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ORIGINAL ARTICLE

Estimation of Body Weight for Korean Cattle Using Three-Dimensional Image

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Abstract

Purpose This study was conducted to estimate the body weight of Korean cattle (Hanwoo) using three-dimensional image.

Methods A time-of-flight camera and a stereo vision camera were used to acquire top-view images for Hanwoo. Multiple linear regression model incorporating body dimensions and age was developed to estimate the body weight.

Results The prediction models with or without age variable were determined. Incorporating age variable that correlates with body weight improved the coefficient of determination for both TOF images and stereo vision images. The weight estimation error was greatly reduced under the condition that calves less than 6 months old were excluded.

Conclusions It was concluded that 3-D image is a promising technique for estimating the body weight of Hanwoo cattle.

Keywords Body weight · Korean cattle · Point cloud data · 3-D camera · 3-D image

Introduction

Body weight of cattle is a key factor in assessing the growth performance (Fox et al. 1999), productivity (Gionbelli et al. 2015), selection, and breeding (Pilarczyk and Wojcik 2008). The periodical measurement of body weight is used to evaluate the growth response to nutrient supply and health anomalies (Kawasue et al. 2013). Some farmers use a measuring tape or a weighing scale with steel frame to measure the body weight of Korean cattle (Hanwoo). However, this work can be labor intensive for the farmer as well as stressful for the cattle. Thus, farmers often rely on their visual judgment in estimating the body weight, which is a subjective method whose accuracy depends on their experience.

Computer vision system has been widely used in engineering. A number of applications have also been reported in animal science (Kashiha et al. 2014; Ozkaya and Bozkurt 2008; Seo et al. 2011; Tasdemir et al. 2011). The advantage of these methods is non-contact and non-destructive measurement. However, most of these applications are limited to two-dimensional (2-D) analyses and thus the accuracy of the results is not so high.

Over the recent decades, the amount of studies related to agricultural three-dimensional (3-D) vision systems has been increasing rapidly (Garrido et al. 2015; Kuzuhara et al. 2015; Piron et al. 2011; Wu et al. 2004). 3-D image is a large collection of distance measurement, which is called depth information, from a known reference coordinate system to surface points on the object scene (Besl 1988). 3-D image generation techniques are essential for handling the extraction of depth information since the 3-D image contains huge amount of information that needs to be handled (Vázquez-Arellano et al. 2016). Basic principles for depth measurement including triangulation, time-of-flight (TOF), and interferometry have been utilized in agricultural applications (Lee et al. 2012; Song et al. 2018; Viazzi et al. 2014).

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3-D image was recently proposed to monitor the body conditioning score and weight for dairy cows (Hansen et al. 2018; Pezzuolo et al. 2018; Spoliansky et al. 2016). Even though 3-D image processing is expected as a promising technique for determining the body dimensions and for predicting the body weight of livestock, no attempts for Hanwoo have been made yet. The aim of the present study was to estimate the body weight, which is the basic data for feeding management of Hanwoo, using a 3-D image.

Materials and Methods

Acquisition of 3-D Image and Body Dimensions

The 3-D image acquisition system consisted of a weighing box with an electronic weighing scale, two 3-D cameras, and a computer (Fig. 1). A TOF camera (StarFoam Swift, Odos Imaging, Edinburgh, UK) and a stereo vision camera (ZED, Stereolabs, San Francisco, USA), were used for acquiring the 3-D images of the samples. A depth-sensing TOF camera had a resolution of 640 × 480 pixels and a field of view of 47° (H) × 37° (V). TOF sensors measure depth using the known speed of light and its time of flight directly. A stereo vision camera had a resolution of 1344 × 376 pixels and a field of view of 90° (H) × 60° (V). The floor of the weighing box was an iron plate (1.8 × 2.3 × 0.12 m) attached to an electronic weighing scale (HFS, CAS Scale, Seoul, Korea) weighing up to 2000 kg with a measurement precision of 0.5 kg. Two 3-D cameras were mounted on the camera support frame to capture top-view image of the samples. The body dimensions including body length, withers height, and chest width were measured by using a measuring tape.

The 3-D images and body dimensions of Hanwoo samples were measured twice. The first measurement for acquiring the 3-D images and body dimensions of 35 samples was performed at Animal Genetics Resources Research Center, National Institute of Animal Science, Republic of Korea, during March through May 2019. The second measurement to determine the 3-D images and the body weight of 209 samples was made at a commercial breeding farm in September 2019.

Image Analysis

All raw images were processed using the Computer Vision System and Image Processing toolboxes in Matlab (2018a, MathWorks, Natick, USA). Each raw 3-D image had point cloud data (PCD) consisting of a set of data points with (x, y, z) coordinates. The coordinates represented the relative position of each point on the object to the center of the camera lens in the x, y, and z directions.

The raw 3-D image included the body surface of the cattle, the frames of the weighing box, the weighing scale, and image noise. The body surface was segmented from the raw image by setting the boundaries of a region of interest (ROI) in the x, y, and z directions and selecting points within the ROI as the cow body. After the body segmentation, all points within the ROI boundaries were saved as the PCD of the body surface. The remaining small groups of points or single point, which were isolated from the Hanwoo's body in the segmented image, were considered as the image noises. The segmented 3-D image was interpolated into a mesh grid. Each grid point had the z value as depth information in the point cloud. A k-nearest

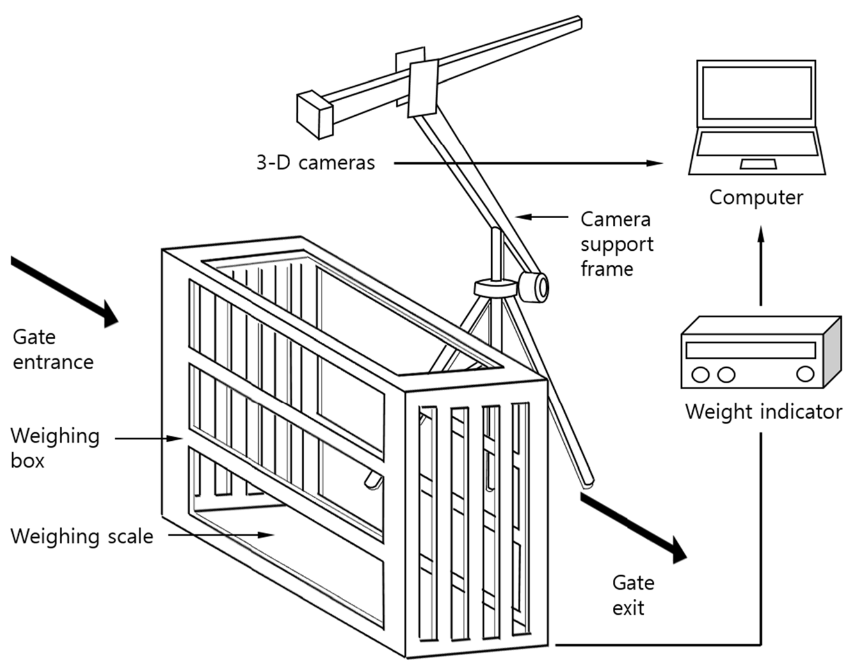

Fig. 1 The schematic diagram of three dimensional image acquisition system used in this study

neighbors (Kramer 2013) algorithm was used for removing noises from PCD. The best choice of k depends upon the data. In this study, k values of 5, 10, 15, 20, 25, and 30 were applied to determine the optimum k value necessary for removing outliers. Body length and chest width of 35 samples determined in the first measurement were used to calculate the mean error defined as follows:

$$\text{Error}(\%) = \left| \frac{v_i - \widehat{v}_i}{v_i} \right| \times 100 \tag{1}$$

where v_i is the measured value and $\widehat{v}_i$ is the estimated value.

Four body dimensions including withers height, body length, chest width, and body width were quantified in the point cloud image. Withers height, defined as the vertical distance from the ground to the highest point (point A) of shoulder, was calculated by subtracting depth value at the withers from the height of camera. Height of camera was defined as the vertical distance from the camera lens to the floor of the weighing box without Hanwoo. A laser distance meter (DISTOX4, Leica, Wetzlar, Germany) was used to measure the vertical distance. Body length was defined as the mean distance from the highest point of shoulder to the pin bone (Fig. 2). Chest width was defined as the minimum width between forelegs and body of the sample. Body width was defined as the maximum width of the body.

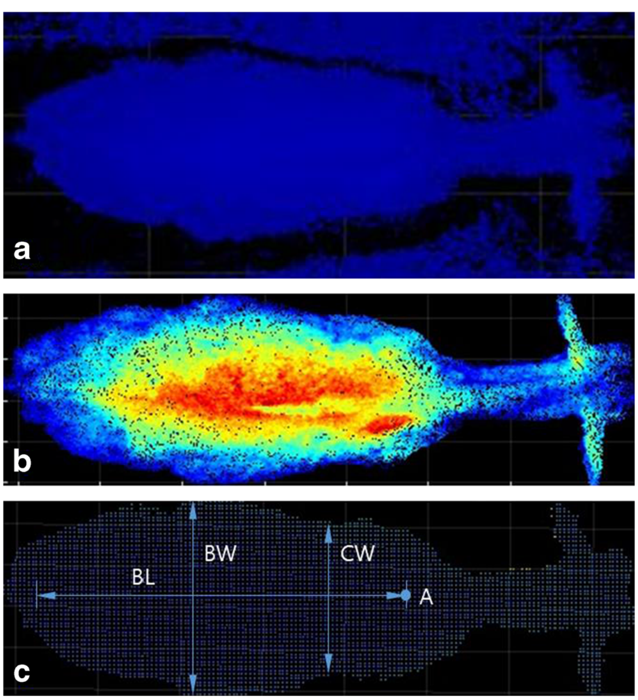

Fig. 2 Top-view three-dimensional image for the body of Hanwoo. **a** A raw image. **b** A segmented point cloud image with different colors representing different distances to the camera lens. **c** A grid mesh image in xy-plane. BL: body length, BW: body width, CW: chest width

Prediction Model for Body Weight

A multiple linear regression (MLR) model was built with the datasets of 209 cows to estimate the body weight of Hanwoo. The MLR model with age and body dimensions as input variables was defined as the full model:

$$\text{BW} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon_i \tag{2}$$

where BW is body weight (kg), X_1 is age (year), X_2 is body length (m), X_3 is withers height (m), X_4 is chest width (m), X_5 is body width (m), β_0 through β_5 are parameters, ε is residual of the model, and i denotes the ith cows.

The body weight and body dimensions acquired in the second measurement were applied to determine all the parameters in Eq. (2). A total of 209 samples were divided into two groups: one for calibration datasets for prediction model development and the other for validation datasets for verification. The ratio of calibration and validation datasets was 70:30. The MLR stepwise procedure in SAS (V9.4, SAS Institute Inc., Cary, USA) was used to determine the parameters shown in Eq. (2). In order to evaluate the fitness of the model, coefficient of determination (R^2) was used. Mean absolute percentage error (MAPE) expressed as a percentage and root mean square error (RMSE) with units of mass were also calculated as follows:

$$\text{MAPE} = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y_i - \widehat{y}_i}{y_i} \right| \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - \widehat{y}_i \right)^2} \tag{4}$$

where n is the total number of samples, y_i is the measured body weight (kg), and $\widehat{y}_i$ is the estimated body weight (kg) from the prediction model.

Results and Discussion

Body Dimensions of Hanwoo Samples Divided by Their Age

Body dimensions including body weight, body length, and chest width of Hanwoo samples determined in the first measurement were presented in Table 1. The samples of within 1.0 year and 1.0 to 2.0 years old were 51.4% and 48.6%, respectively. Mean body weight of the samples was 150.6 kg for within half a year, 220.8 kg for half a year to 1.0 year, 279.8 kg for 1.0 to 1.5 years, and 281.0 kg for 1.5 to 2.0 years, respectively. Mean body length and chest width of the samples was

Table 1 Body dimensions of Hanwoo samples measured at Animal Genetics Resources Research Center

Age (year)	Number of samples	Ratio (%)	Body weight (kg)	Body length (m)	Withers height (m)	Chest width (m)
0–0.5	14	40.0	150.6 ± 20.2	0.93 ± 0.07	0.87 ± 0.07	0.32 ± 0.03
0.5–1.0	4	11.4	220.8 ± 21.8	1.04 ± 0.06	1.05 ± 0.06	0.28 ± 0.02
1.0–1.5	10	28.6	279.8 ± 40.7	1.09 ± 0.09	0.99 ± 0.07	0.38 ± 0.07
1.5–2.0	7	20.0	281.0 ± 68.2	1.14 ± 0.10	1.01 ± 0.15	0.36 ± 0.05
Sum	35	100.0				

0.93 m and 0.32 m for within half a year, 1.04 m and 0.28 m for 0.5 to 1.0 year, 1.09 m and 0.38 m for 1.0 to 1.5 years, and 1.14 m and 0.36 m for 1.5 to 2.0 years, respectively.

Table 2 showed the body weight of Hanwoo obtained in the second measurement divided by their age. Body weight of the samples raised at a commercial breeding farm dramatically increased after 1.0 year passed. Mean body weight means the average of body weight of Hanwoo samples was 127.4 kg for within half a year, 239.5 kg for 0.5 to 1.0 year, 407.5 kg for 1.0 to 1.5 years, 463.6 kg for 1.5 to 2.0 years, and 777.1 kg for 2.0 to 2.5 years, respectively.

Determination of Suitable *k* Value for Removing Outliers

The accuracy of the *k*-nearest neighbor algorithm can be degraded by the presence of noisy or irrelevant data. Six *k* values of 5, 10, 15, 20, 25, and 30 were used to determine the suitable *k* value necessary for removing outliers in this study. The mean error, especially in TOF images, decreased with increasing *k* value (Table 3). Generally, larger values of *k* reduces effect of the noise on the classification (Kramer 2013). The suitable *k* value was set to 20 as considering the lower error for body length and chest width of 35 samples.

Correlations Among Age, Body Traits, and Body Weight

Correlation among body weight, age, and body dimensions determined from PCD was analyzed. Tables 4 and 5 showed that there was a strong, positive, and highly significant correlation between body weight and body dimensions, and weight and age. Correlation coefficient between body weight and withers height estimated from TOF images was the highest of 0.9401 (Table 4). Next, correlation coefficients were high in the order of body width, age, chest width, and body length. However, correlation coefficients were high in the order of withers height, age, chest width, body width, and body length estimated from stereo vision images (Table 5). Body weight was highly affected by withers height, body length, and chest width including chest girth of Hanwoo (Lee and Ohh 1985). Age is a good predictor of feed intake and body weight for beef cattle (Lopez Saubidet and Verde 1976). Therefore, incorporating additional age variable that correlates with body weight might improve the prediction of body weight changes.

Table 2 Body weight of Hanwoo samples measured at a commercial breeding farm

Age (year)	Number of samples	Ratio (%)	Body weight (kg)
0–0.5	28	13.4	127.4 ± 41.3
0.5–1.0	46	22.0	239.5 ± 56.7
1.0–1.5	51	24.4	407.5 ± 96.9
1.5–2.0	55	26.3	463.6 ± 108.1
2.0–2.5	29	13.9	777.1 ± 64.1
Sum	209	100.0	

MLR Model to Predict the Body Weight

The MLR stepwise procedure for estimating the body weight using the input variables of body dimensions and age was applied. The prediction models with or without age variable were as follows:

Table 3 Error as affected by different *k* value for two types of image acquired

Type of image	*k* value	Error (%)	
		Body length	Chest width
TOF	5	1.3	2.4
	10	1.3	1.6
	15	1.5	1.7
	20	1.2	1.5
	25	1.2	1.5
	30	1.3	1.4
Stereo vision	5	2.1	4.7
	10	2.1	4.8
	15	1.9	4.1
	20	2.0	4.2
	25	2.2	4.1
	30	2.1	4.3

Table 4 Correlation coefficients among body weight, age, and body dimensions estimated from TOF image of Hanwoo samples

Variables	Body weight	Age	Body length	Withers height	Chest width	Body width
Body weight	1.0000	0.9190	0.8845	0.9401	0.8985	0.9283
Age		1.0000	0.8382	0.8405	0.8190	0.8917
Body length			1.0000	0.8463	0.7966	0.8742
Withers height				1.0000	0.8383	0.8882
Chest width					1.0000	0.8854
Maximum width						1.0000

For TOF images,
Without age variable

$$BW = -841.77 + 211.10\,X_2 + 566.99\,X_3 + 462.84\,X_4 + 351.92\,X_5 \quad (5)$$

$\left(R^2 = 0.9417\right)$

With age variable

$$BW = -641.16 + 8.35\,X_1 + 145.28\,X_2 + 524.58\,X_3 + 441.51\,X_4 \quad (6)$$

$\left(R^2 = 0.9573\right)$

For stereo vision images,
Without age variable

$$BW = -438.09–70.91\,X_2 + 591.35\,X_3 + 322.85\,X_4 + 400.30\,X_5 \quad (7)$$

$\left(R^2 = 0.9262\right)$

With age variable

$$BW = -321.87 + 9.35\,X_1 + 461.41\,X_3 + 365.33\,X_4 \quad (8)$$

$\left(R^2 = 0.9433\right)$

where BW is body weight (kg), X_1 is age (year), X_2 is body length (m), X_3 is withers height (m), X_4 is chest width (m), and X_5 is body width (m).

From the MLR analysis, withers height was found to be highly dominant variable affecting the body weight. Next, the age and chest width became significant variables necessary for the estimation of the body weight. Body length was included in the MLR model using TOF images, but not in the prediction model using stereo vision images.

Addition of age variable as well as body dimensions increased the coefficient of determination (R^2) of the prediction model to estimate the body weight for both TOF images and stereo vision images. R^2 was 0.9417 for the prediction model without age, 0.9573 for with age, respectively. In the prediction model with age, the body length, withers height, and chest width were selected as the input variables for both TOF and stereo vision images. On the contrary, body width was added as input variable in the model without age for both images. The linearity between measured and estimated body weight for both TOF images and stereo vision images was high (Figs. 3 and 4).

For the validation dataset of 3-D images of Hanwoo, MAPE, and RMSE of the MLR model including age variable was calculated as 17.1% and 51.4 kg for TOF images, 19.4% and 52.8 kg for stereo vision images, respectively (Table 6). These results were consistent with the previous studies for dairy cows (Haile-Mariam et al. 2014; Kuzuhara et al. 2015). As a consequence, it was decided that the estimated body weight would be similar if any of 3-D cameras with appropriate resolution is used for acquiring the body dimensions. Body length and withers height from the 3-D images were calculated according to the criteria applied in this study, but the length and height could not be accurately determined in images where the reference point was not clear. For this reason, the prediction error might increase. This error can be reduced if the measurement criteria are clearly provided. Therefore, it is important to extract evidently the reference point in 3-D images.

Table 5 Correlation coefficients among body weight, age, and body dimensions estimated from stereo vision image of Hanwoo samples

Variables	Body weight	Age	Body length	Withers height	Chest width	Body width
Body weight	1.0000	0.9190	0.7598	0.9371	0.9110	0.9058
Age		1.0000	0.6668	0.8467	0.8619	0.8817
Body length			1.0000	0.7929	0.7488	0.7726
Withers height				1.0000	0.8654	0.8508
Chest width					1.0000	0.9366
Maximum width						1.0000

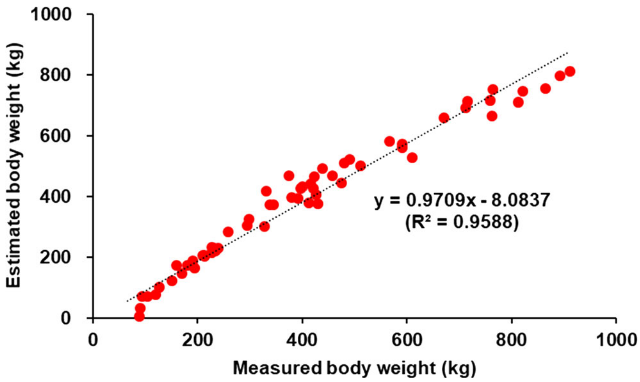

Fig. 3 Comparison of the measured and estimated value of body weight for validation dataset of TOF images

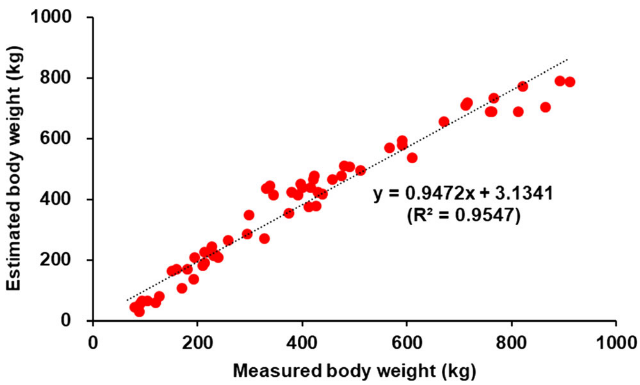

Fig. 4 Comparison of the measured and estimated value of body weight for validation dataset of stereo vision images

The MAPE and RMSE in the model applied to calves increased. There are two reasons for the large error in the calf model. First, calf in a weighing box quickly moved back and forth during the measurement of their body weight and did not maintain a normal posture. Therefore, it is not easy to acquire accurately 3-D images for calves. When a cow or a bull is measured for body parts, the animal needs to be standing with the correct posture. Second, the calf's body was not fully developed as the adult's. For young animals, height-related dimensions are also indicators of early life growth and body weight (Heinrichs et al. 1992). When cows are reaching maturity, height-related dimensions become stable, and this information is less useful for predicting body weight (Song et al. 2018). Therefore, if the body dimensions of calf and adult Hanwoo were combined together for building up the prediction model, the prediction error of the body weight might be increased. The MAPE and RMSE can be reduced when the calf data from all the samples were excluded. In reality, as the calves within half a year were excluded from total samples, MAPE and RMSE lowered to 7.4% and 44.8 kg for TOF images, to 9.9% and 53.6 kg for vision images, respectively. However, MAPE and RMSE of the MLR model without age variable were obtained as 19.1% and 62.0 kg for TOF images, 24.4% and 61.6 kg for stereo vision images, respectively.

Body weight is a primary factor for the feeding management of Hanwoo. The nutrients necessary for growth and reproduction are determined based on the weight. Without the knowledge of cattle weight, appropriate supply levels for feeding management cannot be determined.

Livestock farmers have been recently facing a shortage of labor and reduction of management efforts. There is a need to develop integrated monitoring systems that can measure important performance parameters including physical variables such as weight, size, and shape (Vázquez-Arellano et al. 2016).

Even though it was difficult to obtain 3-D images due to the continuous movement of the cattle, this study has verified the feasibility of non-contact measurement of body weight for other large animals. It will greatly improve the development of healthy growth, automated precision feeding, animal welfare, and genetic breeding. However, due to the different sizes ranging from calves to adult cattle, it is necessary to construct different regression models for body weight.

Conclusions

In this paper, 3-D imaging technology for estimating the body weight of Hanwoo cattle was proposed. A TOF camera and a

Table 6 Comparison of coefficient of determination, mean absolute percentage error (MAPE), and root mean square error (RMSE) of the prediction model obtained by using the validation dataset of three-dimensional images of Hanwoo

Images	Coefficient of determination		MAPE (%)		RMSE (kg)	
	All samples	Excluded within half a year	All samples	Excluded within half a year	All samples	Excluded within half a year
TOF						
With age	0.9573	0.9574	17.1	7.4	51.4	44.8
Without age	0.9417	–	19.1	8.1	62.0	–
Stereo vision						
With age	0.9433	0.9365	19.4	9.9	52.8	53.6
Without age	0.9262	–	24.4	10.7	61.6	–

stereo vision camera were used to acquire top-view images for Hanwoo. Body dimensions including withers height, body length, and chest width were determined from the processed 3-D images. Body dimensions combined with age were used in multiple linear regression model to predict body weight. Coefficient of determination was 0.9417 for the prediction model without age, 0.9573 for with age, respectively. It was suggested that the age variable should be included to improve the accuracy of the prediction model. MAPE and RMSE for the validation dataset were found to be as 19.4% and 51.4 kg for TOF images, 17.1% and 52.8 kg for stereo vision images, respectively. When the data for calves within half a year old were excluded from total samples, MAPE and RMSE lowered to 7.4% and 44.8 kg for TOF images, to 9.9% and 53.6 kg for stereo vision images, respectively. It is necessary to construct different regression models by separating the calf and the adult. From the results, it was concluded that 3-D imaging technology can be a good potential for estimating the body weight of Korean cattle.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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