J. Electrical Systems 20-2 (2024): 64-72

[1,*] Huixiang Xu

Cattle Body Intelligent Measurement based on Improved CenterNet

Journal of Electrical Systems

***Abstract:* -** Traditional cattle body measurement methods have limitations such as manual contact measurement and low efficiency. To improve the efficiency of measuring cattle bodies and reduce labor costs, an improved intelligent measurement network based on CenterNet was proposed. In this study, we used the DenseNet-100 to replace the ResNet-101 to alleviate the vanishing gradient problem. We also improved the cattle body size measurement efficiency by reducing the network parameters. In addition, we conducted a comparative experiment on the cattle posture dataset collected by ourselves to verify the feasibility of the network. The experiment confirmed that the proposed intelligent measurement based on improved CenterNet outperforms the traditional networks and other advanced object measurement networks in accuracy and measurement efficiency, and can effectively solve most of the error problems caused by manual measurement. Besides, our network has good applicability and strong stability, which can meet the requirements of the evaluation of cattle body size measurement indicators.

Keywords: Cattle Body Measurement, CenterNet, Keypoint Detection, Intelligent Measurement, Deep Learning.

I. INTRODUCTION

As the main parameter for cattle growth, the body size is an important indicator for evaluating the growth and health status. Most of the traditional cattle body detection algorithms are manual measurement methods, which not only require the reasonable cooperation of cattles but also need to reduce manual errors 0.

The progress of artificial intelligence technology in computer vision has promoted the development of livestock body measurement, including cattle body measurement 0. For example, Zhu and Tomov used the computer vision library OpenCV to obtain the cattle body size data, but it has poor stability and is more suitable for simple scenes 0. Zhao measured sheep body size through the image data obtained by the Kinect camera 0. Zhou used the multi-scale Retinex and GraCut networks to calculate the key points of the sheep body size 0. Although it obtained a high accuracy, it increased the computational cost. In addition, the above-mentioned networks have limitations such as excessive computing resources and low measurement efficiency, which are difficult to apply in practice.

The Deep Learning based on object detection networks has also been applied in animal body measurement, which has two categories **Error! Reference source not found.**. One is the single-stage model represented by SSD, YOLO, ConerNet, and CenterNet, where CenterNet completes the object detection by introducing central key points based on ConerNet. The other is a two-stage model represented by Faster R-CNN. For example, Zhao JM et al. used Mask RCNN for cattle body detection, which was improved by Faster RCNN0. Although the two-stage models can achieve high accuracy, they also consume more computational resources due to a large number of parameters. It is worth mentioning that the CenterNet single-stage object detection model is the most advanced single-stage model, which uses a CNN to recognize each object as three key points and pays more attention to the information about the central region of each object. Compared with other popular object detection models, CenterNet can model an object as the center of the bounding box through the center pooling operation, which is used to regress on other attributes of the object. This method can better complete the detection of key points in cattle body image 0. Unlike general object detection, cattle body keypoint detection in cattle pose images is a complex task, and the quality of cattle pose image samples affects cattle body keypoint detection. For example, illumination and color changes in cattle housing images affect the quality of cattle housing images. Therefore, an effective keypoint discrimination network is required to accurately detect the key points required for cattle body measurement 0.

However, the size of the central area where the key points are located has a direct impact on the detection results. If the area is too small, the recall rate of small objects is low, and if the area is too large, the accuracy rate of large objects is low, which is not conducive to the calculation of the final key point of the cattle body size regression. To obtain an accurate and stable set of key points, intelligent feature calculation technology must be

[1] School of Information Engineering, Zhengzhou University of Technology, Zhengzhou, China
*Corresponding author: Huixiang Xu

used to replace the traditional feature calculation method performed by hand. Due to the large differences in texture, color, and location of key points in cattles, hand-made keypoint models is not stable in terms of measurement performance. To solve the above problem, we use the basic framework of the CenterNet object detection model, replace the original ResNet-101 backbone network by DenseNet-100 based on CenterNet, so as to sort out the vanishing gradient issue caused by the many parameters of ResNet-101. The network parameters are reduced and the detection efficiency is improved. At last, the effectiveness of the improved intelligent measurement network based on CenterNet is verified.

II. METHODS

Numerous studies have demonstrated CenterNet's superior performance in keypoint detection, and it has been used in many practical tasks. In cattle body measurement, CenterNet uses heat maps and a single-level model structure to detect and classify key points of cattles, which have a higher recognition rate. It can also reduce computational cost and improve measurement efficiency. Based on the above considerations, we propose a cattle body intelligent measurement network that integrates the DenseNet feature extraction network with CenterNet to identify the key points of the cattle body in the cattle stall sample. Compared with the original CenterNet, our improved network has better detection performance for the key points of cattle body size in cattle stall images, while significantly reducing processing time and improving detection efficiency.

A. CenterNet

CenterNet has proven effective in a variety of computer vision tasks and can perform both object detection and keypoint location estimation tasks simultaneously. In addition, CenterNet is also excellent for cattle-body keypoint detection. The block diagram of CenterNet is shown in Figure 1.

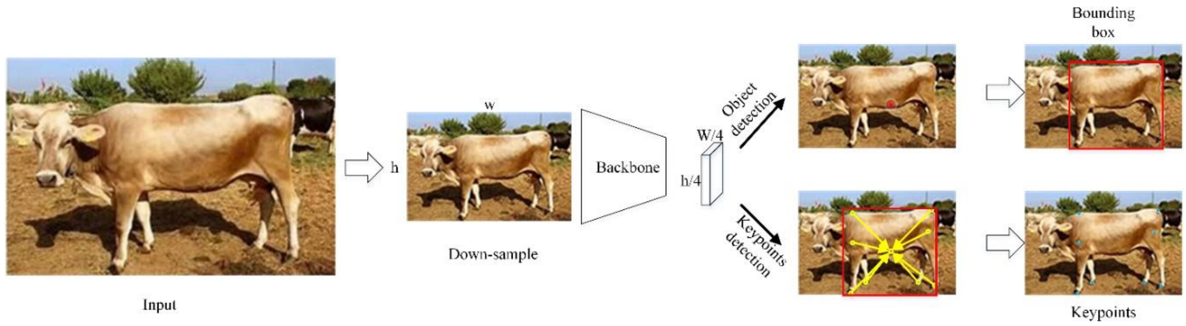

Figure 1: Block Diagram of CenterNet

CenterNet uses ResNet to extract image features and detect object keypoints. ResNet solves the problem of increasing the depth of the network and degrading the stacking effect of the deeper network to some extent by adding a residual network to the network. Here we take ResNet-101 as an example to analyze ResNet.

ResNet-101 explicitly stores the state information of the previous layer by adding a link. Moreover, ResNet adds identity mapping to the rest network and skips the operation of one or more layers. At the same time, in back propagation, the gradient of the next layer of the network is directly passed to the previous layer, which solves the problem of the disappearing gradient of the deep network. However, the number of parameters of the ResNet network is still large, the training time is long, and the hardware requirements are relatively high. The ResNet cannot fully utilize the image features, and the ability to solve the vanishing gradient problem is not good enough. Figure 2 shows the structure diagram of ResNet-101 network

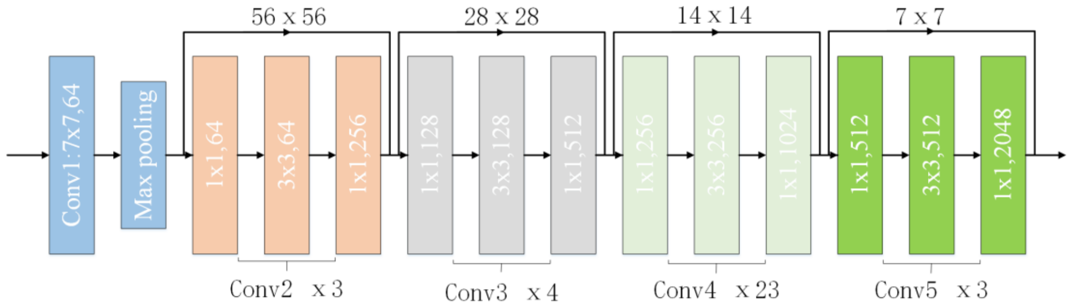

Figure 2: Structure Diagram of ResNet-101 Network

To solve the problems of ResNet-101, we use a dense convolutional network, namely DenseNet, to replace ResNet. Based on the original CenterNet, we replace ResNet-101 with DenseNet-100**Error! Reference source**

not found.. Compared with ResNet-101, the feature extraction network DenseNet-100 uses dense blocks (Dense Blocks, DB) to reuse the extracted features, so it is not necessary to relearn new redundant feature mappings. DenseNet-101 uses the dimension concat operation to merge feature maps. This not only enriches the feature information and obtains more feature maps, but also reduces the convolution operations, which significantly reduces the network parameters, saves computational cost, and improves the detection efficiency. DenseNet contains multiple dense blocks connected by convolutional layers and pooling layers. DenseNet has more complex transformations that help to compensate to some extent for the lack of semantic information in top-level feature fusion.

B. Feature Extraction

DenseNet-100 contains four dense modules and has the same number of layers as ResNet-101, but compared to ResNet101, DenseNet-100 has fewer network parameters, which composed of convolutional kernel (CK) and average pooling (AP). so DenseNet-100 can save more computational cost. The network parameters of DenseNet-100 are listed in Table 1.

Table 1: Network parameters of DenseNet-10

Layers	Feature Drawing Size	Parameter of Each Layer	Quantity
First layer	32×32×24	3×3 CK	1
Densely connected layer	32×32×216	1×1 CK	16
Transition layer	32×32×108 16×16×108	1×1 CK 2×2 AP	1
Densely connected layer	16×16×300	1×1 CK	16
Transition layer	16×16×150 8×8×150	1×1 CK 2×2 AP	1
Densely connected layer	8×8×342	1×1 CK	16
Last layer	1×342 1×10	8×8 AP	1

DB is the base unit of DenseNet-100, as shown in Figure 3. The feature map size is N, the total number of channels is M_0, and the feature map of level $n-1$ is shown as $N \times N \times M_0$. The nonlinear transformation $H(\cdot)$ includes several methods, such as a Batch Normalization layer (BN), the activation function ReLU, a convolution layer (Conv) to minimize the total channels, and a 3×3 Conv for keypoint rearrangement. The long solid arrows are used to represent dense connections, connecting $n-1$ layers to n layers through transformations $H(\cdot)$. Finally, the output of the $n+1$ layer is $N \times N \times (M_0 + 2M)$.

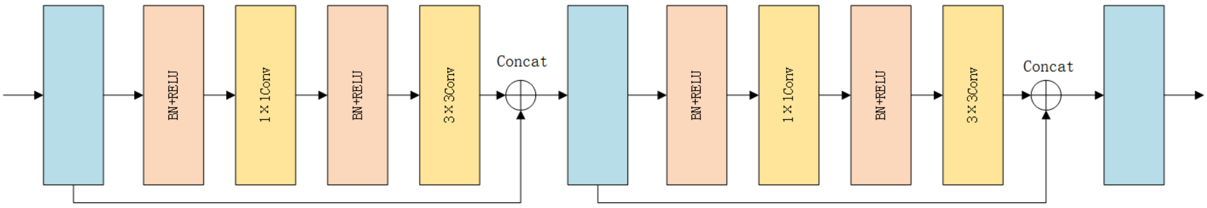

Figure 3: Architecture of DenseNet-100

A large number of densely connected modules increases the number of feature maps. So, we use transition layer to diminish the dimension of the feature map. In feature extraction, DenseNet-100 takes the sample with a stride rate of R=4, then passes it down and the detector performs the next processing step.

C. Detector

The thermal image detector performs feature estimation on the features extracted from Densenet-100 to calculate the central point of the cattle body size keypoint group and the category information to which the cattle body size keypoint group belongs. The central keypoint is the midpoint of the target bounding box and is calculated as follows.

$$\hat{O}_{i,j,c} = \exp\left(-\frac{\left(i-\hat{p}_i\right)^2 + \left(i+\hat{p}_j\right)^2}{2\sigma_p^2}\right) \tag{1}$$

Where, i and j are the coordinates of the actual key points. $\hat{p}_i$ and $\hat{p}_j$ are the locations of the predicted downsampling key points. σ_p represents the adaptive standard deviation of the target size. c is the number of categories and there is only one category in this paper. $\hat{O}_{i,j,c}$ represents the center of the candidate keypoint group. When the parameter value is 1, it is marked as the target, otherwise, it is marked as the background.

The size detector is in charge of predicting the coordinates of the frame. The offset detection head performs downsampling on the input sample, and then the center point offset is obtained by minimizing the discretization error. Finally, the coordinates of the center point after offset regression are mapped to a higher dimensional input image.

CenterNet is an end-to-end deep learning network, and we use a multi-task loss method to improve positioning accuracy of key areas of cattle body size. To this end, we use a multi-task penalty L on each sampling head, which is calculated as follows.

$$L = L_h + \lambda L_d + \gamma L_o \tag{2}$$

Where, L is the total loss for CenterNet. L_h, L_d and L_o are the losses of thermal image, size, and offset respectively. λ and γ are constants, $\lambda = 0.1$, $\gamma = 1$. In the training process, the epoch is set as 200, and the learning rate is set as 0.001.

D. 2.4 Cattle Body Data

Accurate determination of the size of each part of the cattle's body is key to reflecting the cattle's growth status, which can be a reference for breeding excellent breeds or evaluating meat quality and body weight. The schematic representation of cattle body size data can be found in Figure 4.

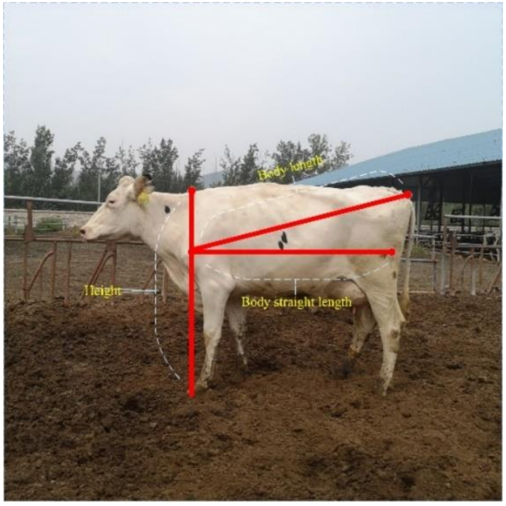

Figure 4: Schematic diagram of cattle size data

In Figure 4, we can see that the initial and final positions of the straight length of the cattle's body are the horizontal distance from the end of the shoulder to the rear edge of the end of the ischium, the initial and final positions of the height of the cattle's body are the vertical distance from the highest point of the nail to the ground, and the initial and final positions of the length of the cattle's body are the straight distance from the end of the shoulder to the end of the ischium.

III. EXPERIMENTAL RESULTS

A. Pre-training

Usually, a stable deep learning network needs large amount of training data, but in most real-world scenarios, it is difficult to find enough high-quality training data that meets the needs of the task. We refer to the transfer learning proposed by Boonkong **Error! Reference source not found.** to solve the above problem and improve the detection accuracy. Transfer learning includes a source domain and a target domain. The specific process is described as follows:

$$D(s) = \{x, P(x)\}, D(t) = \{x, P(x)\} \tag{3}$$

Where, $D(s)$ represents the source domain. $D(t)$ represents the target domain. x and $P(x)$ represent the feature space and boundary probability distributions respectively and $X = \{x_1, K, x_n\} \in x$.

Since our detection data is the camera image of cattle posture, which has similar color and basic texture characteristics to natural images, so we have to pre-train the COCO dataset firstly, use the pre-trained model weights as the initial weights of our network, initialize our network, and finally fine-tuning the network parameters in the training process. By using transfer learning, it can not only accelerate the convergence speed of model training but also.

B. The Creation of a Dataset

The main research object of this paper is the cattle husbandry image data collected on the farm, which contains only one category of cattles. The cattle husbandry dataset contains a total of 1000 images. We divide the dataset into a training dataset (600 images) and a test dataset (400 images), and use data augmentation techniques including random image rotation, mirroring, and random pruning to augment the training dataset, which is expanded to 3000 images.

The creation of the cattle training dataset mainly involves image acquisition and image processing. Image acquisition is capturing images of cattle husbandry at different distances and angles. Image processing is increasing the number of images collected. To ensure effective training of the model, the position of the area of cattle posture must be accurately determined based on the input image patterns of cattle posture. In this work, we used Labelme to create annotations for the examples. The annotations generated after labeling are stored in an XML file, which contains two things. One is the position of the keypoint group in the standing area of each cattle, and the offset of the keypoint from the center can be calculated based on the position information. The other is a rectangular box drawn on the detected cattle stand object. In this work, we use the keypoint annotation to get the minimum bounding box of the keypoint group.

C. Evaluating Indicator

The test images were tested by the trained model to determine the number of cattles, and we draw a bounding box around each detected cattle. Thus, the number of bounding boxes represents the number of recognized cattles in each test image. To check the effect of our proposed improved network, we use precision, recall rate, and F1 score to evaluate the detection performance of cattle body size. The precision represents the accuracy of the trained model in predicting positive samples, while the recall rate represents the accuracy of how many true positive samples the trained model detects. The F1 score was developed to balance these two indicators. Average precision (AP) evaluates the shape of the precision and recall rate, defined as the average precision at a set of 11 uniformly spaced recall levels [0, 0.1, 0.2, …, 1]. The precision, recall rate, and F1 score are calculated as follows.

$$\begin{cases} P = \dfrac{TP}{TP+FP} \\ R = \dfrac{TP}{TP+FN} \\ F1 = 2\times\dfrac{P\times R}{P+R} \\ AP = \dfrac{1}{11}\displaystyle\sum_{r\in\{0,0.1,0.2,\ldots,1\}} P_{interp}(r) \\ P_{interp}(r) = \max\limits_{\tilde{r}:\tilde{r}\geq r} p(\tilde{r}) \end{cases} \tag{4}$$

Where, TP is the number of positive samples correctly classified. FP is the number of negative samples with positive samples incorrectly labeled. FN is the positive sample number with negative samples incorrectly labeled. P is the accuracy rate. R is the recall rate. $P_{interp}(r)$ is the interpolation precision at the maximum precision. $p(\tilde{r})$ is the measurement precision at the time of recall $\tilde{r}$.

D. Results and Analysis

To study the detection performance of the improved network on the cattle posture dataset, some images from the test set are randomly selected as detection objects. The detection results are shown in Figure 5.

Figure 5: Detection results of the network in this paper

From Figure 5, it can be seen that the network in this work can fully detect the key points required by the cattle body size parameters. To better show the effect, the keypoint group with the bounding box of the red dotted line is selected. However, there are still some shortcomings, such as the positioning of some key points of the scapular in the plot, which can be improved by collecting more image data of cattle bodies in the following study.

To evaluate the measurement effect of the network more comprehensively in this work, the experiment is conducted with a self-generated test set of cattle postures and compared with Faster-RCNN, original Centernet0, and Centernet -PWVS0. The comparison results of detecting key points for cattle body size are shown in Table 2.

Table 2: Comparison Results of Different Networks

Networks	P/%	R/%	AP/%	F1/%	Time(ms)
Faster-RCNN	77.2	96.4	85.7	89.6	197
Centernet	78.7	96.5	86.6	95.1	136
Centernet -PWVS	80.4	97.1	87.5	95.2	124
Ours	83.5	97.6	90.0	95.4	115

By comparing with the key point detection network in cattle body measurement of different networks, it can be found that compared with Faster-RCNN, the original CenterNet and Centernet -PWVS, the of measurement results by our cattle body measurement network outperform the above three advanced measurement networks in all evaluation indicators, the detection efficiency is greatly improved, and the running time is reduced by 21 ms compared with original CenterNet.

To further verify the performance of our intelligent cattle body detection network, we selected 5 cattles in the pasture and manually measured the actual body size parameters, then compared the actual measured values with the measured values calculated by our proposed detection network. The results are shown in Table 3-5.

Table 3: Comparison Results of Body Straight Length

No.	Measurement/cm	Faster-RCNN/cm	Centernet/cm	Centernet -PWVS/cm	Ours/cm
1	131.2	151.2	119.2	131.2	127.0
2	142.6	118.6	157.6	139.6	145.0
3	123.4	107.4	102.4	111.4	125.8
4	136.6	112.6	151.6	139.6	133.6
5	135.8	135.8	132.8	132.8	140.6

Table 4: Comparison Results of Body Height

No.	Measurement /cm	Faster-RCNN/cm	Centernet/cm	Centernet -PWVS/cm	Ours/cm
1	129.1	157.1	138.1	123.1	130.3
2	134.3	138.3	128.3	122.3	130.7
3	114.2	138.2	135.2	111.2	114.2
4	138.9	158.9	117.9	138.9	134.7
5	137.5	105.5	125.5	142.0	135.1

Table 5: Comparison Results of Body Length

No.	Measurement /cm	Faster-RCNN/cm	Centernet/cm	Centernet -PWVS/cm	Ours/cm
1	148.5	120.5	145.5	148.5	145.5
2	149.2	133.2	167.2	156.7	154.0
3	139.7	171.7	142.7	139.7	139.1
4	150.3	130.3	135.3	139.8	146.1
5	156.6	144.6	162.6	168.6	156.0

The results in Tables 3-5 indicate that all the measurement networks used in the experiment can effectively measure the body strength length, body height, and body length of cattle. However, compared to other comparative networks, the proposed intelligent measurement based on improved CenterNet has the highest measurement accuracy. Since the positioning of the scaffold can be easily influenced when the catch body length is straight, the measurement error is highest when the catch body length is straight, but the detection effect is best when the catch body length is straight. The above experiments confirm the effectiveness of the proposed cattle body intelligent measurement network, and we observe approximate actual measurements in a non-contact way.

To further analyze the accuracy of different measurement networks, quantitative evaluation was conducted using RMSE, MAE, and MAPE. The calculation formulas are as follows.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{i=m}\left(\boldsymbol{L}_r(i) - \boldsymbol{L}_p(i)\right)^2} \tag{5}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{i=m}\left(\boldsymbol{L}_r(i) - \boldsymbol{L}_p(i)\right)^2} \tag{6}$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{i=m}\left|\frac{\boldsymbol{L}_r(i) - \boldsymbol{L}_p(i)}{\boldsymbol{L}_r(i)}\right| \tag{7}$$

Where, i represents the number of measurements. m represents the total number of measurements. $\boldsymbol{L}_p(i)$ represents the i-th measurement value. $\boldsymbol{L}_r(i)$ is the corresponding true value.

Using formulas (5) - (7) to calculate a total of 15 measurement results in Tables 3 to 5. The evaluation results are shown in Table 6.

Table 6: Evaluation Results

Indicator	Faster-RCNN	Centernet	Centernet -PWVS	Ours
RMSE/cm	21.93	13.64	6.79	3.16
MAE/cm	20.00	12.00	5.10	2.76
MAPE/%	14.63	8.91	3.6	1.99

From Table 6, we can see that the proposed intelligent measurement based on improved CenterNet has the smallest values in the three indicators of RMSE, MAE, and MAPE, the RMSE and MAPE are only 3.16cm and 1.99%, respectively, which further demonstrates that the proposed intelligent cat tle body measurement network can more accurately measure the size of cattle, while MAE is only 2.76cm, indicating that the measurement accuracy also has higher stability.

IV. CONCLUSION

To solve the cattle body measurement problem, an intelligent cattle body size measurement network based on improved CenterNet is proposed, which uses the most advanced single-stage object detection model CenterNet as the base network and replaces the feature extraction network ResNet with a more efficient network DenseNet. Moreover, the collected dataset of cattle body images is used as an experimental dataset to validate our proposed network. The experimental results show that our cattle body measurement network can better adapt to the cattle body image and achieve a good detection effect. Compared with the original CenterNet, the cattle body measurement network accuracy is significantly improved, and it is significantly better than other detection networks. Our network provides technical support for improving the precision level of animal husbandry and promoting the development of intelligent animal husbandry. Although our experimental results are excellent, there are still some shortcomings. For example, although the cattle body measurement network we proposed has high measurement accuracy, the regression of some key points is still not accurate enough, including the positioning of the key points at the scapular end. In future work, we consider collecting more images of animal posture poses in different scenarios to solve more intelligent measurement problems of animal body size. At the same time, we should also improve the cattle body measurement network, including the regression accuracy of key points, and provide a measurement network with fast convergence speed, good stability, and high precision for intelligent animal husbandry.

ACKNOWLEDGMENT

The work was supported in part by Henan Province Science and Technology Research Program (212102110168), Undergraduate Innovation and Entrepreneurship Project of Zhengzhou University of Technology (202111068008), Henan Province Science and Technology Research Projects (232102320015), and Key Research Projects of Higher Education Institutions in Henan Province (23B520024).

REFERENCES

[1] B. Kristijan, B. David, P. Tomislav, et al, "A review of body measurement using 3D scanning", IEEE Access, vol.9, pp.67281-67301, April, 2021.

[2] W. Erda, F. S. Daniel, P. M. Patrick, et al, "Channel characterization of magnetic human body communication", IEEE Transactions on Biomedical Engineering, vol. 69, no.2, pp.569-579, February, 2022.

[3] T. Gao, F. M. Li, Y. Q. Yang, et al, “Gentle adaboost based cattle detection,” Application Research of Computers, vol.33, no.11, pp. 3495-3498, 2016.

[4] S. Mathavaraj, Eric A. Butcher, "SE(3)-constrained extended kalman filtering for rigid body pose estimation", IEEE Transactions on Aerospace and Electronic Systems, vol.58. no.3, 2482-2492, June, 2022.

[5] W. Shi, S. Q. Zhang, “Application of edge-based image segmentation in cattle body measurement,” Digital Technology and Application, vol.32, no.2, pp.48-51, 2020.

[6] Y. M. Hu, S. M. Zhang, “Dairy cattle body measurement based on machine vision,” Electronic Measurement Technology, vol.43, no.20, pp.115-120, 2020.

[7] L. Zhu, W. Zhang, Q. Li, et al, “Measuring system of sheep body size based on embedded machine vision,” Computer Measurement & Control, vol.22, no.8, pp.2396-2398, 2014.

[8] N. P. Tomov, V. Kokalanov, S. Koceski, "Deep learning-based real-time body measurements using device camera", 12th Mediterranean Conference on Embedded Computing, Budva, June 2023.

[9] J. M. Zhao, Z. X. Zhao, Q. Li, “Measurement method of sheep body size based on Kinect sensor,” Jiangsu Agricultural Sciences, vol.43, no.11, pp.495-499, 2015.

[10] Y. Q. Zhou, H. R. Xue, X. H, “Jiang, et al. Non-contact measurement of sheep body size based on multi-scale Retinex image enhancement,” Journal of China Agricultural University, vol.23, no.9, pp.156-165, 2018.

[11] A. Hirata, T. Miyazawa, R. Uematsu, et al, "Body core temperature estimation using new compartment model with vital data from wearable devices", IEEE Access, vol.9, pp.124452-124462, September 2021.

[12] C. Romano, D. Formica, E. Schena, et al, "Investigation of body locations for cardiac and respiratory monitoring with skin-interfaced inertial measurement unit sensors", IEEE Sensors Journal, vol.23, no.7, pp.7806-7815, April 2023.

[13] J. M. Zhao, B. Wen, Q. Li, “A bull body ruler measurement system based on Mask R-CNN,” Animal Husbandry & Veterinary Medicine, vol.53, no.5, pp.42-48, 2021.

[14] S. Vandermeeren, H. Steendam, "Deep-learning-based step detection and step length estimation with a handheld IMU", IEEE Sensors Journal, vol.22, no.24, December, 2022.

[15] J. Y. Xu, A. J. Xu, S. Y. Zhou, et al, “Research on the algorithm of curved body size measurement of pig based on Kinect camera,” Journal of Northeast Agricultural University, vol.52, no.9, pp.77-85, 2021.

[16] M. Everingham, L. V. Gool, C. K. I. Williams, et al, “The pascal visual object classes (VOC) challenge,” International Journal of Computer Vision, vol.88, no.2, pp.303-338, 2010.

[17] K. Duan, S. Bai, L. Xie, et al, “CenterNet: Keypoint triplets for object detection,” In Proceedings of the IEEE International Conference on Computer Vision, Seoul, Korea, pp.6568–6577, October, 2019.

[18] A. Boonkong, K. Khampitak, D. Hormdee, "Performing and evaluation of deep learning models for uterus detection on soft-tissue cadavers in laparoscopic gynecology", IEEE Engineering in Medicine and Biology Society Section, vol.11, pp.72027-72036, July, 2023.

[19] X. Wang, S. Kang, W. D. Zhu, “Defect detection of laminated surface in the automated fiber placement process based on improved CenterNet,” Infrared and Laser Engineering, vol.50, no.10, pp.202-212, 2021.

[20] S. Aladhadh, R. Mahum, “Knee osteoarthritis detection using an improved CenterNet with pixel-wise voting scheme,” IEEE Access, PP.22283–22296, February, 2023.