Research Progress and Technology Trends in Intelligent Monitoring of Dairy Cow Locomotor Behavior: A Postprint

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Abstract

Dairy cow locomotor behavior contains substantial health information. The application of information and intelligent technologies assists farms in timely grasping the health status of dairy cows and improving farming efficiency. This paper primarily analyzes the research progress of intelligent monitoring technology for dairy cow locomotor behavior. First, it elaborates on the monitoring significance of basic behaviors (lying, walking, standing), estrus, respiration, rumination, and lameness, thereby clarifying the necessity of dairy cow behavior monitoring. Second, it reviews the current research status both domestically and internationally in chronological order from two aspects: contact-based monitoring methods and non-contact monitoring methods, providing a detailed introduction to the principles and achievements of related research and conducting a categorical summary. It also analyzes the current development status of the dairy cow behavior monitoring industry, introducing the main business and representative products of major foreign pasture automation equipment suppliers. Subsequently, it respectively proposes the problems and challenges of current contact-based and non-contact dairy cow locomotor behavior monitoring methods. Finally, it provides prospects for the development trends of related key technologies.

Full Text

Preamble

Research Progress and Technology Trends in Intelligent Monitoring of Dairy Cow Motion Behavior

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Abstract: Dairy cow motion behavior contains substantial health information. The application of information and intelligent technologies helps farms promptly understand cow health status and improve breeding efficiency. This paper analyzes research progress in intelligent monitoring technology for dairy cow motion behavior. First, it elaborates on the monitoring significance of basic motions (lying, walking, standing), estrus, respiration, rumination, and lameness, establishing the necessity of cow behavior monitoring. Second, it reviews domestic and international research chronologically from both contact-based and non-contact monitoring methods, detailing the principles and achievements of relevant studies with categorical summaries. The development status of the cow behavior monitoring industry is analyzed, introducing the main business and representative products of major international pasture automation equipment suppliers. Subsequently, current problems and challenges in contact and non-contact monitoring methods are presented. Finally, future development trends for related key technologies are discussed.

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1 Introduction

Dairy farming constitutes a vital component of animal husbandry. In 1978, China's dairy cattle inventory was merely 480,000 head, but by the end of 2020, it had reached 5.2 million head, with large-scale farms (over 100 head) accounting for 67.2% of operations [1-3]. Cow behavior represents responses to internal physiological changes or external environmental stimuli, directly or indirectly reflecting health and physiological status [4]. For instance, lying is the most prioritized daily behavior for dairy cows, with lying time positively correlating with milk yield—each additional hour of lying time increases milk production by approximately 1.7 kg [5]. During estrus, cows ovulate, and timely insemination is essential for successful conception and reproduction [6]. Additionally, normal respiratory and rumination frequencies are relatively fixed in healthy cows, and fluctuations may indicate abnormal conditions such as heat stress or disease [7,8]. When cows develop foot diseases, lameness often occurs, leading to reduced milk yield and reproductive capacity [9]. As dairy operations scale up, traditional manual monitoring methods have become inadequate due to low efficiency and unreliable accuracy, making intelligent monitoring of cow motion behavior an inevitable research direction [10].

Precision farming has emerged as a new development direction for dairy husbandry and represents an essential requirement for modernizing China' s dairy industry [11]. To clarify current research progress and technical bottlenecks in intelligent monitoring of dairy cow motion behavior, this paper focuses on monitoring basic motions (walking, lying, standing), estrus, respiration, rumination, and lameness. It summarizes research developments from both contact and non-contact monitoring perspectives, discusses industry development status, identifies existing problems based on research and industry conditions, and finally prospects future technology trends.

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2 Research Progress in Intelligent Monitoring of Dairy Cow Motion Behavior

Current monitoring methods for dairy cow motion behavior are primarily divided into contact-based and non-contact approaches. Contact-based methods rely on sensors fixed to different body parts to monitor various behaviors, as shown in Table 1 . Most contact methods utilize accelerometers, pressure sensors, and pedometers to obtain head, neck, and leg motion data, employing classification algorithms for behavior monitoring. For respiratory behavior, which features subtle and singular characteristics, sensors directly record abdominal fluctuations or nasal airflow patterns. Although some researchers have investigated temperature- and sound-based behavior recognition, these approaches face numerous interference factors that hinder practical application.

Non-contact methods include traditional video analysis, deep learning-based video analysis, sound signal analysis, laser ranging, and thermal imaging, as summarized in Table 2 . Traditional video analysis requires manual feature design, with thresholds set manually or through algorithmic learning to classify behaviors based on feature values, where manual analysis dominates. Deep learning-based video analysis collects large image datasets, annotates relevant behaviors, and employs data-driven networks to learn features automatically, enabling end-to-end learning without manual feature extraction. However, this approach demands sophisticated network design and sufficiently large datasets.

2.1 Monitoring of Basic Cow Motion Behaviors

2.1.1 Significance of Basic Motion Behavior Monitoring Basic dairy cow motion behaviors primarily include lying, walking, and standing. Research indicates that lying is the most prioritized daily behavior, with healthy cows requiring 10-14 hours of lying time per day. Each additional hour of lying time increases milk yield by approximately 1.7 kg [5]; reduced lying time may indicate uncomfortable bedding or estrus [56]. Similarly, abnormalities in standing and walking behaviors reflect important health information. Intelligent monitoring of basic motion behaviors is crucial for predicting cow health status and forms the foundation for recognizing advanced behaviors such as mounting and rumination [57].

2.1.2 Contact-Based Basic Motion Behavior Monitoring Methods Basic motion behaviors can be discriminated through activity levels and posture features, with accelerometers and pedometers being the most common contact-based monitoring methods. Yin et al. [12] installed a three-dimensional accelerometer on cow necks to record motion acceleration values across axes, using K-Means clustering to classify behaviors into stationary, slow walking, fast running, and mounting for health monitoring. While effective at distinguishing dynamic from static behaviors, this method showed limited ability to differentiate dynamic behavior subcategories. Jiang et al. [20] used pedometers to monitor activity levels in cows at different pregnancy stages across seasons, finding decreasing activity with advancing pregnancy months, enabling dynamic feed adjustment to improve farm efficiency.

Wang et al. [13] fixed accelerometers and RF transceivers to cow legs to obtain acceleration and location data, combining both data types using D-S evidence theory to classify seven behaviors (feeding, lying, standing still, lying down, standing up, normal walking, and active walking), achieving over 80% accuracy for each behavior and nearly 100% accuracy for lying down, walking, and standing. Hoang et al. [14] attached multi-dimensional accelerometers to neck collars, obtaining X, Y, Z-axis motion data and achieving 90.24% accuracy in classifying standing, lying, feeding, and walking behaviors using SVM. Balasso et al. [15] fixed accelerometers to cow flanks, extracting different features and using machine learning algorithms to classify postures and behaviors, achieving up to 99.2% accuracy for posture prediction and 75.9% for behavior prediction. Wang et al. [16] used neck-mounted accelerometers and location data with BP-AdaBoost to classify feeding, lying, standing, lying down, standing up, normal walking, and active walking, with most behaviors exceeding 80% accuracy.

In practical applications, contact sensors demonstrate high accuracy for basic motion behavior monitoring but show weak fine-grained discrimination between standing still and lying behaviors, requiring algorithmic improvements for better differentiation.

2.1.3 Non-Contact Basic Motion Behavior Monitoring Methods Non-contact monitoring of basic motion behaviors primarily relies on video image analysis, including optical flow and feature classification methods. With advances in big data and hardware, deep learning-based video monitoring methods have emerged. He et al. [36] proposed a boundary cyclic search method based on maximum connected regions to detect and extract calf targets, clustering basic calf behaviors (lying, standing, walking, running) using structural similarity, achieving recognition accuracies of 100%, 96.17%, 95.85%, and 97.26% respectively. Wu et al. [48] collected cow activity information through a remote monitoring platform, using the VGG16 framework to extract feature vector sequences for each video, then inputting these features into a bidirectional LSTM classification model to recognize five behaviors (lying, standing, walking, drinking, and rumination), achieving 97.6% average accuracy with feature extraction and behavior recognition times of 2.958 s and 0.712 s respectively, as shown in Figure 1 [Figure 1: see original paper].

Ma et al. [50] fed preprocessed video frames into a Rexnet 3D network to obtain feature vector space, using a Softmax network to classify lying, standing, and walking behaviors, achieving 95.00% accuracy in natural scenes at 76.52 f/s. Using a sliding window mechanism on unedited videos, they achieved 91.02% accuracy at 101.02 f/s. Qiao et al. [51] collected side-view videos of calves and adult cows, extracting 3D convolutional features from video frames, using convolutional LSTM to extract spatiotemporal features, and classifying five behaviors through a Softmax layer, achieving 90.32% and 86.67% accuracy for calves and adult cows respectively.

Since cow activities span multiple scenes, single cameras face limitations in fixed monitoring scenarios, creating spatial-temporal discontinuities for comprehensive behavior recognition. Additionally, target overlap and occlusion pose new challenges for continuous tracking and recognition.

2.2 Monitoring of Cow Estrus Behavior

2.2.1 Significance of Estrus Behavior Monitoring Timely estrus detection is crucial in modern dairy farming, enabling optimal insemination timing, reducing calving intervals, and improving farm profitability [58]. The primary estrus indicators include chasing, mounting, and vocalization [59]. Traditional manual monitoring methods, including vaginal examination and tail paint methods, are time-consuming, labor-intensive, and prone to missed detection. Consequently, researchers have proposed estrus monitoring methods based on multi-category sensors and big data mining technologies [60,61].

2.2.2 Contact-Based Estrus Monitoring Methods During estrus, both external behaviors and internal physiological features change significantly. External changes include increased activity and reduced lying time, while internal changes involve elevated body temperature and increased vaginal mucus secretion [62]. Contact sensors primarily record these physiological changes for analysis. Tian et al. [30] established a learning vector quantization neural network prediction model based on increased activity and reduced lying time during estrus, achieving over 70% accuracy in estrus prediction. Tan et al. [22] used AfiCollar pedometers to collect activity data including step counts, training an SVM model embedded in the Storm platform, achieving 98.9% average detection accuracy, 85.71% prediction accuracy, and 6-hour prediction cycles, though this method only considered activity data without temperature variations. Liu and He [29] designed a resistive sensor implanted in the vagina to monitor physiological resistance changes, achieving $±$2% measurement precision, over 98.5% data transmission success rate, and 38 days of continuous operation. Wang et al. [16] installed electronic tags on cow necks to obtain acceleration and location data, monitoring seven behavioral indicators including estrus using an optimized BP neural network with 14 hidden neurons and 0.1 learning rate, achieving 95.46% accuracy, 72.80% precision, 98.29% sensitivity, 95.08% specificity, and 83.65% F1-score for estrus detection.

Contact-based estrus monitoring enables 24-hour continuous monitoring of multiple physiological indicators with high accuracy through data fusion. However, high stocking density or lameness can affect activity measurements, and body temperature is significantly influenced by ambient temperature, reducing method accuracy.

2.2.3 Non-Contact Estrus Monitoring Methods Beyond activity and temperature changes, mounting behavior is the most prominent estrus indicator. Additionally, vocalization intensity and duration change during estrus [63], prompting research into sound- and image-based monitoring methods. Chung et al. [54] analyzed Korean native cow vocalizations, extracting Mel-frequency cepstral coefficients and using support vector data description for automatic estrus monitoring with over 94% accuracy. Tsai and Huang [34] observed mounting behavior from a top-view perspective in barns, noting regular changes in bounding box length around two cows, proposing a video monitoring method with 0.33% false positive rate when threshold was set to 0.7, though limited to indoor use. Gu et al. [37] used image entropy for target recognition, judging estrus by intersecting area between minimum bounding boxes of two cows during mounting, achieving over 80% accuracy with minimum miss rate of 3.28%, though without considering temporal correlation. Liu and He [46] used mounting videos as positive samples and others as negative samples, constructing a CNN model based on LeNet-5 that achieved 98.25% mounting behavior recognition accuracy with 0.257 s average processing time per image. Guo et al. [42] used color and texture-based background subtraction to detect cow regions, extracting geometric and optical flow features for SVM-based mounting recognition, achieving 90.9% average accuracy and 4.2% false positive rate. Xie et al. [45] collected side-view mounting videos, extracting minimum bounding rectangles and using KNN algorithm fusing width (W), height (H), and aspect ratio (Z) features, achieving 99.21% accuracy, though only effective for side-view mounting. Wang and He [49] improved YOLOv3 by optimizing anchor sizes, introducing Dense-

Block structures, and proposing a new bounding box loss function, achieving 99.15% accuracy, 97.62% recall, and 31 f/s processing speed for mounting image recognition. Figure 2 [Figure 2: see original paper] shows examples of geometric feature-based mounting behavior recognition.

Compared with contact methods, video-based estrus monitoring eliminates sensor installation, reduces costs, and avoids disturbing normal cow activities. However, studies show 62.1% of estrus occurs at night [64], where video quality is poor, making nighttime estrus monitoring challenging.

2.3 Monitoring of Cow Respiratory Behavior

2.3.1 Significance of Respiratory Behavior Monitoring Cow respiratory behavior is closely related to health status. Healthy cows have respiratory rates of approximately 12-28 breaths/min [65], and abnormal fluctuations may indicate disease, barn comfort issues, or environmental temperature problems [7,66,67]. Timely detection of abnormal respiratory frequency changes helps caretakers promptly address health issues. Traditional manual counting is time-consuming, labor-intensive, and inaccurate, making intelligent respiratory monitoring crucial for precision farming in large modern dairies.

2.3.2 Contact-Based Respiratory Monitoring Methods Due to the subtle nature of respiratory behavior, contact-based methods rely on high-precision sensors to monitor abdominal and nasal changes during breathing. Eigenberg et al. [24] used a belt to fix a thin-film pressure sensor on cow abdomens to record regular fluctuations and calculate respiratory rates, finding no statistical difference ($P = 0.45$) with manual measurements, though signals could weaken when exhaled gas temperature approached ambient temperature. Strutzke et al. [25] designed a differential pressure sensor device monitoring pressure differences between nasal exhalation and environment, calculating respiratory frequency with high correlation to manual counts ($r = 0.92$ during sleep, $r = 0.98$ when lying, $r = 0.99$ when standing). Milan et al. [32] fixed temperature sensors near nostrils to monitor air temperature changes, calculating respiratory rate from temperature signal oscillations. The device showed no statistical difference with manual measurements ($P = 0.45$), but signal strength could diminish when exhaled gas temperature was close to ambient temperature.

Contact-based respiratory monitoring provides accurate results but involves complex installation and maintenance, whether chest-mounted or noseband-fixed, significantly impacting feeding behavior and lying comfort, making practical application difficult. Figure 3 [Figure 3: see original paper] shows examples of contact-based respiratory monitoring methods.

2.3.3 Non-Contact Respiratory Monitoring Methods Non-contact methods cause less stress and have been explored using microwave radar, thermal imaging, and machine vision technologies. Pastell et al. [53] used laser ranging sensors during milking to perceive weak abdominal movements from respiration, extracting respiratory frequency to study stress responses, finding that extended milking intervals caused significant agitation and increased respiratory rates. Zhao et al. [33] collected video of cows resting in stalls, using optical flow to calculate relative motion speeds of pixels, screening respiratory motion points through cyclic Otsu processing, dynamically calculating velocity direction curve periods to determine respiratory frequency and abnormalities, achieving 95.68% detection accuracy and 89.06% anomaly detection success. Song et al. [43] obtained single-target cow lying videos, converting frames to HSV color space to extract cow targets and spot boundaries, then using Lucas-Kanade sparse optical flow for respiratory behavior detection with 98.58% average accuracy and 0.10-0.13 s frame processing time.

Jorquera-Chavez et al. [55] used a FLIR ONE thermal camera on smartphones to capture non-radiometric infrared videos of cow faces, calculating respiratory frequency from pixel intensity changes in nasal regions caused by breathing airflow, achieving correlation coefficient r = 0.87 with manual observations. Wu et al. [47] used Deeplab V3+ for target segmentation in video sequences, applied phase-based video magnification to amplify weak respiratory movements, then used Lucas-Kanade sparse optical flow to detect standing cow respiration with 93.04% average accuracy and 2.4 breaths/min average error. Wu [68] extended single-target to multi-target monitoring using YOLACT segmentation and CNN-bidirectional LSTM fusion to identify lying rest and standing rest states, achieving 95.42%, 91.33%, and 93.25% accuracy for lateral, standing, and mixed states respectively.

Non-contact respiratory monitoring using microwave radar and thermal imaging is costly and susceptible to environmental temperature effects. Due to the subtlety of respiratory behavior, video-based methods require cameras positioned close to cows, and cow movement interference affects accuracy, making practical implementation challenging.

2.4 Monitoring of Cow Rumination Behavior

2.4.1 Significance of Rumination Behavior Monitoring Rumination behavior contains substantial health information. Normal cows have relatively fixed daily rumination frequency and duration. Reduced or ceased rumination may indicate illness, such as heat stress or inflammatory reactions [8,69-71]. Timely rumination monitoring enables early detection and treatment of abnormalities, improving animal welfare and reducing farm losses.

2.4.2 Contact-Based Rumination Monitoring Methods Contact-based rumination monitoring fixes sensors near the mouth to detect regular changes during chewing, including sound and pressure patterns. Braun et al. [26] integrated pressure sensors into nosebands, analyzing regular pressure changes during chewing to calculate rumination counts, showing comparable results to direct observation. Pahl et al. [27] used pressure sensors to record feeding and chewing times for accurate intake estimation, finding average daily intake of

49.6$±5.1*kgandchewingtimeof*262±$48 min. Chelotti et al. [31] fixed microphones on necks to identify jaw movements for rumination and feeding detection, finding that a multilayer perceptron-based bottom-up foraging activity recognizer achieved F1 scores above 0.75 for both activities with fast computation, enabling portable device development. Shen et al. [17] fixed triaxial accelerometers to jaw centers to capture jaw movements, using KNN, SVM, and probabilistic neural networks, with KNN achieving 93.7% accuracy and 94.3% recall for rumination. Iqbal et al. [18] used AfiCollar accelerometer collars to monitor grazing and rumination in 48 cows over one year, showing strong correlations with manual observations (Pearson r = 0.91, concordance r = 0.71 for grazing; Pearson r = 0.89, concordance r = 0.80 for rumination), confirming accurate monitoring.

Current rumination and feeding monitoring methods are primarily based on accelerometers and pressure sensors with high accuracy but cannot identify chewing-biting composite behaviors during feeding [72]. Mouth-mounted sensors affect feeding, cause stress responses, reduce rumination, and are prone to damage from contact with feed and rails.

2.4.3 Non-Contact Rumination Monitoring Methods Non-contact methods use cameras to capture videos and track mouth regions for rumination recognition. Chen et al. [38] used Mean Shift algorithm to track mouth regions, extracting centroid trajectory curves for intelligent rumination monitoring with 92.03% average accuracy, unaffected by head raising or turning. Song et al. [73] proposed a Horn-Schunck optical flow method for multi-target mouth detection, segmenting and superimposing regions with large optical flow changes to detect ruminating cows, achieving 66.7% success for two-cow detection and 83.3% for single-cow detection. Song et al. [40] used kernel correlation filtering to track multi-target mouths, drawing rumination curves from tracking box centers to calculate chewing counts, achieving 7.37 f/s multi-target tracking speed, 10.11 f/s dual-target speed, and 7.72% average false detection rate for dual-target chewing counts. Bezen et al. [74] designed a computer vision system using CNN and RGB-D cameras, achieving mean absolute error of 0.127 kg and mean square error of 0.034 kg^2 for intake measurement, working well under non-specific lighting without retraining for different barns, though limited to single-cow monitoring and unable to identify discarded feed.

Video-based rumination monitoring offers advantages but faces challenges: (1) most methods are limited to single targets, requiring multi-target synchronous monitoring algorithms; (2) small rumination motion amplitude demands high algorithmic precision for accurate tracking and segmentation.

2.5 Monitoring of Cow Lameness Behavior

2.5.1 Significance of Lameness Behavior Monitoring Lameness refers to abnormal gait caused by foot diseases or other factors. Pain makes cows reluctant to stand or walk, affecting normal physiological activities, reducing milk yield and reproductive performance, and potentially causing premature culling [9,75,76]. In modern dairy farming, lameness has become the second most common disease after mastitis [77], severely impacting farm economics. Early to mid-stage lameness detection and treatment are therefore critical.

2.5.2 Contact-Based Lameness Monitoring Methods Lameness increases lying time and reduces activity while altering gait characteristics. Contact-based methods primarily target these features. Jiang et al. [21] used pedometers to monitor 1,280 cows for one year, finding that foot disease significantly affected step counts, enabling effective early detection. Haladjian et al. [19] fixed wearable motion sensors to left hind legs, recording initial walking data to establish baseline gait models for classifying subsequent gait as normal or abnormal with 91.1% accuracy. Taneja et al. [23] used remote pedometers with fog node data aggregation and cloud-based hybrid clustering-classification models, detecting lameness three days earlier than manual observation with 87% overall accuracy.

Contact-based lameness devices are typically ankle-mounted, prone to detachment and contamination from manure and bedding, affecting lifespan and accuracy. Commercial leg pedometers require complex procedures, specific left-right leg placement, and regular inspection and adjustment [78]. Pressure walkway devices require additional large installations that should minimize space usage or integrate with existing facilities.

2.5.3 Non-Contact Lameness Monitoring Methods Foot diseases cause inflammatory responses that increase local blood flow and temperature, enabling thermal imaging detection [79,80]. Machine vision can also analyze back curvature, head-neck slope, and hoof tracking features for lameness detection. Zhao and He [35] used K-Means for automatic lameness classification from walking videos, achieving 91.15% overall accuracy and 100% severe lameness detection. Wen et al. [39] performed spatiotemporal interest point detection on side-view walking videos, applying secondary detection on dense trajectory maps, fusing features, and using sparse overcomplete dictionary learning with conjugate gradient tracking for semantic feature description, achieving 92.7% online lameness recognition accuracy. Song et al. [41] decomposed walking videos into image sequences, segmented target regions, extracted anterior body pixel areas and upper body contour lines, fitted slopes, and used KNN for lameness detection with 93.89% accuracy. Kang et al. [44] proposed a spatiotemporal interpolation algorithm based on the phenomenon that healthy cows' hind hoof landing points are close to ipsilateral front hoof points, accurately locating hoof positions, reorganizing and matching motion data to detect lameness with 93.3% detection accuracy and 77.8% severity classification accuracy. Jiang et al. [52] processed side-view walking frames, extracting back position coordinates and pixel regions, combining them to extract back curvature data, and using noise+bidirectional LSTM to predict curvature features for lameness classification with 96.61% average accuracy.

Thermal imaging-based lameness detection requires clean, dry hooves and is susceptible to ambient temperature. Vision-based methods typically require cameras in walkways, where hoof detection is affected by rail occlusion, and early-stage lameness features are subtle, making recognition difficult.

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3 Development Status of Dairy Cow Motion Behavior Monitoring Industry

Due to early sensor technology adoption, contact-based monitoring devices were developed earlier and have achieved commercial success. Most existing products are contact devices, such as Afimilk' s AfiActll Tag leg pedometer and AfiCollar neck pedometer, Allflex electronic ear tags, and COWLAR smart collars (Figure 4 [Figure 4: see original paper]).

Afimilk, a leading global pasture information management solutions provider, offers the AfiActll Tag leg pedometer containing 3D acceleration spiral sensors and timers that collect activity, lying time, and standing/lying frequency data, transmitting them to terminals at set intervals for software processing to detect estrus and other events, while also monitoring comfort, calving 预警, and cow identification [81]. COWLAR' s smart collar monitors temperature, activity, rumination, and step count, transmitting data via routers and cellular connections to servers for machine learning and big data analysis, automatically sending health information and recommendations to farmers' smartphones [82].

For grazing operations, New Zealand' s Gallagher developed the eShepherd neckband using GPS for real-time positioning, allowing farmers to draw virtual fences on terminals that trigger audio cues or electrical stimuli when cows approach boundaries, with studies showing cows adapt to the system after training [83].

Table 3 lists major international livestock farm automation equipment suppliers and products, showing mature industrial systems in developed countries where companies have integrated big data, cloud computing, IoT, AI chips, and robotics into "smart pasture" construction, developing comprehensive solutions including smart management systems, precision feeding, health monitoring, intelligent milking, milk preservation and transport, and environmental control systems, promoting precision livestock farming. However, recent non-contact monitoring methods from academia have not been widely applied commercially, indicating significant development potential. While China' s animal husbandry has progressed considerably, gaps remain compared to developed countries, with fewer domestic equipment suppliers and heavy reliance on imports.

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4 Limitations of Monitoring Methods and Technology Trends

4.1 Limitations of Contact-Based Monitoring Methods

As the first commercially applied devices, contact-based monitors have revealed several issues during practical promotion:

(1) Existing devices (neck collars, leg pedometers, ear tags) rely on high-precision sensors, making them costly and difficult to install. Leg pedometers require complex installation procedures with specific positioning and tightness requirements. Post-installation, regular manual inspection is needed; if pedometers slip below the small toe, they must be cut off and reinstalled [78]. For large farms, installation and maintenance pose significant manpower and material challenges.

(2) As foreign objects, contact devices affect cow comfort. For example, first-lactation heifers' hooves continuously grow, requiring pedometer removal during dry periods to prevent constriction [78]. When debris accumulates between pedometer straps and hooves, abrasion can cause lameness. Thus, contact devices can induce stress responses, reducing behavior recording accuracy or causing disease.

(3) Dairy farms have abundant contaminants where manure and feed accumulation affect devices. Daily activities cause scratches, moisture infiltration, and weather damage, reducing sensor lifespan.

(4) Current devices are typically single-function, monitoring only one physiological indicator or behavior. Monitoring multiple behaviors requires multiple sensors, which is impractical.

4.2 Limitations of Non-Contact Monitoring Methods

Non-contact monitoring offers simple installation without causing stress, attracting increasing research attention. With big data and hardware acceleration, computer vision-based methods have emerged. However, due to short development time, several challenges remain:

(1) Unlike industrial assembly lines, vision-based behavior recognition in agriculture faces greater challenges from complex lighting, weather, occlusion, interference, and self-motion. Song et al. [43] found that occlusion and vigorous movement reduced respiratory monitoring accuracy.

(2) For data acquisition and processing, traditional image-based methods require manual feature extraction with low efficiency and accuracy. Deep learning requires large datasets where quality directly affects model accuracy, demanding substantial human resources for collection and annotation. For computer vision-based lameness scoring systems, subjective annotation also reduces automatic scoring accuracy [85].

(3) Most vision-based methods for feeding, rumination, respiration, and lameness remain in laboratory stages, with some algorithms only effective in specific studied environments, lacking universality, robustness, and precision.

4.3 Technology Trends

Intelligent monitoring of dairy cow motion behavior is key to precision farming, with both contact and non-contact methods being important for improving welfare, efficiency, and reducing losses. Future research should focus on:

(1) **Miniaturization and integration of contact devices.** Contact sensors should become smaller, lighter, and more functionally integrated while considering manufacturing costs and lifespan for large-scale modern farms. However, cow stress responses require further investigation.

(2) **Improving computer vision robustness.** While existing algorithms perform adequately in laboratories, robustness and accuracy must improve for real farm environments. For special scenarios requiring edge computing deployment, algorithm lightweighting is essential.

(3) **Multi-target monitoring with limited equipment.** Video-based methods mostly remain at single-target monitoring with high costs. Future research must address how to monitor more cows with limited equipment.

(4) **Promoting technology commercialization.** Commercial applications require not only accurate behavior monitoring but also precise individual identification, abnormal cow tracking, and alert generation. Behavior recognition is only one component; integrating technologies into closed-loop management systems is necessary for marketization. Since emerging industries require substantial early investment, cost control is critical to maximize benefits while meeting commercial functions.

As society develops, global agricultural employment is declining with increasingly prominent labor aging, particularly in China. Although China’ s livestock industry has achieved preliminary scale and intensification, gaps remain compared to developed countries. Achieving low-cost, multi-functional, miniaturized animal information collection and diagnosis, developing agricultural robots to replace manual labor, and designing real-time multi-link data acquisition, dynamic aggregation, comprehensive sharing, and highly integrated information analysis and decision-making systems still face numerous challenges. Integrating IoT, big data, AI, and intelligent equipment with robotics to achieve more thorough information perception, deeper intelligent regulation, and more comprehensive interconnectivity represents the core of future smart animal husbandry development and the key to transforming China from a major livestock country to a powerful one.

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Note: Figure translations are in progress. See original paper for figures.