# Cow behavior recognition based on image analysis and activities

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**Abstract:** For the rapid and accurate identification of cow reproduction and healthy behavior from mass surveillance video, in this study, 400 head of young cows and lactating cows were taken as the research object and analyzed cow behavior from the dairy activity area and milk hall ramp. The method of object recognition based on image entropy was proposed, aiming at the identification of motional cow object behavior against a complex background. Calculating a minimum bounding box and contour mapping were used for the real-time capture of rutting span behavior and hoof or back characteristics. Then, by combining the continuous image characteristics and movement of cows for 7 d, the method could quickly distinguish abnormal behavior of dairy cows from healthy reproduction, improving the accuracy of the identification of characteristics of dairy cows. Cow behavior recognition based on image analysis and activities was proposed to capture abnormal behavior that has harmful effects on healthy reproduction and to improve the accuracy of cow behavior identification. The experimental results showed that, through target detection, classification and recognition, the recognition rates of hoof disease and heat in the reproduction and health of dairy cows were greater than 80%, and the false negative rates of oestrus and hoof disease were 3.28% and 5.32%, respectively. This method can enhance the real-time monitoring of cows, save time and improve the management efficiency of large-scale farming.

**Keywords:** cow behavior, target segmentation, image entropy, image moment, activities, intelligent analysis
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## 1 Introduction

Video recording is the most commonly used method for monitoring the daily behavior of large-scale animal husbandry units. As the amount of high-definition surveillance video data increases, the valuable information is masked by ordinary information, resulting in massive key intraframe information searching that requires thoroughness and orderly playback, with much more time consumed in reviewing than the original video length. A key frame is the smallest unit in a continuous video. Through intelligent analysis, video and image processing technologies are used to unearth the typical behavioral characteristics of animals in single key frames and to automatically identify and prompt the associated researchers. These technologies greatly improve viewing efficiency.

Cows have their own lifestyle habits and behavioral characteristics. Reproductive testing and healthy behaviors of cows are important in maintaining the status of cows with herd breeding management during the breeding process. Timely detection of cow oestrus is conducive to in-season conception for healthy cows,

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calving, and prolonged lactation, which improves the economic benefits of cow breeding[1-3]. A correct and thorough grasp of cow behavior and real-time monitoring of the health and/or physical conditions of cows are conducive to disease prevention, diagnosis, and treatment, controls that contribute greatly to the appropriate management of breeding and feeding, the improvement of production efficiency, and the maximization of production benefits[4-6]. Therefore, in cow breeding, the real-time perception, as well as intelligent recognition and analysis of physiological behaviors of cows at various stages of conception, plays an important role in increasing the productivity of the farm. Furthermore, the monitoring of key behaviors of cows at different developmental stages has been previously performed, including the monitoring of oestrus and hoof disease[7,8].

In terms of internet of things (IoT) technology in cow husbandry, the development of standards for cow husbandry is regarded as an important indicator of modern agriculture, especially that of livestock husbandry, by foreign developed countries[9-11]. IoT technology has been widely applied in cow husbandry abroad[12-15], which has greatly promoted the precision and level of informationization in cow husbandry and led to a leap in quality for the cow breeding industry. Nilsson et al.[16] combined video tracking and behavior analysis to extract the target animal object in an environment of fixed scenes, and they also analyzed animal behavior patterns through real-time tracking of animal motion trajectories; However, actual behaviors, such as animal feeding, cannot be automatically identified. The animal video tracking system studied by Cattelan can recognize the simple behaviors of mice, such as their motion and certain body movements[17], but it cannot accurately track an arbitrary behavior. Leroy and Vranken[18] analyzed the abnormal behavior of hens throughout their growth periods by monitoring their growth process. However, due to insufficient resolution of images and the dynamic movement of the hens, the accuracy of abnormal behavior recognition is low. Egnor et al.[19] autotracked animals that require monitoring from different dimensions of spatial location and orientation, and the real-time tracking and processing capacity can reach up to 50 fps. Balch et al.[20] analyzed the spatial activity behavior of an ant colony by integrating the tracking of colors and ant motion. Shao and Xin[21] combined infrared imaging and the impact of breeding environment on pig growth to assess the comfort level of a breeding environment via the sleeping posture of the pigs.

Domestic studies on the dynamic monitoring and intelligent analysis of animal behavior have been lagging, but with the extensive application of IoT technology, numerous research results have been obtained[22-24]. Kunming Leading Process Machine Vision Engineering Co., Ltd. used machine vision technology to identify the position coordinates, movement trajectory, movement distance, movement time, and stopping time of white mice to predict their learning ability, memory mechanism, and mental activity. Liu et al.[25] of Jiangsu University performed skeleton extraction and trimmed key behavioral frames of target objects, as well as selected the step frequency characteristics of pigs from the collected deep image sequences of pig movements. Zhu et al.[26] used real-time camera monitoring of the regions where pigs discharged excretions inside the pigpen to locate pigs with suspicious illness based on their abnormal behaviors and determined the status of shortness of breath. The Computer Network Information Center of the Chinese Academy of Sciences has carried out research on key techniques such as bird behavior modeling frameworks, target detection, tracking, bird posture classification, and a behavioral analysis identification algorithm to implement the analytical recognition of birds' common behaviors at a Qinghai Lake research site. Li et al.[27] effectively monitored the individual behavior of aquaculture subjects through a video surveillance system. In terms of cow behavior identification, Pang et al.[28], from Northwest A&F University, analyzed calf activity, feeding frequency, sleep duration, respiratory rate, and other physiological and behavioral information to achieve automatic monitoring and regulation of calves' physiological conditions. He[29] collected parameters such as cow body temperature, respiratory rate, and movement acceleration through various sensors to classify cow behaviors. Tian et al.[30] realized the recognition of cow estrous behavior using a neural network algorithm based on the monitoring of parameters such as cow activity, prone position duration, and body temperature. Liu et al.[31] used a pedometer to collect cow activity information, and the data were uploaded through wireless transmission and analyzed, achieving effective recognition of cow oestrus.

The techniques and systems mentioned above have high interactivity and flexibility. Researchers can achieve basic dynamic posture recognition for an analysis of animal behavior, but some limitations still exist in target autotracking and behavioral analysis:

1) The current techniques and systems only perform the process of analyzing motion patterns according to quantitative parameters, such as animal position, movement trajectory, velocity, and distance;

2) They can only recognize some basic behavioral patterns, such as animal movement and stationary rest;

3) They do not form a generalized typical animal behavioral model;

4) Their process of recognition is prolonged, and there are only a few classification types of animal postures; and

5) They are only applicable to the tracking of an individual animal, and the analysis of interactive behaviors among animals is lacking.

At present, most domestic cow farms rely on manual observation to recognize cow behavior, and this recognition is based on empirical experiences. This method can only be used for small-scale cow husbandry and is not suitable for large-scale and intensive cow husbandry. The published data of “the 6th China Dairy Exhibition Conference” revealed that the national stock of cows had reached 14.6 million head as at the end of 2014, of which the large-scale husbandry units with cow stocks of more than 100 head account for 45%. Subjective manual observation cannot achieve fast and accurate cow behavior monitoring and has great demand in terms of labor force. To resolve the drawback of manual observation, domestic and foreign scholars have used IoT technology, which requires the installation of automatic sensor monitoring equipment, such as a triaxial accelerometer and Bluetooth equipment, on different body parts of the cow to perform real-time monitoring of physical signs and behaviors of cow at different stages of conception, and the recognition results have been very good. However, the methods described above are based mainly on invasive collection; furthermore, those methods are susceptible to environmental pollution, which can lead to signal transmission deviation and can indirectly affect the normal behaviors of cows and disturb the correct assessment of cow behaviors.

The infiltration of smart internet into animal husbandry makes image analysis technology more widely used in the field of small-scale husbandry, such as poultry husbandry[32-33]; however, the application of technology in large-scale husbandry (pig, cow, and sheep) is still rare. In this study, cow oestrus and hoof disease-associated behavior were monitored, and high-definition cameras were used to capture real-time cow movement behavior in the activity area, and the hoof and back features were captured on the ramp (s) of the milking parlor. Additionally, the most-recent-week cow activity was considered when issuing timely alerts on cow oestrus and hoof disease to reduce untimely breeding and the delayed treatment of hoof disease due to misjudgment, thus improving the productivity of the breeding caretakers and promoting the annual milk production, as well contributing to the continuous development of the entire cow husbandry industry.

## 2 Material and method

### 2.1 Test subjects and environment

Fengning County, Hebei Province, is a major dairy production county, and most small breeding units in the county have upgraded to modern ranch husbandry methods. This study used the Holstein cow in the Yinhe Ranch ecological breeding base in Fengning County in 2015 as the study subject. Breeding cow estrous monitoring can avoid the breeding delay caused by missed signs of rutting; estrous monitoring in lactating cows can avoid the lower milk production induced by rutting. Therefore, high-definition cameras and cow movement detection equipment were used to collect behavioral video data and activity data for 400 cows for the entire year of 2015 in cowsheds for breeding and lactating cows in real time for an analysis of rutting behaviors.

### 2.2 Test equipment

A Hikvision DS-2CD2155F(D)-I(W)(S), 5 MP day-night network dome camera was utilized in the test to collect cow behavior surveillance video in real time. The cow behavior image features are ensured to have sufficient clarity for use as the basis of subsequent image processing experiments.

A pedometer (Model: HEATTAG-002, Tianjin Sunbroad Software Co., Ltd.) was used in the test to obtain cow movement for monitoring rutting and rutting time. The total activity value in a milking time frame (the 2 h period between two adjacent readings) was obtained during the cow milking process, and the activity value in a time frame was compared with that of the same time frame in the past; if a cow's activity is much greater than the historical value of the same time frame, this cow could be rutting.

### 2.3 Test method

2.3.1 Content of dynamic monitoring of cow breeding in the different growth stages

Data collection and management for cow breeding are done in accordance with the different growth stages because a different monitoring focus is needed at the different cow growth stages. Using cow oestrus and hoof disease as actual examples, the real-time monitoring mostly concentrates on the cow activity area and the ramp(s) of the milking parlor. The key video frames pertaining to oestrus, hoof disease, and targeted cows are automatically extracted from a large amount of video surveillance content using the image entropy method. Combined with the activity data collected from the pedometer worn by the cows and a comprehensive consideration of the images of the features of cow physical signs and activity data, cow-hoof-disease and estrous behaviors are judged and used as alerts.

2.3.2 Intelligent analysis method for cow behaviors

Cow behavior recognition can be simply defined as the matching of test video sequences and predefined typical behavior features and the tracking of the behavior and behavioral change of the targeted cows in real time. Based on cow estrous- and hoof-disease-associated behavioral patterns, an assessment is made of whether the health and breeding of a targeted cow is affected.

To achieve real-time monitoring of cow behavior, the surveillance video contents collected by high-definition cameras deployed throughout the cow farm were analyzed. First, the identity of a targeted cow is extracted from the video contents; then, the activity of that cow is tracked to obtain continuous movement behaviors. Based on hoof disease and estrous behavior model matching, an alert will be issued when abnormal behaviors occur during the cow breeding process. The approach effectively saves time for the workers and enhances the management efficiency of large-scale husbandry.

1) Targeted cow extraction

Cows are animals that are bred in groups; to achieve effective analysis and identification of an individual cow's behaviors, a targeted cow needs to be located, and the relevant information needs to be first extracted from a huge amount of surveillance video contents. However, a cow is a moving object, and the method used to extract variation from the background images among the image sequences is the first problem that needs to be resolved.

Entropy can describe the aggregation characteristics of the grayscale distribution of an image, but it cannot reflect the spatial characteristics of the corresponding grayscale distribution; thus, this study combines a clustering algorithm with entropy for analysis. From the angle of the clustering pixels within the characteristic space, the image size will be $M\times N$, with a grayscale of $[0, L]$; therefore, if $n_i$ represents the number of pixels that have a grayscale value $i$, then the probability of the grayscale $i$ is:

$$P_i=\frac{n_i}{N} \tag{1}$$

If the threshold values are set as $T_1$, $T_2$, and $T_3$ and if the image grayscale is divided into three regions of target object $O$, sky $S$, and ground background $G$, then the average relative entropy of the three regions is:

$$E_O=-\sum_{i=0}^{T_1}\frac{P_i}{P_{T_1}}\ln\frac{P_i}{P_{T_1}},\ E_S=-\sum_{i=T_1+1}^{T_2}\frac{P_i}{P_{T_2}}\ln\frac{P_i}{P_{T2}} \tag{2}$$

$$E_G=-\sum_{i=T_2+1}^{L-1}\frac{P_i}{1-P_{T_1}-P_{T_2}}\ln\frac{P_i}{1-P_{T_1}-P_{T_2}} \tag{3}$$

where, $P_{T_1}=\sum_{i=0}^{T_1}P_i$, $P_{T_2}=\sum_{i=T_1+1}^{T_2}P_i$.

Let:

$$H_{T_1}=-\sum_{i=0}^{T_1}P_i\ln P_i,\ H_{T_2}=-\sum_{i=T_1+1}^{T_2}P_i\ln P_i,\ H_{T_3}=-\sum_{i=T_2+1}^{L-1}P_i\ln P_i \tag{4}$$

so the image entropy is:

$$E=\sum_{i=1}^{K}(\ln P_{T_i}+\ln P_{L-1})+\sum_{i=1}^{K}\frac{H_{T_i}}{P_{T_i}}+\frac{H_{L-1}}{P_{L-1}},\ K=3 \tag{5}$$

Therefore, the optimal threshold values are:

$$\begin{aligned}T_1&=\arg\max_{0\le T_1}(E_O)\\ T_2&=\arg\max_{T_1+1\le T_2}(E_S)\\ T_3&=\arg\max_{T_2+1\le L-1}(E_G)\end{aligned} \tag{6}$$

where, $T_1$ is the optimal threshold value of target object region O; $T_2$ is the optimal threshold value of sky region S; and $T_3$ is the optimal threshold value of ground background region G

To achieve effective segmentation of a targeted cow, the characteristic vectors in the image Euclidean space are clustered. As described above, they were clustered into three separated subset $X_O$, $X_S$, and $X_G$; in this image, if $x_l$, $x_m$, and $x_n$ are the arbitrary characteristic vectors:

$$x_l\in X_O,\ x_m\in X_S,\ x_n\in X_G \tag{7}$$

then the following must be satisfied:

$$\begin{aligned}\|x_l-v_O\|^2&=\min(\|x_l-v_S\|^2,\|x_l-v_G\|^2)\\ \|x_m-v_S\|^2&=\min(\|x_m-v_O\|^2,\|x_m-v_G\|^2)\\ \|x_n-v_G\|^2&=\min(\|x_n-v_O\|^2,\|x_l-v_S\|^2)\end{aligned} \tag{8}$$

where, $v_O$, $v_S$, $v_G$ are the average values of subset $X_O$, $X_S$, $X_C$, respectively.

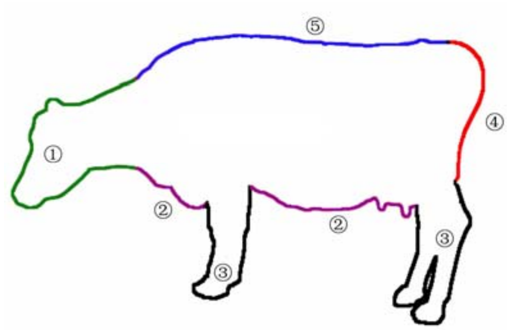
The image is then classified based on the above threshold values.

2) Typical cow behavior recognition

a) Image-based intelligent analysis of cow hoof disease

Cow hoof disease is one of the diseases to which cows are most susceptible in the cow breeding process; its susceptibility is second only to mastitis and reproductive system disease. Although the disease is a chronic process and will not lead to death, foot and hoof health is the foundation of high yield and general health of cows. Hoof disease not only can cause reduction in cow milk production but also can induce high elimination rates in the cows, which increases cow breeding costs.

A contour map model structure method was used in this research to divide the cow body contour into five modules, namely, head, abdomen, limbs, buttocks, and back, and an undirected graph was used to represent the connection among the modules. $R$ is the contour edge set. $V$={$v_1$, $v_2$, …, $v_5$} and $v_i$ ($i$=1,2,3,4,5) correspond to the five segments of a cow's contour, as shown in Figure 1. If $v_i$ and $v_j$ are connected, then ($v_i$, $v_j$)∈$E$.




Note: The item ① is the cow head contour, expressed in green; ② is the abdomen and neck contour, expressed in purple; ③ is the hoof contour, expressed in black; ④ is the buttocks contour, expressed in red; and ⑤ is the buttocks contour, expressed in blue.

Figure 1 Contour segmentation of a cow

The characteristics of the hoof disease appear as an arcing back, mainly reflected in the degree of bending of the back (body contour ⑤ characteristic), and obviously limping, mainly reflected in the angle between the hoof and the ground (body contour ③ characteristic). During walking, the angle between the center points (where the front and the back hoofs on the same side of the cow touch the ground) is $\alpha$, as shown in Figure 2. The hoof disease can be divided into the following four degrees according to the degree of back arcing and the angle between the hoof and ground, as shown in Figure 3.

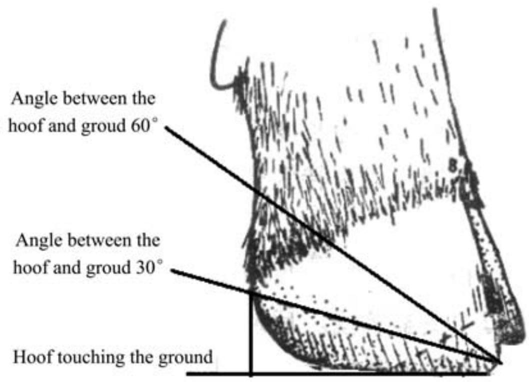
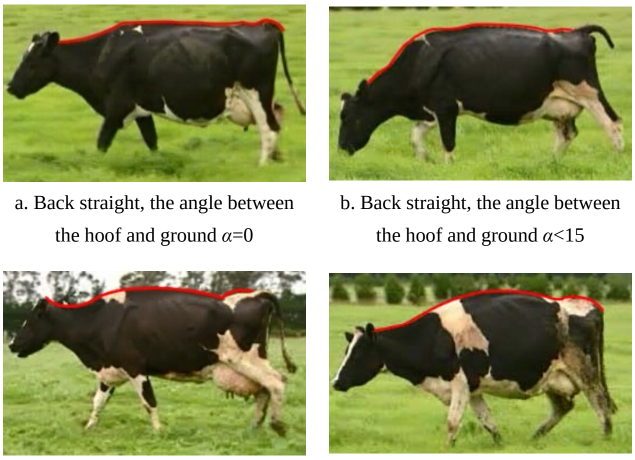



Figure 2 Distance from beef to ground



a. Back straight, the angle between the hoof and ground $\alpha$=0

b. Back straight, the angle between the hoof and ground $\alpha$<15

c. Back bent, the angle between the hoof and ground 30°<$\alpha$<60°

d. Back bent, the angle between the hoof and ground $\alpha$>60°

Figure 3 Four degrees of hoof disease

The angle between the hoof and the ground is difficult to obtain from video images; presently, the main monitoring method for hoof disease is to judge by the degree of back arcing.

b) Image-based intelligent analysis of cow estrous behavior

The best conception period of a cow is 12-24 h after oestrus; the typical characteristic is mounting (front hoof movement) and increases in activity, accompanied by feeding and milk reduction. Generally, the obvious characteristic behavior appears after 12 h of oestrus. The current manual surveillance cannot ensure continuous day-time monitoring, nor can it accomplish night-time estrous monitoring.

The mounting behavior of a cow is obvious; compared with images of normal behavior when cows are together, and the bounding box area containing the mounting behavior is different. Based on the above-mentioned image entropy method to recognize the targeted cow, this study calculates the intersection area between the minimum bounding boxes. Judgement of estrous behavior proceeds as follows in Figure 4.

The area of the minimum bounding box of the targeted cows can be obtained from image moment calculation. Let the 0-th moment $M_{00}$ be the area of the minimum bounding box:

$$M_{00} = \sum_{n=1}^{l}\sum_{n=1}^{w} I(x, y) \tag{9}$$

where, $I(x, y)$ is an arbitrary pixel in the minimum bounding box, and $l$ and $w$ are the length and width of the bounding box, respectively. Then, the coordinates of the center of mass of the rectangle $x_c$ and $y_c$ are:

$$x_c = \frac{\sum_{n=1}^{l}\sum_{n=1}^{w} xI(x, y)}{\sum_{n=1}^{l}\sum_{n=1}^{w} I(x, y)},\ y_c = \frac{\sum_{n=1}^{l}\sum_{n=1}^{w} yI(x, y)}{\sum_{n=1}^{l}\sum_{n=1}^{w} I(x, y)} \tag{10}$$

When the targeted cows in the surveillance video intersect, the center coordinates of the minimum bounding boxes of the targeted cows are calculated separately:

$$[(x_1, y_1),\ (x_2, y_2),\ (x_3, y_3), L] \tag{11}$$

The widths of the minimum bounding box are $w_1$, $w_2$, $w_3$, $L$, respectively.

Take $R = \min\{\sqrt{(x_i - x_1)^2 + (y_i - y_1)^2}\}$, where $i = 2, 3, L$; when $R < \min(w_i),\ i = 1, 2, 3, L$, the cow is suspected of oestrus.

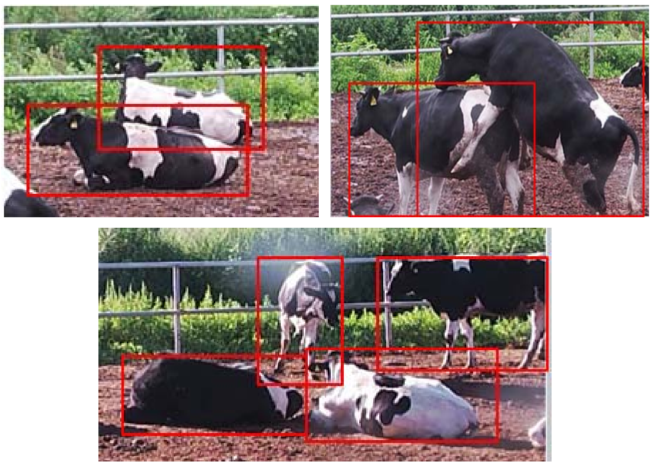


Figure 4 Cow intersection area

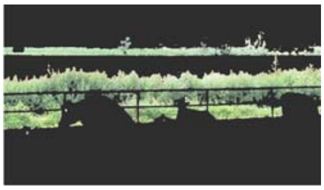
## 3 Results and analysis

To verify the practicability and reliability of monitoring of hoof disease and estrous behavior, surveillance videos for Holstein cow acquired from March 2015 to October 2015 were collected from the Yinhe Ranch in Fengning, Hebei. The video cameras focused on the cow activity area and collected real-time daily behavior of cows from the current monitoring screen on average every 10 min, then saved the behavior as a jpg. image. A single frame image size is approximately 45 kB, and more than 30 000 valid images of cows were obtained. Among those, 15 000 of the images (3476 images of estrous behaviors, 5217 images of hoof disease, and 6307 images of normal behaviors) were first manually identified and then auto-identified. At the same time, the pedometer devices were attached to the right hind leg of each cow to retrieve its real-time activity data.

### 3.1 Segmentation of the targeted cows

The targeted cows are segmented using the stated segmentation method based on image entropy to attain to targeted cows, as shown in Figure 5b, and the background image is shown in Figure 5c.


a. Original image



b. Object c. Background image

Figure 5 Object Recognition

### 3.2 Experimental analysis of cow estrous behavior

Among the 3476 estrous behavior images, 1800 of them were randomly selected as the training set to determine the range of the minimum intersecting area for evidence of oestrus through analyzing and comparing the calculated minimum intersecting areas of the image bounding boxes. Here, $w_i$ ($i$=1,2,3,4) is the shortest edge of the bounding boxes, and $l_i$ ($i$=1,2,3,4) is the longest edge of the bounding boxes. A, B, C and D are four bounding boxes, and $R$ and $R_i$ ($i$=1,2) are the distances between the centers of two intersecting bounding boxes.

Figure 6a and 6b show the minimum bounding boxes A and B intersecting, where the shortest sides of the two minimum bounding boxes in Figure 6a are $w_1$ ($w_1<R$); the shortest sides of the two minimum bounding boxes in Figure 6b are $w_1$ ($w_1>R$).

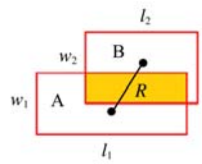
In Figure 6c, A intersects the two minimum bounding boxes B and D, where the shortest sides of the bounding box satisfy $w_1 = w_2$ and $w_1 = w_2 < R_1 < R_2$.

In Figure 6d, B intersects the two minimum bounding boxes A and D, where the shortest sides of the bounding box satisfy $w_1 = w_2$ and $w_1 = w_2 < R_1 < R_2$.

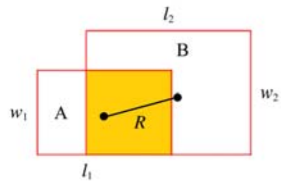
In Figure 6e, C intersects D, where the shortest sides of the bounding box are $w_4$ ($w_4 < R$).

In Figure 6f, D intersects B and C, where the shortest sides of the bounding box are $w_2$ ($w_2 < R_2 < R_1$).

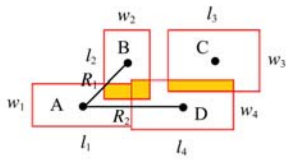
The estrous identification formula in Section 1.2.2 can be applied to determine the possibility of suspected oestrus in Figure 6b.



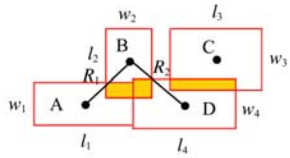
a. Bounding boxes A and B intersection $w_1<R$



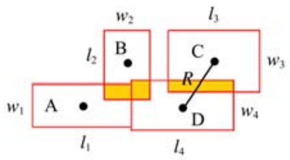
b. Bounding boxes A and B intersection $w_1>R$



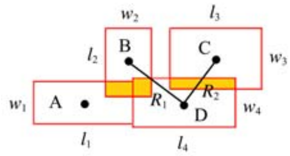
c. Bounding boxes A, B, and D intersection $w_1=w_2$, $w_1=w_2<R_1<R_2$



d. Bounding boxes A, B, and D intersection $w_1=w_2$, $w_1=w_2<R_1<R_2$



e. Bounding boxes C and D intersection $w_4$, $w_4<R$



f. Bounding boxes D, B, and C intersection $w_2$, $w_2<R_2<R_1$

Figure 6 Minimum bounding intersection

The preliminary inspection of suspected oestrus is carried out through the above-stated method. The activity data of 7 days in succession can be retrieved by means of the pedometer installed on the leg of each cow, and then, the activity data are statistically analyzed. If the activity suddenly increases and mounting behavior occurs, the cow is likely to exhibit oestrus within 24 h; if the activity level did not increase but mounting behavior occurs, the monitoring of activity level and mounting behavior need to be repeated.

### 3.3 Experimental analysis of cow hoof-disease-associated behavior

To effectively capture the cow hoof-disease-associated behavior, high-definition cameras were installed at the ramp (s) of the milking parlor where the cows enter to acquire close and real-time observation of the back and hoof features of each cow.

The degree of back curvature of each cow was matched with the four grades of hoof disease, and each curvature degree corresponded to a grade of hoof disease; this provides early warning of the appearance of hoof disease.

Since the angle between the hoof and ground was not considered, the determination of a hoof-disease grade based on the degree of back curvature alone is not an adequate method. In this study, the determination of the hoof-disease grade is based on the degree of back curvature and the activity of the cow; if the cow has hoof disease, its activity level will drop drastically within a week. Early stages of hoof disease can be detected through the combination of back feature imaging and the activity of the cow, and the progression of disease can be prevented with timely treatment to avoid a reduction in cow milk production.

The estrous behaviors and hoof-disease-associated behaviors of 200 dairy cows and 200 calves of Yinhe Ranch in Fengning, Hebei, were automatically identified. In addition, the recognition accuracy and missed detection rate were analyzed and compared with the results of the manual identification to verify the robustness of the autorecognition method, as shown in Table 1.

**Table 1 Accuracy analysis**

unit: %

| | Breeding cows | | Lactating cows | |
|---|---|---|---|---|
| | Autorecognition | Manual recognition | Autorecognition | Manual recognition |
| Oestrus | 0.867 | 0.977 | 0.852 | 0.963 |
| Hoof disease | 0.812 | 0.969 | 0.805 | 0.958 |

**Table 2 Miss rate comparative analysis**

unit: %

| | Breeding cows | | Lactating cows | |
|---|---|---|---|---|
| | Autorecognition | Manual recognition | Autorecognition | Manual recognition |
| Oestrus | 4.17 | 6.35 | 3.28 | 7.34 |
| Hoof disease | 5.32 | 8.21 | 6.29 | 6.87 |

As seen in Table 1, the image features of estrus and hoof disease are prone to feature-extraction deviation caused by shading and lighting factors; the accuracy of automatic identification of cow estrus and hoof disease is 0.8 or greater. However, due to the participation of experienced personnel, the manual identification accuracy of cow estrus and hoof disease is above 0.9. Although the automatic identification accuracy of estrus and hoof disease is slightly lower than that of manual identification, the automatic identification method can achieve 24 h uninterrupted monitoring to make up for what manual identification lacks in long-term observation. Furthermore, the miss rate of estrus cow and hoof-disease-associated behaviors was obtained through the analysis of video surveillance images. The automatic identification method has a miss rate of 6.3% or less, while manual identification, in contrast, has a greater miss rate due to visual and physical fatigue resulting from long-term monitoring. Therefore, a comprehensive analysis of this method can improve the identification efficiency of cow estrus and hoof disease-associated behaviors.

## 4 Conclusions

To resolve issues of subjectivity and the large workload required for the manual surveillance of cow behaviors, the video surveillance of estrous and hoof-disease behaviors at different stages of conception were analyzed. The study extracted the information of targeted cows based on the key techniques of targeted cow detection (based on image entropy) and classification and recognition of postures. The area of the minimum bounding boxes was calculated to capture real-time mounting behavior and the degree of back curvature of cows in the activity area. The study also collected the activity level via pedometers to issue alerts and early warning of abnormal behaviors due to estrus and hoof disease in the breeding process. The approach has a advantage of time-saving for husbandry caretakers and yields a high estrous and hoof-disease-recognition rate greater than 80%. In addition, the lowest miss rate of estrus reached 3.28%, and that of hoof disease was 5.32%. The results indicate the important application value of this approach for the improvement in efficiency of large-scale husbandry management and scientific research of healthy cow reproduction. In this paper, the collected behavioral images of cows via surveillance video were studied through comparison of the analyzed behavioral features to automatically identify estrous and hoof-disease-associated behaviors. However, the correlation between adjacent frames in the surveillance video was not considered here. Therefore, in future research, the time correlation of cow behaviors needs to be integrated by retrieving the behavioral features of a cow within a certain time, which can then serve as a behavioral model to improve the accuracy of behavior recognition.

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