Depth-Image-Based Automatic Body Measurement Method for Multi-Pose Beef Cattle: Postprint

Authors: Ye Wenshuai, Kangxi, He Zhijiang, Li Mengfei, Liu Gang, Liu Gang

Date: 2023-02-17T00:00:00+00:00

Abstract

In breeding farms, beef cattle exhibit high levels of activity, resulting in highly variable postures in the acquired image data with limited frames showing cattle in standard upright postures, which poses significant challenges to automatic body measurement. To address these issues, this study proposes an automatic body measurement method for multi-posture beef cattle through analysis of skeletal features and edge contour characteristics. First, an Azure Kinect DK depth camera was employed to collect top-down depth video data of beef cattle from directly above, with subsequent frame extraction. Second, the original depth images were preprocessed to segment cattle from the complex background. Third, the Zhang-Suen algorithm was utilized to extract the skeleton of cattle from target images, detect skeleton intersections and endpoints, analyze head characteristics, determine head removal points, and remove head information from the images. Finally, an improved U-chord length curvature algorithm was employed to extract the contour curvature curve of cattle, identify body measurement points based on curvature values, transform these points into three-dimensional space, and compute body measurement parameters. Based on extensive analysis of depth image data, this study categorized cattle postures in images into five types: left-tilted, right-tilted, upright, head-down, and head-up. Experimental results demonstrate that the proposed skeleton-based multi-posture head removal method achieved head removal success rates exceeding 92% across all five postures. When applied to 46 depth images of 23 cattle in various postures using the improved U-chord length curvature-based body measurement point extraction method, the mean absolute error was 2.73 cm for body straight length measurement, 2.07 cm for body height measurement, and 1.47 cm for abdominal width measurement. These findings provide support for accurate body size measurement of beef cattle in multi-posture scenarios.

ChinaRxiv

Full Text

Automatic Measurement of Multi-Posture Beef Cattle Body Size Based on Depth Image

YE Wenshuai[1,2], KANG Xi[2,3], HE Zhijiang[1,2], LI Mengfei[1,2], LIU Gang[1,2]*

[1]Key Laboratory of Smart Agriculture Systems Integration Research, Ministry of Education, China Agricultural University, Beijing 100083, China
[2]Key Laboratory of Agricultural Information Acquisition Technology, Ministry of Agriculture and Rural Affairs, China Agricultural University, Beijing 100083, China
[3]School of Computing and Data Engineering, NingboTech University, Ningbo 315200, Zhejiang, China

Abstract

Beef cattle in farms are highly active, resulting in variable postures in collected image data with few frames showing standard postures, which makes automatic body measurement challenging. To address this issue, this study proposes an automatic measurement method for multi-posture beef cattle body size by analyzing skeletal features and edge contour characteristics of cattle images. First, an Azure Kinect DK depth camera was used to collect top-view depth video data from directly above the cattle, and the video data were frame-separated. Second, the original depth images were preprocessed to extract the cattle from complex backgrounds. Third, the Zhang-Suen algorithm was applied to extract the skeleton of the cattle in the target images, detecting skeleton intersections and endpoints to analyze head characteristics and determine head removal points, thereby removing head information from the images. Finally, an improved chord length curvature algorithm was used to extract the contour curvature curve of the cattle, with body measurement points determined based on curvature values, converted into three-dimensional space to calculate body size parameters. Through analysis of extensive depth image data, this study classified cattle postures into five categories: left-leaning, right-leaning, standard posture, head-down, and head-up. Experimental results demonstrated that the proposed skeleton-based head removal method for multi-posture cattle achieved head removal success rates higher than 92% across all five postures. Using the improved chord length curvature-based body measurement point extraction method, the average absolute error for body length measurement was 2.73 cm, for body height measurement was 2.07 cm, and for belly width measurement was 1.47 cm. The research results provide an effective approach for accurately measuring beef cattle body size in multi-posture scenarios.

Keywords: beef body size measurement; depth image; multi-posture; Zhang-Suen algorithm; improved U-chord curvature algorithm

1 Introduction

With improvements in dietary structure among Chinese consumers, demand for beef in terms of both quantity and quality has grown increasingly high. According to the latest data from the Food and Agriculture Organization of the United Nations, per capita beef consumption in China increased 5.25-fold between 1990 and 2020 [?]. Beef cattle body size parameters serve as critical indicators for assessing growth development and breeding selection. However, most farms currently still rely on traditional manual measurement methods [?], which are labor-intensive, inefficient, inaccurate, cause stress to the animals, and compromise animal welfare. Therefore, research on automated body size measurement for beef cattle is of significant importance [?].

Numerous studies on computer vision-based livestock body measurement technologies have been conducted both domestically and internationally, achieving promising results. Spoliansky et al. [?] used Kinect cameras to automatically extract individual characteristics of dairy cows in pastures and designed regression models to assess body condition scores, demonstrating that machine learning methods can automatically evaluate cattle condition. Nir et al. [?] used a single Kinect V2 sensor to obtain depth images of dairy cows and employed machine learning methods, ellipse fitting, and quantile regression to extract body size parameters such as shoulder height and hip height, showing that depth information from depth cameras can automatically measure cattle body dimensions with high accuracy. Salau et al. [?] used six Kinect cameras to capture depth images of dairy cows and, combined with manually marked fore teats and ischial tuberosity points, successfully calculated ischial length and height for cows in both stationary and moving states. Zhao et al. [?] proposed a beef cattle measurement method based on Kinect v4 sensors, collecting color and depth images and combining target detection with edge detection to measure withers height, body oblique length, and body straight length, achieving measurement errors of only 0.76%, 1.68%, and 2.14%, respectively. Li et al. [?] constructed a 3D point cloud acquisition system using Kinect DK depth cameras, infrared photoelectric grating triggers, and RFID technology, achieving a 91.89% acquisition success rate and 0.6% body size reconstruction error. Zhao [?] used convex hull algorithms to remove cattle heads and tails to obtain the body region, then applied corner analysis to acquire body height, width, and length data with average errors within 3.2%. Chang [?] categorized cattle postures into head-up and head-down, designing different measurement algorithms for different postures to achieve body height measurement with an average error of 1.9%, and estimated chest and abdominal girth errors of 2.865% and 3.463%, respectively.

However, most previous livestock body measurement research has been based on images with standard postures. In practical automated measurement applications, the measured animals are often in motion, resulting in non-standard postures in captured images and consequently low measurement efficiency. To address this problem and improve livestock body measurement efficiency, this study utilizes beef cattle skeleton features and contour edge characteristics to investigate head removal methods and body measurement point extraction techniques for multi-posture images, enabling automatic measurement of beef cattle body size across various postures.

2 Materials and Methods

2.1 Data Acquisition

The experimental data were collected at a beef cattle farm in Dingxing County, Baoding City, Hebei Province. The subjects were Simmental cattle approximately 10 months old, totaling 34 head, with data collection conducted on September 30, 2021. The data collection area measured 2.37 m in length and 1.53 m in width. The acquisition device is shown in [Figure 1: see original paper]. When cattle entered the data collection area, the front and rear gates were closed, and top-view depth video data were collected using a depth camera. After collection, the front gate was opened, allowing the cattle to enter the rest area. The depth camera bracket was installed outside the wall to minimize animal stress. The camera height and angle were adjusted to capture complete cattle images, with the camera positioned 2.92 m from the plane of the weighing scale. The camera was set to NFOV 2$×$2 binning mode at 15 f/s. The ffmpeg tool was used to frame-separate the collected top-view depth video data to obtain individual depth images.

2.2 Image Preprocessing

Depth images captured by the camera contain certain distortions. To detect acquisition errors and correct image distortion, the camera was positioned at a known distance from an object of known size. Using Matlab to annotate the actual captured object size, the data acquisition error was 2.49 cm, as shown in Figure 2: see original paper. To reduce data acquisition error, this study calibrated the camera’ s internal parameters and distortion coefficients using an 8$×$9 calibration board, reducing the acquisition error to 0.35 cm after calibration, as shown in Figure 2: see original paper, which meets data collection requirements.

Due to the complex farm environment, the original depth images contained not only cattle but also complex background information such as railings, ground, and weighing scales, which affected the extraction accuracy of body measurement points. Therefore, this study removed background information from the images, with processing effects shown in [Figure 3: see original paper]. The specific steps were as follows:

(1) The shadow difference method [?] was used to obtain the depth difference image $D(x,y)$ between the depth image $f_i(x,y)$ and the background depth image $f_b(x,y)$:

$$D(x,y) = f_i(x,y) - f_b(x,y)$$

(2) The 16-bit depth image was normalized [?] to obtain the image shown in Figure 3: see original paper. If the maximum pixel value in Figure 3: see original paper is $D(x_{max}, y_{max})$ and the minimum is $D(x_{min}, y_{min})$, the normalized pixel value D_{norm} at point (x, y) becomes:

$$D_{norm} = \frac{D(x,y) - D(x_{min}, y_{min})}{D(x_{max}, y_{max}) - D(x_{min}, y_{min})} \times 255$$

(3) The watershed-based image segmentation method [?] was used to obtain a binary image containing the cattle. However, because the cattle were close to the railings with small depth value differences, the segmented images contained a few railing pixels, as shown in Figure 3: see original paper.

(4) The connected domain extraction method was used to obtain the target image containing only the cattle, as shown in Figure 3: see original paper.

2.3 Multi-Posture Head Removal Based on Skeleton

To address the problem of large body measurement errors caused by cattle head swinging, Zhao [?] used convex hull analysis to remove head information, using the cattle body region as the measurement object. However, the convex hull analysis method only works for images with standard postures and has poor robustness.

To remove head information from cattle in multiple postures, this study extracted the main backbone skeleton of the cattle, with results shown in [Figure 4: see original paper]. First, the Zhang-Suen algorithm [?] was applied to iteratively thin the cattle skeleton in the target image $C(x, y)$ to obtain the original cattle skeleton. Second, a single-pixel thinning algorithm was used to reduce the skeleton width to 1 pixel. Third, a 3$×$3 convolution kernel was used to traverse foreground points in the image to extract skeleton intersection and endpoints, setting pixel values within the 8-neighborhood of skeleton intersections to 0. The maximum connected domain method divided the entire cattle skeleton into several components, as shown in Figure 4: see original paper. Finally, the minimum bounding rectangle area of each skeleton component in Figure 4: see original paper was calculated, and the skeleton with the largest rectangle area was identified as the main skeleton, as shown in Figure 4: see original paper.

The intersection constraint condition is given by formula (3), and the endpoint constraint condition by formula (4), where $N(P)$ is the number of foreground points among the 8 neighboring pixels of P, and $S(P)$ is the pixel value at point P.

Scanning the main skeleton pixels in Figure 4: see original paper reveals two points with $N(P) = 1$ in their 8-neighborhood. Comparing their coordinate positions, the point positioned more leftward and upward is the main skeleton front endpoint P_{st}, while the other is the main skeleton rear endpoint P_{en}.

Since the cattle skeleton in the image consists of discrete points, the backward difference method was used to calculate the slope at point P_{st}. Let the front skeleton point be $G_1(x_l, y_l)$. Starting from G_1, the distance d between adjacent points in the main skeleton sequence $G_i(x_i, y_i)$ was calculated sequentially, with N recording the number of times $d = 2$ appears. If $N = 3$, the last point $G_l(x_l, y_l)$ involved in the distance calculation was recorded and the calculation terminated. The slope calculation at the main skeleton front endpoint is given by formula (5):

$$\text{slope} = \frac{y_l - y_{l-1}}{x_l - x_{l-1}}$$

The straight line equation for the dividing line is given by formula (6). Using the Canny operator to extract the edge contour of image $C(x, y)$ and calculating the line using formula (6), the cattle contour was divided into two parts. Comparing the areas of the two parts, the larger area region $A(x, y)$ was retained.

Using the convex hull analysis method combined with formula (6) to calculate the dividing line, the cattle contour was separated into upper and lower contours to analyze head characteristics and determine head removal points, as shown in [Figure 5: see original paper]. First, convex hull analysis was used to obtain convex hull points on the edge contour of image $A(x, y)$, as shown in Figure 5: see original paper. Second, main skeleton pixels were sampled and fitted into a straight line, which intersected the tail contour at point P. The convex point on the tail closest to point P was identified as the tail root point P_{ta}, as shown in Figure 5: see original paper. Finally, based on the tail root point and formula (6), the line was calculated to divide the entire cattle contour into upper and lower contours, as shown in Figure 5: see original paper and Figure 5: see original paper.

To determine the cattle head removal point, the distance from each skeleton endpoint in Figure 6: see original paper to the main skeleton front endpoint P_{st} was first calculated, with the shortest distance being D_{min}. Next, the pixel point T_{sk} on the main skeleton at distance D_{min} from P_{st} was located, as shown in Figure 6: see original paper. Finally, the upper and lower contour edges of the cattle were traversed to find the points O_u and O_d closest to T_{sk}, which were identified as the head removal points, as shown in Figure 6: see original paper and Figure 6: see original paper.

After determining the head removal points, connecting them yielded a headless cattle binary image. A logical "AND" operation between this binary image and the original depth image produced a depth image without the cattle head, as shown in [Figure 7: see original paper]. The results demonstrate that the proposed method can remove head information from cattle in multiple postures, and the trunk after head removal can be used for body measurement point extraction.

2.4 Body Measurement Point Extraction

2.4.1 Body Measurement Point Extraction Based on Improved U-Chord Curvature By analyzing cattle contour features in images, the shoulder point with maximum curvature and the abdominal point with maximum curvature on the contour curve were identified as body measurement points. Compared with k-cosine curvature, differential curvature with curve smoothing, and L-chord curvature, U-chord curvature exhibits stronger rotation invariance and noise resistance, and the curvature corresponding to U-chord length has a linear relationship with the true curvature of discrete curves [**?**].

When calculating U-chord curvature for discrete curves, the support neighborhood must first be determined [**?**]. To prevent support neighborhood endpoints from falling on burr points of the cattle contour curve, which would affect measurement accuracy, this study proposes a body measurement point extraction method based on improved U-chord curvature.

Let $l = \{P_i : (x_i, y_i), i = 1, 2, \ldots, n\}$ represent the upper contour curve of the cattle trunk after head removal, where p_i is a pixel point on the contour curve, as shown in [Figure 8: see original paper]. The support neighborhood of point P_i is given by formula (7):

$$\Omega(P_i) = [P_f^i, P_b^i]$$

where P_f^i and P_b^i are the front and back endpoints of the support neighborhood for point P_i, respectively.

The support neighborhood constraint conditions are given by formula (8). If foreground point P_i and its support neighborhood endpoints P_f and P_b fall on burr points as shown in [Figure 9: see original paper], the accuracy of U-chord curvature calculation would be affected, reducing body measurement point extraction precision.

By analyzing the characteristics of burr points on cattle contour edges, this study designed a 5$×$5 convolution kernel divided into positive and negative regions, as shown in [Figure 10: see original paper], with red areas as positive regions and blue areas as negative regions. The convolution kernel traverses foreground points and their support neighborhood endpoints on the cattle contour edge. If formula (9) is satisfied, the point is considered to fall on a burr point and is removed, with the foreground point coordinates repositioned using formula (10).

The constraint conditions for support neighborhoods are given in formula (8), where $N(P)$ is the number of points with pixel value 255 within the 5$×$5 region centered at P (excluding P itself), $S(P)$ is the pixel value at point P, $N^+(P)$ is the number of points with pixel value 255 in the positive region of the 5$×$5 convolution kernel centered at P, and $N^-(P)$ is the number of points with pixel value 255 in the negative region.

Since the cattle contour curve is discrete, points satisfying the support neighborhood constraint conditions for P_i may not exist on the curve. Therefore, linear interpolation was used to estimate the coordinates of front and back endpoints meeting the constraints, with interpolation calculations given by formula (11):

$$u < 1$$

where u is a coefficient used to determine the front neighborhood point P_f^i, and similarly for the back neighborhood point P_b^i.

The U-chord curvature calculation formulas are given by (12) and (13):

$$s_i = \operatorname{sign}[(x_i - x_{i-1})(y_f - y_i) - (x_f - x_i)(y_i - y_{i-1})]$$

where (x_b, y_b) and (x_f, y_f) are the coordinates of the back and front neighborhood points, respectively, and $D_i = \|P_{iP} f\|$.

The improved U-chord curvature algorithm proposed in this study first determines whether a foreground point is a burr point. If it is, the point is removed and its position is recalculated using the mean coordinates of surrounding pixels to improve U-chord curvature calculation accuracy.

Using the improved U-chord curvature algorithm, the curvature values of each pixel point on the cattle contour were extracted and connected sequentially to obtain the curvature curve. This curve was smoothed using five-point outlier removal and linear five-point smoothing methods. The extreme curvature points at the shoulder and abdomen were extracted as body measurement points.

2.4.2 Beef Cattle Body Size Calculation In traditional manual measurement, body height refers to the vertical distance from the highest point of the withers to the ground, body straight length refers to the horizontal distance from the shoulder point to the ischial tuberosity, and belly width refers to the maximum width of the abdomen [?], as shown in [Figure 11: see original paper].

First, n pixel points were selected from the ground position in the background depth image. Using the camera' s internal parameters, these pixel points were converted to three-dimensional coordinates, and a ground plane was fitted from the n points to obtain the plane equation (14):

$$Ax + By + Cz + D = 0$$

Second, all Z-value data within the front 1/2 region of the cattle were selected [?] to obtain the minimum Z-value point $H_i(x, y)$. Finally, this minimum point was converted to three-dimensional coordinates as $H_i'(x', y', z')$, and the distance from H_i' to the plane was calculated as the cattle body height.

The extreme curvature point in the abdominal region was obtained as the belly width measurement point $f_1(x_1, y_1, z_1)$ and $f_2(x_2, y_2, z_2)$. The Euclidean distance between these two belly width measurement points was calculated as the belly width parameter A_b using formula (15):

$$A_b = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2}$$

When cattle have severe body skew, two curvature extreme points may appear in the shoulder region. To obtain the front endpoint of body straight length, the number of shoulder curvature extreme points was first determined. If two extreme points existed, their mean point was taken as the front endpoint of body straight length $P_{le}(x_{le}, y_{le}, z_{le})$, with the tail root point $P_{ta}(x_{ta}, y_{ta}, z_{ta})$ serving as the rear endpoint. The Euclidean distance from the body straight length front endpoint to the belly width midpoint was calculated as d_1, and the distance from the belly width midpoint to the tail root point was d_2. The body straight length L was then calculated using formula (16):

$$L = d_1 + d_2$$

3 Results and Analysis

3.1 Head Removal Results Analysis

Depth image data from 23 beef cattle were randomly selected. Since posture differences between adjacent frames were minimal, a frame-sampling method was used for head removal testing across different postures, extracting one frame every 10 frames as test data, yielding 674 frames total. First, human observation was used to preliminarily classify the 674 depth images into five categories: standard posture, left-leaning (head and neck skewed toward the left side of the passage), right-leaning (head and neck skewed toward the right side), head-down, and head-up. Then, the skew angle θ and head-down/up amplitude values were calculated to further determine cattle posture.

The degree of non-standard posture can be measured by angle θ. First, the minimum bounding rectangle of the main skeleton was extracted, and the intersection point M between the X-axis line at the midpoint of the rectangle' s Y-axis direction and the main skeleton was calculated to determine the main skeleton front endpoint H. Then, the shoulder skeleton point S was determined. Finally, lines MS and HS were connected, and the angle θ between lines l_1 and l_2 was calculated, as shown in [Figure 12: see original paper]. Using this method, the 674 depth images were divided into three categories: if $|\theta| < 15°$ [?], the depth image was marked as a standard posture frame; if $|\theta| > 15°$ and human observation identified left-leaning, it was marked as left-leaning; if $|\theta| > 15°$ and identified as right-leaning, it was marked as right-leaning.

To calculate head-down and head-up amplitude values, depth images were converted to 3D point clouds. CloudCompare software was used to annotate cattle head and shoulder heights, and the height difference H_u was calculated to represent the head-down/up amplitude.

Previous studies have primarily used convex hull analysis for head removal [?]. To verify the effectiveness of the proposed method, convex hull analysis and the proposed method were compared across the five postures, with results shown in . The success rates of the proposed skeleton-based head removal method were 94.63%, 98.88%, 92.31%, 93.25%, and 100% for the five postures, respectively, all outperforming the convex hull method.

To further verify the head removal effectiveness under different skew angles, the mean θ value for 376 left-leaning and right-leaning images was calculated as 33.67°. Based on skew degree, images with θ values below the mean were marked as mildly skewed, while those at or above the mean were marked as severely skewed. The head removal results after this subdivision are shown in and .

For mildly left-leaning images (mean $\theta = 21.75°$) and mildly right-leaning images (mean $\theta = 22.09°$), convex hull analysis achieved success rates of 62.00% and 28.57%, respectively, while the proposed method achieved 98.00% and 97.62%. For severely left-leaning and severely right-leaning images, convex hull analysis success rates were 29.79% and 10.20%, respectively, while the proposed method achieved 93.62% and 87.76%. These results indicate that larger posture skew angles θ make head removal more difficult, with success rates decreasing for both methods. However, the proposed method consistently outperformed convex hull analysis across all five postures.

To analyze the impact of head-down/up amplitude and posture skew degree on head removal results, statistics were compiled for 244 frames, as shown in [Figure 13: see original paper]. Blue and green points represent failed head removal frames, with blue points concentrated in regions with larger H_u values and green points in regions with larger θ values. Thus, when cattle exhibit large head-down/up amplitudes or high posture skew degrees, head removal failures occur. Only 13 out of 224 frames failed head removal, demonstrating the effectiveness of the proposed method.

3.2 Body Measurement Results Analysis

To automatically extract body measurement points, the cattle contour underwent several processing steps. First, posture correction was performed using the tail root point and main skeleton front endpoint. Second, the U-chord curvature algorithm and improved U-chord curvature algorithm were used to calculate curvature curves for the upper and lower contours, with results shown in [Figure 14: see original paper]. Analysis reveals that the improved algorithm produces smoother curvature curves, enabling more accurate calculation of curvature values for contour edge pixels.

Based on the test data from Section 3.1, two frames of depth images were randomly selected for each of 23 cattle (totaling 46 frames) to evaluate body measurement accuracy. CloudCompare point cloud processing software was used to annotate body size parameters in the top-view point clouds, with each parameter manually measured three times and averaged as the ground truth. The measurement results are shown in .

The average absolute errors were 2.73 cm for body straight length, 2.07 cm for body height, and 1.47 cm for belly width. The body height measurement error for cattle #11 was relatively large (9.79 cm), primarily because high-resolution depth data captured floating dust from feed processing, causing the measurement point extraction method to mistakenly use dust-to-camera distance as back-to-camera distance. The belly width measurement error for cattle #44 was 4.32 cm, mainly due to severe contour edge information loss in that depth image. Although the study repositioned foreground points identified as burr points, significant errors remained in belly width point extraction, also resulting in higher body straight length measurement error.

To verify measurement accuracy for non-standard postures, the 46 frames were divided into standard posture and non-standard posture images, with average errors calculated separately, as shown in . The proposed method achieved low measurement errors for both categories. Compared with standard posture measurements, non-standard posture measurements showed body height error 0.81 cm lower, body straight length error 0.264 cm higher, and belly width error 0.418 cm higher. These results demonstrate that the improved U-chord curvature method can extract measurement points effectively across different postures with small errors.

To validate the multi-posture measurement effectiveness, the proposed method was compared with literature methods [?, ?, ?] that target standard postures, as shown in . The proposed method' s body straight length error was similar to [?] and smaller than [?], while its body height error was larger than [?] but smaller than [?, ?]. These comparisons demonstrate that the proposed method enables multi-posture measurement while significantly improving accuracy.

4 Conclusion

Beef cattle body size parameters are critical indicators for growth assessment and breeding selection. However, cattle in farms are active, resulting in few standard posture frames and diverse postures that challenge traditional measurement methods. This study proposes an automatic multi-posture beef cattle body size measurement method based on depth image analysis of skeleton and contour edge features:

(1) A skeleton-based head removal method for multi-posture cattle was proposed. Testing on 674 frames across five postures (standard: 298 frames, left-leaning: 194, right-leaning: 182, head-down: 252, head-up:

30) achieved success rates of 94.63%, 98.88%, 92.31%, 93.25%, and 100%, respectively, all outperforming convex hull analysis.

(2) An improved U-chord curvature-based body measurement point extraction method was proposed. Testing on 46 frames from 23 cattle in various postures achieved average absolute errors of 2.73 cm for body straight length, 2.07 cm for body height, and 1.47 cm for belly width. For non-standard postures specifically, the errors were 2.779 cm, 1.932 cm, and 1.544 cm, respectively, demonstrating effective multi-posture measurement capability with small errors across all postures.

References

[1] Food and Agriculture Organization of the United Nations, FAOSTAT[EB/OL]. [2022-02-17]. https://www.fao.org/faostat/zh/#data/QCL.

[2] LI M, KANG X, WANG Y, et al. Side-view point cloud completion method combining cubic b-spline curve fitting and edge detection based on threshold analysis[J]. Transactions of the CSAM, 2021, 52(S1): 81-88.

[3] FREITAG G P, LIMA L G F, JACOMINI J A, et al. An accurate image analysis method for estimating body measurements in horses[J]. Journal of Equine Veterinary Science, 2021, 101: ID 103418.

[4] SPOLIANSKY R, EDAN Y, PARMET Y, et al. Development of automatic body condition scoring using a low-cost 3-dimensional Kinect camera[J]. Journal of Dairy Science, 2016, 99(9): 7714-7725.

[5] NIR O, PARMET Y, WERNER D, et al. 3D Computer-vision system for automatically estimating heifer height and body mass[J]. Biosystems Engineering, 2018, 173: 4-10.

[6] SALAU J, HAAS J H, JUNGE W, et al. A multi-Kinect cow scanning system: Calculating linear traits from manually marked recordings of Holstein-Friesian dairy cows[J]. Biosystems Engineering, 2017, 157: 10-21.

[7] ZHAO J, ZHAO C, XIA H. Cattle body size measurement method based on Kinect v4[J]. Journal of Computer Application, 2022, 42(5): 1598-1606.

[8] LI J, MA W, LI Q, et al. Automatic acquisition and target extraction of beef cattle 3D point cloud from complex environment[J]. Smart Agriculture, 2022, 4(2): 64-76.

[9] ZHAO X. Measurement and test of dairy cattle body size based on Kinect[D]. Taian: Shandong Agricultural University, 2018.

[10] CHANG H. The study on the non-contact measurement system of cattle body[D]. Changchun: Changchun University of Technology, 2018.

[11] SI Y, AN L, LIU G, et al. Ideal posture detection and body size measurement of pig based on Kinect[J]. Transactions of the CSAM, 2019, 50(1): 58-65.

[12] ZHANG L, ZHOU W, LI J, et al. Histogram of oriented gradients feature extraction without normalization[C]// 2020 IEEE Asia Pacific Conference on Circuits and Systems (APCCAS). Piscataway, New York, USA: IEEE, 2020: 252-255.

[13] ZHANG W, HAN J, GUO B, et al. Application of improved watershed algorithm in adhesion image segmentation[J]. Computer Applications and Software, 2021, 38(6): 243-248.

[14] ZHANG T, SUEN C. A fast parallel algorithm for thinning digital patterns[J]. Communications of the ACM, 1984, 27(3): 236-239.

[15] GUO J. An algorithm for fragments re-assembly based on U-chord curvature[D]. Suzhou: Soochow University, 2014.

[16] NIU J. Body size measurement and weight prediction for dairy cows based on 3D point cloud[D]. Yangling: Northwest A&F University, 2018.

[17] ZHANG X. Research on automatic measurement technology of pig body size based on depth camera[D]. Beijing: China Agricultural University, 2021.

[18] RUCHAY A, KOBER V, DOROFEEV K, et al. Accurate body measurement of live cattle using three depth cameras and non-rigid 3-D shape recovery[J]. Computers and Electronics in Agriculture, 2020, 179: ID 105837.

[19] LI Q, LIU W, ZHAO J. Non-contact measurement of bovine body size based on binocular vision and Mask RCNN[J]. Heilongjiang Animal Science and Veterinary Medicine, 2020(6): 46-50, 159-160.