Postprint: Application of Image Information Technology in Dairy Cattle Production

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Abstract

The high costs and low efficiency of dairy cattle farming impede the development of the domestic dairy industry. Image information technology can enable production managers to evaluate dairy cattle health status and production needs more objectively and effectively, reduce animal stress, and enhance the level of intelligent farm management. This paper reviews the imaging principles of visible-light cameras, thermal imaging cameras, and depth cameras, evaluates the application methods and effects of image information technology in dairy cattle production, compiles research progress on image vision systems in areas such as body weight measurement, body condition scoring, animal body temperature monitoring, gait scoring, feed intake measurement, and lying behavior monitoring, and discusses the performance of vision systems in terms of accuracy, sensitivity, and error. This technology can be applied to daily herd observation by farm managers in preparation for future fully automated farm construction.

Full Text

Application of Image Information Technology in Dairy Cow Production

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Abstract: High costs and low efficiency hinder the development of China' s dairy industry. Image information technology can help production managers evaluate dairy cow health status and nutritional requirements more objectively and effectively, reduce animal stress, and improve intelligent farm management. This review describes the imaging principles of visible light cameras, thermal imaging cameras, and depth cameras, evaluates the application methods and effectiveness of image information technology in dairy production, and summarizes research progress on image vision systems in body weight measurement, body condition scoring, body temperature monitoring, gait scoring, feed intake measurement, and lying behavior monitoring. The performance of these systems in terms of accuracy, sensitivity, and error is discussed. This technology can support daily herd observation by farm managers and prepare for future fully automated farm construction.

Keywords: dairy cow; image information technology; production management; application

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1 Camera Classification

Animal image detection and classification represent two core challenges in image recognition. When animals pass through specific locations, the system automatically identifies individual information and captures photographs, which are then transmitted to a computer. Different model algorithms extract features for image classification to determine the final recognition result [Figure 1: see original paper][6]. Image recognition constitutes the first step in image information digitization, and different objectives require selecting appropriate cameras for image acquisition. Based on recent literature, three main camera types are used in ruminant production: visible light cameras, thermal imaging cameras, and depth cameras.

1.1 Visible Light Cameras

Visible light cameras are two-dimensional imaging devices that capture images by absorbing visible light wavelengths and utilizing sunlight illumination [7], such as common surveillance cameras. Applications for observing daily animal production are widespread, including monitoring both animal behavior and staff operational protocols in dairy barns. During experiments, appropriate images can be selected from collected footage based on color, shape, and structural characteristics, and corresponding algorithms can extract and quantify image features [5]. Visible light cameras can capture the three primary colors (red, blue, green) of target objects, and different image processing techniques can convert this color information into grayscale, hue, saturation, and other parameters. In ruminant production, visible light cameras are used to monitor body weight, body condition scoring, lying behavior, and lameness [8].

1.2 Thermal Imaging Cameras

Thermal imaging cameras operate on principles similar to visible light cameras, focusing lens energy onto a series of sensors to generate images [Figure 2: see original paper]. These cameras obtain information by receiving and measuring thermal radiation from objects, producing intensity images where each pixel's intensity value relates to the thermal energy reaching the photosensitive electronic components. Target animals emit infrared radiation, and higher temperatures produce greater emission intensity, resulting in brighter images. While visible light cameras detect shorter wavelengths (0.32–1.30 m), thermal imaging cameras can detect wavelengths of 3–14 m from target objects [9]. Thermal imaging cameras have been widely applied in industrial, agricultural, and military fields, and are used on dairy farms to evaluate animal energy requirements, monitor health status, and observe daily behavior. Early reports indicated low correlation coefficients (0.47) between thermal imaging features and beef cattle fat thickness and backfat because effective frames were manually selected from videos. However, recent research demonstrated that fully automatic thermal imaging recorders achieve correlation coefficients up to 0.94 [10].

1.3 Depth Cameras

Benefiting from rapid technological advancement, depth camera technology has developed significantly over the past decade and become commonplace in daily life. Depth cameras serve as core components in many vision systems, such as Time-of-Flight (TOF) technology and Kinect sensors. TOF sensors emit modulated near-infrared light that reflects off objects; the sensor calculates the time difference or phase difference between emission and reflection to determine distance and generate depth information [Figure 3: see original paper]. Combined with conventional camera imaging, this produces topographic maps presenting object three-dimensional contours with different colors representing different distances [11]. Depth cameras can overcome systematic limitations of visible light and thermal imaging cameras, such as lack of background removal functionality, inability to automatically extract effective features, and sensitivity to lighting conditions. However, TOF cameras are limited by video capture duration, number of data points in images, and relatively narrow field of view. The Kinect sensor, developed based on TOF technology, can build real-time image models through software integration without requiring calibration [12]. Compared with two-dimensional images, depth image information provides three-dimensional data. While two-dimensional images require obtaining feature points for information extraction, Kinect sensors can capture key image information in real-time without marking numerous feature points [13]. Although depth cameras are not sensitive to color resolution, they can fully capture shape details, making them particularly suitable for shape-based observation indicators in dairy production, including body condition scoring, conformation scoring, and lameness scoring.

2 Application of Image Information in Production

To promptly monitor individual animal condition in dairy herds without affecting production status, farms can employ image technology to identify animals with special conditions. Research has shown that body weight and condition reflect different physiological health statuses, and image acquisition technology can infer various physiological indicators to guide production.

2.1 Body Weight

Animal body weight is a crucial production indicator closely correlated with other physiological and production states, including feed conversion efficiency, feeding consistency, age, health status, and culling requirements. However, weighing animals is labor-intensive for workers and increases animal stress. Image acquisition technology was initially applied more extensively in pig production, where top-view images were used to extract features including area, perimeter, eccentricity, axis length, and boundary position to estimate body weight [14-15]. For ruminants, body condition features can be extracted from top and side views, such as hip height, body length, and chest circumference, combined with multivariate general linear models to predict body weight. Stajnko et al. [16] used near-infrared cameras to estimate beef cattle weight through side-view image acquisition, accurately capturing individual features from the hip joint posteriorly to below the scapula. However, correlation coefficients between near-infrared cameras and body weight varied widely, ranging from 0.11 to 0.74 across different age groups. Buranakarl et al. [17] compared various measurements in water buffalo including body height, chest circumference, shoulder width, ilium width, ischial tuberosity width, and body diagonal length, using stereo cameras to obtain three-dimensional images and calculating a correlation coefficient of 0.81 with actual body weight. In Anglart' s [18] study using 3D technology to estimate body weight, the highest correlation coefficient between camera measurements and weight reached 0.87.

2.2 Body Condition Scoring

Body condition scoring (BCS) reflects energy utilization in dairy cows and serves as an important indicator of productivity, health status, and reproductive potential. Dairy farms typically require regular BCS assessment [19], traditionally performed by experienced managers through visual observation and palpation, yielding subjective results. Image acquisition methods now enable objective, accurate, and rapid BCS evaluation. Early researchers used visible light cameras to sample herds, manually identifying dairy cow conformation feature points

[FIGURE:4-A], then positioning cameras directly above cows to capture frames and determine sample feature locations. The sacral-to-hip region is typically selected, with the tailhead depression and hip angularity serving as key observation points [FIGURE:4-B]. When measuring only hip angularity, BCS estimates achieved 100% accuracy within a 0.50-point error range and 92.79% accuracy within a 0.25-point range [20-21]. However, this method cannot utilize complete image information, primarily relying on pre-set feature locations to extract and analyze corresponding position data from high-resolution images.

Compared with partial information processing in visible light cameras, depth cameras can improve BCS accuracy by capturing complete image information, as they detect three-dimensional stereoscopic information and are more sensitive to subtle shape changes. Depth cameras require capturing 90–120 frames, extracting the same dorsal posterior region to ensure consistency in analyzed areas and identical numbers of three-dimensional sample points, then selecting optimal formulas for calibration. The calibration process standardizes three-dimensional image dimensions by superimposing analyzed region surfaces to find consistent surface sizes, thereby eliminating effects of individual shape and size variations. A coordinate system is established in the determined 3D image with the sacral line as the X-axis, tailhead midline as the Y-axis, and their orthogonal intersection as the Z-axis for image calibration [Figure 5: see original paper][22-23]. Fischer et al. [23] found that after comparing manual BCS measurement (standard error 0.210), the depth camera method was more accurate (standard error 0.075). Spoliansky et al. [24] reported a coefficient of determination of 0.75 with standard deviation less than 0.33, demonstrating good repeatability using a simple 3D camera, proving that depth cameras can be widely applied in commercial dairy farms.

2.3 Health Status

Early disease detection and abnormal behavior identification can effectively improve production efficiency, reduce costs, and decrease mortality rates. Thermal imaging technology can directly detect animal body temperature to identify individual surface temperature abnormalities early. For example, mastitis is a common disease where cameras capture and analyze udder surface images to judge temperature elevation [25]. Recent research found that thermal imaging cameras can detect parasites attached to cattle surfaces, as louse and fly eggs on cow bodies appear in top thermal maps [26]. Although image analysis technology can monitor animal health, many obstacles remain for health observation through body surface temperature, including animal surface cleanliness and distance between lens and measured object.

Image analysis technology can visually identify lameness in modern dairy farms. Lameness increases cow stress levels, reflects management deficiencies, and severely affects production efficiency in free-stall operations. Current farms apply lameness scoring to identify severity by observing standing posture and gait movements, as hoof pain causes unstable standing or abnormal gait during locomotion. Researchers have developed automatic lameness vision systems using different tools. Visible light cameras can predict and detect lameness by separating cow limbs in different directions based on distances between four hooves in images, determining center points, marking fore and hind limbs, and presetting horizontal and vertical coordinate axes [27]. Pluk et al. [6] combined pressure sensor data on sacral position, enabling automatic computer calculation of angles between limbs and ground during locomotion [Figure 6: see original paper]. The correlation coefficient between visible light camera gait images and lameness scoring reached 94.8%. Three-dimensional depth cameras also show good application results in monitoring dairy cow lameness. Jabbar et al. [14] found that depth cameras could detect 100% of lame cows in gait asymmetry monitoring, with lameness scoring accuracy reaching 95%. After image acquisition, the system automatically removes backgrounds, with different depth colors reflecting varying back heights. Following image processing, lameness feature data is extracted and matched [Figure 7: see original paper]. While this method achieved 100% sensitivity for lame cows, it produced 25% false positive rates in normal herd monitoring.

2.4 Other Applications

Other important observation indicators in ruminant production include feeding, drinking, and lying behaviors, which reflect farm management levels and animal welfare, directly affecting production performance such as milk yield and daily weight gain. Traditional feed and water intake detection relies on farm managers' daily observations to judge normality and determine feeding amounts based on experience. Image analysis technology can record dairy cow feeding behavior. Porto et al. [5] and Viola et al. [28] positioned multifunctional cameras above feeding areas to capture images, applying the Viola-Jones algorithm from facial recognition technology to calculate individual cow feed intake. The method identifies feed intake for only one cow per image, with neighboring cows deleted as background, achieving 87% sensitivity compared to traditional methods.

Lying behavior reflects stall comfort and cow health, affecting farm production efficiency. Cangar et al. [29] installed visible light cameras above stall center points, establishing coordinate axes based on animal back geometry to calculate back area and movement distance during standing to distinguish standing from lying behavior, achieving 85% accuracy. Porto et al. [30] upgraded to panoramic cameras using the same Viola-Jones algorithm, improving lying behavior observation accuracy to 92%. This method has minimal lighting requirements, with little impact from natural or artificial light.

3 Application of Image Information Technology in China' s Dairy Production

Compared with mature farm information management systems abroad, China' s application of image information technology in dairy farming remains in its infancy, with related research still in laboratory exploration stages. Main research directions include conformation evaluation in genetic breeding, body condition scoring selection, and individual cow identification, all showing promising results. For example, Huang et al. [31] developed image recognition software for dairy conformation detection based on Lab View virtual instrument platform and IM AQ Vision image processing package, achieving 90% accuracy. Similar reports show that whether using 2D or 3D cameras with different recognition algorithms, image feature extraction in dairy linear conformation evaluation demonstrates good application prospects [32-33]. Additionally, Liu [34] evaluated the feasibility of image information technology in dairy BCS application, but accuracy was only 57-62%. In Wang' s [35] study using 3D image technology for BCS analysis, limited feature extraction numbers affected final accuracy and stability. Due to disciplinary limitations, current integration of image information technology with dairy production in China has only been conducted in information engineering fields, with few reports from ruminant nutrition research teams, resulting in singular technology application. Other important but technically feasible production indicators still require extensive work, such as application methods and effects of image information management systems in lameness scoring, udder evaluation, and feeding behavior monitoring. Furthermore, current domestic research on the relationship between images and dairy BCS remains insufficient, with accuracy and stability in practical application needing improvement.

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4 Summary

Image vision systems can improve farm management levels, enabling more rational and effective allocation of limited resources while facilitating health monitoring and animal welfare. Currently, most camera-based vision management systems in dairy farms use visible light cameras, covering animal behavior observation, body condition scoring, feed intake, lying behavior, and gait scoring. Thermal imaging cameras effectively monitor body temperature, while depth cameras provide more accurate body condition scoring. Future vision systems must overcome environmental variations affecting image interpretation, as lighting and measurement distance significantly impact result accuracy. Additionally, algorithms must automatically adjust according to different farm conditions; for example, growing heifers show substantial conformational changes, and the same algorithm cannot accurately calculate body condition scores and weight across all growth stages. Future image vision systems could enable automatic grouping, feeding, culling, peripartum management, health assessment, and comfort facility construction based on image analysis results, providing technical support for fully automated farm management.

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