health and welfare indicators showed similar results for the automated and manual techniques. The quality of this vision system is adequate to replace current labour-intensive methods. Hence, the automation allows continuous calf growth monitoring. Furthermore, the combination of automatic feeding and body measuring not only offers information about animal health, but will also facilitate better informed breeding selections.

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