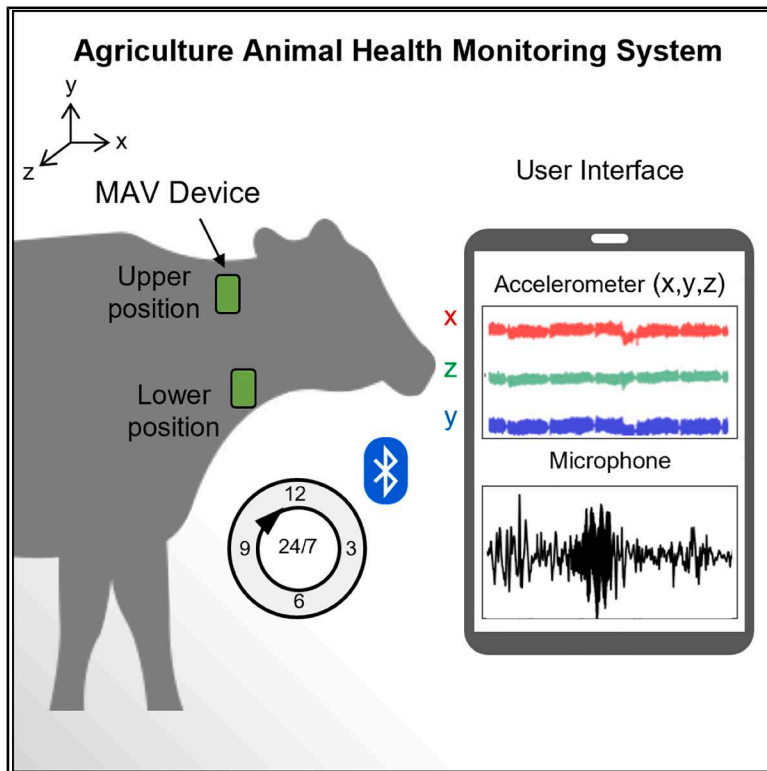


Monitoring bovine health using wireless mechano-acoustic biophysical sensors

Graphical abstract



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In brief

Kwak et al. present a lightweight, body-mounted mechano-acoustic and vibration sensor that enables continuous, real-time monitoring of bovine health. The system supports early detection of illness and reduces the labor and stress associated with herd-wide checks. The platform allows farmers to track multiple animals simultaneously, offering a practical and scalable solution for livestock management.

Highlights

- Wireless, real-time monitoring of health signals in multiple bovines within a herd
- High-specificity, high-accuracy sensing as the basis for precision livestock farming
- A user-friendly, easy-to-deploy system enabling farmers to monitor bovine health
- Multi-modal analysis of activities and physiological processes using a single device



Validate

Functional device with real-world testing, ready to scale



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Article

Monitoring bovine health using wireless mechano-acoustic biophysical sensors

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THE BIGGER PICTURE The dairy industry faces economic and animal welfare consequences when health issues of the herd are not detected promptly. A device that monitors the health of each bovine can improve procedures in animal care and help manage farming operations by tracking measurements such as rumination time and chewing rates. When these values fall outside their normal ranges, they can serve as early indicators that intervention may be needed, such as isolating the affected animal or performing a veterinary examination. In this work, we designed and tested a surface-mounted device that yields real-time, multi-modal information on the health of multiple bovines within a herd. The device tracks key biological signals related to activity, behaviors, and vital signs, and helps farmers avoid unnecessary examinations, reducing labor costs, minimizing stress on the animals, and supporting informed care decisions.

SUMMARY

Cost-effective methods for monitoring the behavior and health status of animals in agricultural settings can help detect early signs of disease, track feeding behaviors, and manage environmental impacts. Existing technologies that support precision livestock farming guided by such information fail, however, to provide comprehensive, accurate, and individualized data across multiple animals. In this work, we present a body-mounted wireless sensor that allows continuous tracking of motions and sounds associated with animal behaviors and physiological processes in formats capable of revealing aberrant activities and/or health problems, such as reduced rumination associated with rumen dysfunction or altered resting behavior suggestive of early lameness. As demonstrated with dairy cows in an operating farm environment, the use of this device with advanced data analytics approaches offers features of broad utility in animal care.

INTRODUCTION

For all of the 250 million dairy cows that exist worldwide, proper management of welfare, care, and ecological impacts on soil, water, air, and biodiversity relies on monitoring herd health and behaviors.¹ Assessment methods such as visual observations and intermittent physical examinations, while relatively low cost, accessible, and effective in identifying overt clinical signs,

depend critically on the skill, experience, and consistency of the observer.² For the management of larger herds, these methods are time consuming and labor intensive. Furthermore, detection of subclinical conditions can require cumbersome, invasive procedures that place additional stress on the animals and can fail to provide quantitative information for evaluations.³

Recent advances in this context, and more generally in management of animals in agricultural settings, involve the use of



wearable or implantable electronic sensors or video surveillance methods^{4,5} as technologies for precision livestock farming (PLF). The goals are to enhance specificity and reliability, with reduced frequency of manual health assessments. Video tracking for continuous monitoring of physical movements can provide early indicators of individuals that require clinical support by using real-time data to inform decisions associated with the herd, housing, climate, and feed.⁶ Body-mounted devices that include accelerometers can capture relevant features to assess the well-being of the animals, such as increased resting behavior commonly associated with lameness, offering metrics of activity levels and indicators of bovine reproductive performance.^{3,7} Thermal sensors can provide insights into peripheral and body temperature for identifying health deterioration and physiological disturbances.⁸ Despite these and other examples, current technologies remain comparatively narrow in comprehensive data on health status, especially when benchmarked against analogous monitoring approaches for human subjects in hospital settings. These shortcomings arise mainly from limited sensing capabilities, as well as poor stability and reliability in operation under various challenging scenarios that routinely occur in housing, feeding, and other basic operations involved in animal care and natural behaviors.^{9–14} This situation motivates the development of technologies that can function effectively in this context to yield quantitative physiological metrics of health status and detailed behavioral patterns. Measurements from devices of this type could enable data-driven methods for monitoring, predicting, and improving the transport, training, and care of animals.

Here, we introduce a wireless, body-mounted mechano-acoustic and vibration (MAV) sensor that can track a range of activities and vital signs, independent of practitioner expertise and environmental variability, with accuracy and specificity. This platform includes a high-bandwidth, triaxial accelerometer and a broadband vibration microphone to capture mechanical and acoustic (i.e., mechano-acoustic) parameters of the behavior and health status of the animal. The MAV sensor integrates multiple sensing modalities into a single device for health assessment and disease prediction. The MAV sensor is designed for quick and easy deployment on large farms and enables real-time monitoring of multiple animals simultaneously. Algorithms extract key parameters from the raw data, including chewing rate, heart rate, and respiration rate, along with various activities such as rumination, eating, resting, general activity, mooing, ructus, and rumen contraction, for display in real time on a wirelessly connected smartphone or tablet computer. Studies illustrate operation of the system across six dairy cows in an operating farm environment, with correlation to analysis of time-synchronized digital video. The results have broad potential to enhance methods for managing and caring for agricultural animals at the herd level, with positive implications for cost, efficiency, and environmental impact.

RESULTS AND DISCUSSION

Design and operating principle of the MAV sensor

The MAV sensor is suitable for use as a surface-mounted or subdermally implanted device for monitoring parameters related to

the physiological health and natural activities of bovine animals. The sensors capture linear accelerations (and optional rotational accelerations) associated with physical motions, as well as high-frequency vibrations associated with body sounds, as demonstrated here in a surface-mounted configuration located on the neck. The MAV sensors include a wirelessly rechargeable battery that enables a sealed enclosure without external connectors, enhancing environmental resistance and ensuring long-term reliability during field deployment. Inside the enclosure are the signal-conditioning electronics for filtering the bandwidth frequency, a wireless communication module (Bluetooth low energy [BLE]) and an on-board memory unit, with an operating time of 48 h in a continuous data-streaming mode.

The MAV sensor is similar to a system reported for human use in a clinical setting,^{15,16} with the main difference being the use of a high-bandwidth micro-electromechanical system (MEMS) instead of a microphone, which provides similar performance in capturing body sounds with reduced sensitivity to environmental noise. The construction features a flexible printed circuit board (fPCB) that integrates all passive and active components. Folding the battery and antenna sides of the platform minimizes overall size.

As shown in [Figures 1A](#) and [S1](#), layers of the thermoplastic polymer acrylonitrile butadiene styrene (ABS; 1.524-mm thick; Interstate Plastics) form a robust structure that encapsulates the system and can withstand the weight of the animals and the types of impacts that occur frequently in a farm setting. The encapsulation structure exhibits low water permeability and chemical resistance,¹⁷ thereby maintaining functional stability even in high-humidity and contamination-prone barn environments. Owing to these characteristics, ABS serves as a material of choice for durable and reliable field operation of the MAV sensor over extended periods.

Mounting on the neck allows access to key signals of highest relevance ([Figure 1B](#)). Here, the sensors detect respiratory sounds from airflow through the trachea, along with sounds and motions associated with pulsatile flow of blood through the carotid arteries during periods of stillness. This location also enables monitoring of chewing and rumination behaviors due to essential involvement of the neck muscles in these processes.¹⁸ Motions of the neck lend insights into feeding and other related activities.¹⁹ The neck also involves more frequent and larger-bandwidth signals compared to the limbs, improving the sensor's ability to capture physiological information, well-separated signals, and minimal motion artifact interference.²⁰

Experiments reported here utilize standard BLE communication over distances of 5 m and up to 12 separate devices. To ensure signal quality and minimize phase distortion, Butterworth bandpass filters as zero-phase filters were applied for each physiological domain (1–50 Hz for chewing, 2–45 Hz for heart rate, and 0.1–0.8 Hz for respiration), while mechanical decoupling within the device minimized motion artifacts and surface deformation

Data analysis for the MAV sensor

[Figure 1C](#) presents a block diagram of operation of the system. The device exploits a BLE system on a chip (SoC, ISP1807,

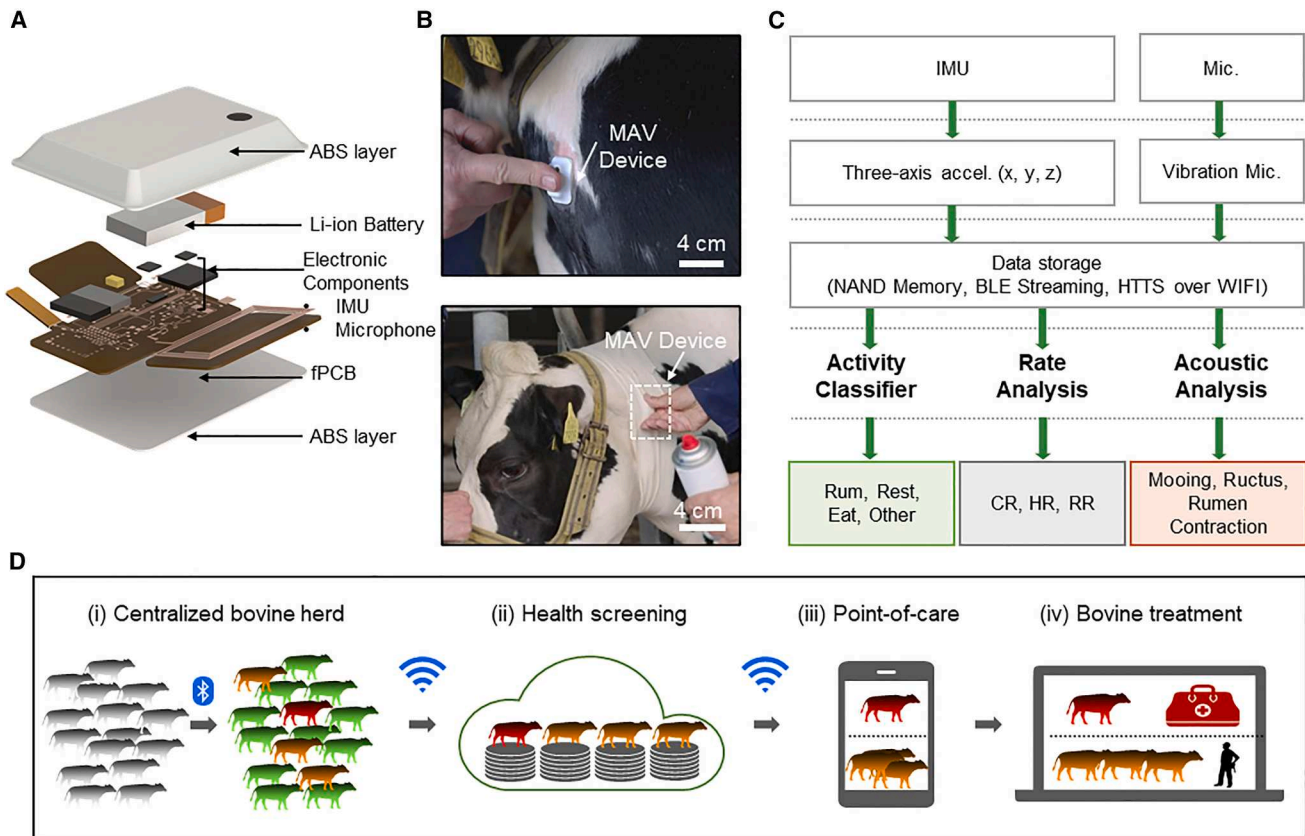


Figure 1. Wireless skin-interfaced biophysical sensors of body motions and sounds for continuous physiological monitoring and diagnostics in agricultural animals

(A) Schematic exploded-view illustration of an MAV sensor.

(B) Photographs of devices placed at two locations on the neck of a bovine subject. The devices adhere to the skin using a cyanoacrylate adhesive applied after removing the fur.

(C) Flow diagram showing the management of data collected from a device.

(D) Depiction of a mode of use that relies on comparisons of real-time data against a baseline of recent daily traits and behaviors: (1) daily trait frames are extracted at feeding locations, (2) trait frames are passed to a centralized system for health screening and management, (3) a window of recent frames is processed through a recurrent model to infer the need for farmhand or veterinary attention, with a user interface to facilitate point-of-care interactions, and (4) bovine treatment is delivered with high specificity.

Insight SIP) that configures a 6-axis inertial measurement unit (IMU, LSM6DSO, STMicroelectronics) for mechano-acoustic measurements at a sampling frequency of 208 Hz for x, y, z accelerations and a vibration microphone (V2S200D, Knowles) with a sampling frequency of 12.5 kHz decimated to 781 Hz, which has a sensitivity of -26 dBFs. This MEMS vibration sensor exhibits frequency flatness within ± 3 dB relative to 1 kHz, ensuring minimal non-linear distortion even under large-amplitude vibrations. Such stability preserves signal integrity and enables accurate analysis of vibration and acoustic-mechanical coupling across a broad frequency range, making it a suitable choice for high-fidelity sensing in dynamic environments. This sensor also offers fewer parasitic contributions from ambient sounds compared to a conventional microphone.

The MAV sensor stores and wirelessly transmits data to portable base stations for displaying the data and transferring to the cloud for activity classification, rate analysis, and acoustic analysis. The naive activity classifier, using the frequency

domain, categorizes the data into groups corresponding to rumination, resting, eating, and other activities. Rate analysis captures episodic values during periods of sufficient quiet of chewing rate (CR), heart rate (HR), and respiration rate (RR). Acoustic analysis identifies features associated with mooing, ructus, and rumen contraction. To optimize battery life, activity classification can be designed against target features computed on the sensor for data reduction prior to transfer to the base station (Figure S2).

Figure 1D illustrates the concept of a bovine adaptive baseline to define recent daily traits and behaviors. In one use scenario, data from the device create daily trait frames captured at feeding locations via wireless links established to receiver units at these positions for use in a centralized system to assist with management of the farm. Each color in this schematic representation corresponds to a different health status (green, healthy; orange, possibly ill; red, ill). These indications serve to guide intervention by a farmhand or veterinary physician, not only to help the individual animal but also to protect

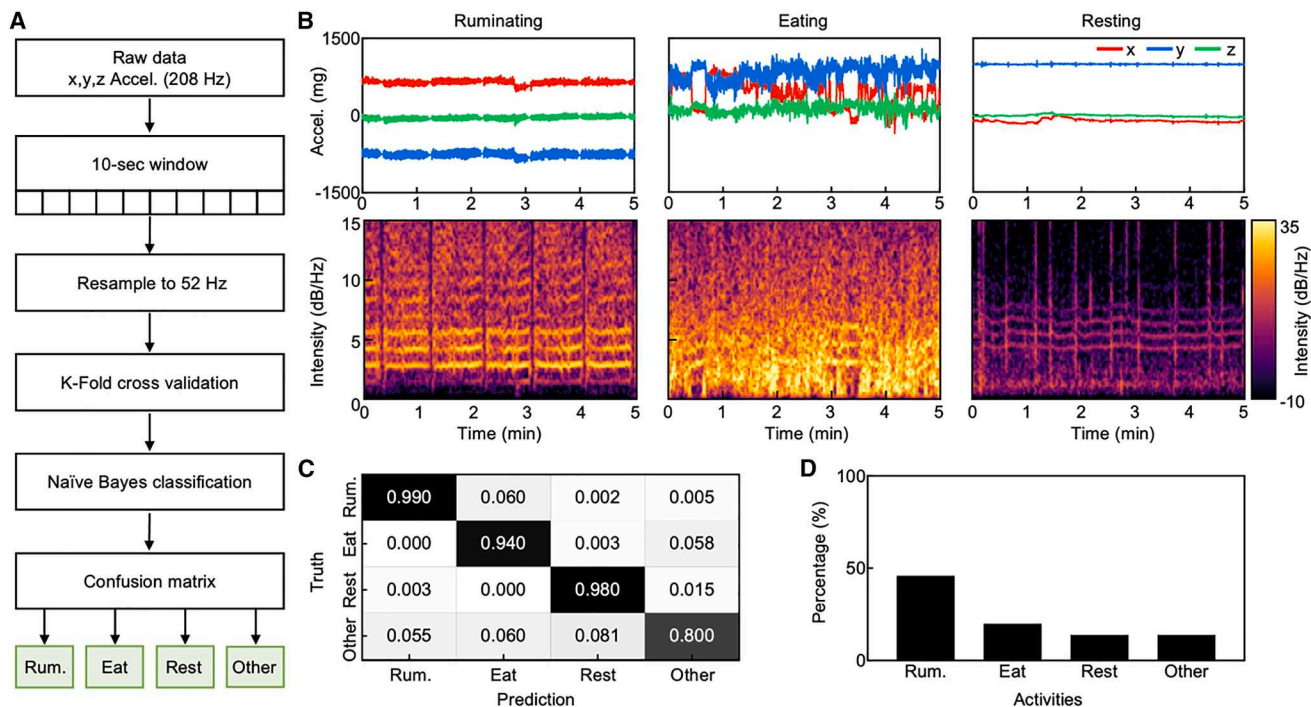


Figure 2. Flow diagram of activity classification and corresponding results from representative data acquired from the healthy bovine subjects

(A) Flow diagram of the activity classification analysis that uses the x , y , and z axes accelerometer data.

(B) Raw acceleration signals and corresponding spectrograms for various activities, including ruminating, eating, and resting, with devices placed on the upper and lower parts of the neck.

(C) Confusion matrix for activity classification.

(D) Bar chart that summarizes the percentage of time in each of the four activities.

the herd from disease transmission, thereby minimizing the environmental impact of dairy farming.

Bovine activity classification

Classification of bovine activities, such as ruminating, eating, and resting, captures lifestyle and behavior trends related to bovine health, evaluated through the raw acceleration signals from the IMU of the MAV sensor. Figure 2A presents a block diagram of the classification process, tracked with a sampling rate of 208 Hz. Resampling to 52 Hz enables detection of general activity patterns over time while reducing the power consumption of the accelerometer. Based on real-time biosignal analysis, we defined labels every 10 s for each activity following comparisons with the video recordings. The following features from the accelerometer data serve as the basis for behavior activity classification: (1) standard deviation of the L2 norm of the x , y , z axes; (2) fast Fourier transform (FFT) bands of a 10-s window of the x , y , z axes; and (3) number of seconds of rumination in the directly preceding two 10 s window. The performance of a Naive Bayes classification model based on K-fold cross validation ($K = 5$) demonstrates feasibility for energy-efficient deployment on sensor. The area under the curve-receiver operating characteristic (AUC-ROC) for the performance of this model in identifying rumination results in a value close to 1.0, highlighting the discriminative power and ability to distinguish

between positive and negative classes with minimal false positives and false negatives (Figure S3).

The acceleration data and the corresponding spectrograms exhibit distinct raw motion signals with dominant frequency patterns over time. The results indicate distinct, classifiable patterns during various activities, including ruminating, eating, and resting (Figure 2B). Ruminating corresponds to stable x , y , and z acceleration signals with mild variations compared to resting. Eating signals feature fluctuations due to the rhythmic and dynamic head and jaw movements while chewing and biting food. These processes involve repetitive mandibular motions and associated vibrational forces that propagate through the head and neck. The resting state corresponds to minimal noise in all axes, consistent with minimal movements. Furthermore, while these x , y , and z signals are different in expected ways when attached to various locations of the neck, the spectrograms show comparable characteristics (Figure S4). The relevant vibrational signatures of activities are spatially stable and reproducible across the neck region. For practical applications, only a single sensor, placed in this general location, is sufficient. Ruminating features repetitive cycles of mastication, swallowing, and regurgitation. As observed in the spectrograms, changes in food composition, intake volume, and associated head motion lead to distinct signal patterns compared to other activities, including resting and eating. This observation suggests that

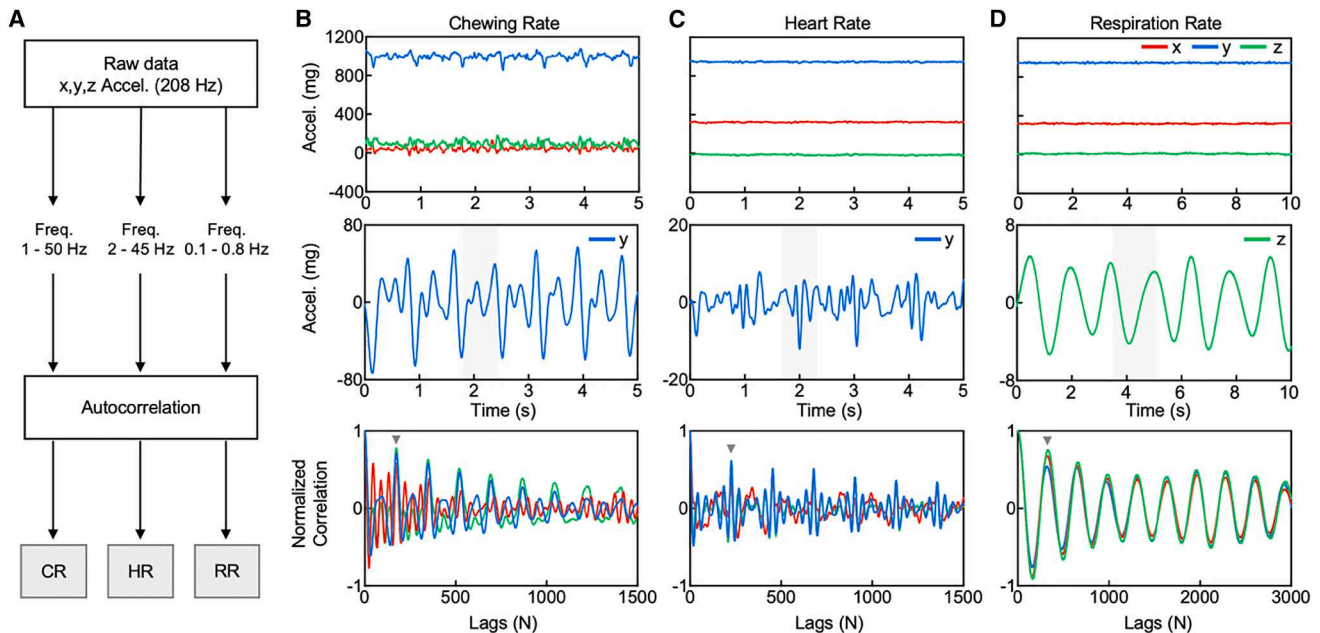


Figure 3. Flowchart for analysis of rates of chewing, cardiac, and respiratory cycles and representative results

(A) Diagram of the process for rate analysis based on three-axis accelerometer data.

(B–D) Raw acceleration signals from x, y, and z axes (top), corresponding band-pass-filtered signals (middle), and normalized autocorrelation of each axis (bottom) to highlight the periodicity for various rates: chewing rate (CR), heart rate (HR), and respiration rate (RR) analysis during rumination or resting periods comparing CR, HR, and RR. Shaded regions show the peaks from the filtered signals, while the arrows show the first peak corresponding to the first full cycle of the repeating pattern for analyzing periodic signals.

behavioral features appear in the data in a manner independent of exact device location across this general anatomical region.

Figure 2C presents the confusion matrix associated with these results, emphasizing the high sensitivity of the activity classification. The model achieves high true positives, indicating strong overall accuracy. For rumination, eating, and resting activities, the accuracy values are 0.99, 0.94, and 0.98, respectively. This performance exceeds that of previous work using other types of sensors.^{21,22} Figure 2D presents the percentage of each activity derived using the current model. Rumination in this particular case accounts for the highest proportion at 46%, followed by eating at 20%, and resting and others (walking, drinking, defecating, and all other activities) at 14%. The low false positives indicate high specificity of bovine activity classification, which is essential as herds become more centralized.

This type of activity distribution can further provide vital indicators of health, welfare, and productivity.¹¹ The rumination time directly links to rumen function. A decrease in rumination, which is the most important factor in identifying health status, can indicate stress, illness, or discomfort.²² The presence of disease, such as gastroenteric disorders, reduces rumination duration by approximately 9.9 min per 2 h of rumination time.²³ Insufficient resting time can signal lameness or poor stall comfort, while too much rest can indicate possible illness or lethargy. Eating time reflects feed intake behavior and can be related to feed quality or health. A sudden change in the distribution of activities has the potential to help identify health problems before clinical symptoms arise. Detailed status summaries for six different bovine animals are shown in Figure S5.

Analysis of chewing, cardiac, and respiratory activities

Analysis of additional metrics, such as CR, HR, and RR, enables detection of stressors, as an additional means to guide care decisions to improve animal welfare and prevent productivity losses. Figure 3A shows a block diagram of the analysis approaches in these cases. Band-pass filtering of data from the accelerometer facilitates the detection of various rates. Evaluation of autocorrelations of these signals determines the periodicity, as the basis for determining these three rates. These robust procedures reduce noise interference and enhance the reliability of detecting each pattern. CR is directly linked to rumination efficiency and feed digestibility, while HR is a key physiological indicator of stress or pain. Additionally, RR can signal respiratory health or heat stress and can also reflect efforts to maintain thermal balance.^{24,25}

Figures 3B–3D and S6 show representative raw data before and after applying the band-pass filters with autocorrelations to estimate CR, HR, and RR, respectively. The CR band-pass filter preserves the fundamental chewing rhythm and higher-frequency impact components; the HR band-pass filter captures mechanical harmonics of cardiac motion; and the RR band-pass filter isolates slow respiration while removing faster physiological signals. Masking the CR by rumination period and HR and RR by resting period reduces the influence of other activities and produces clean signals, without effects of motion or other artifacts, for evaluating and detecting abnormalities. Autocorrelation analysis applied across x, y, z signals identifies periodic patterns corresponding to physiological rhythms, estimating the rate. This algorithm compares a signal with time-shifted

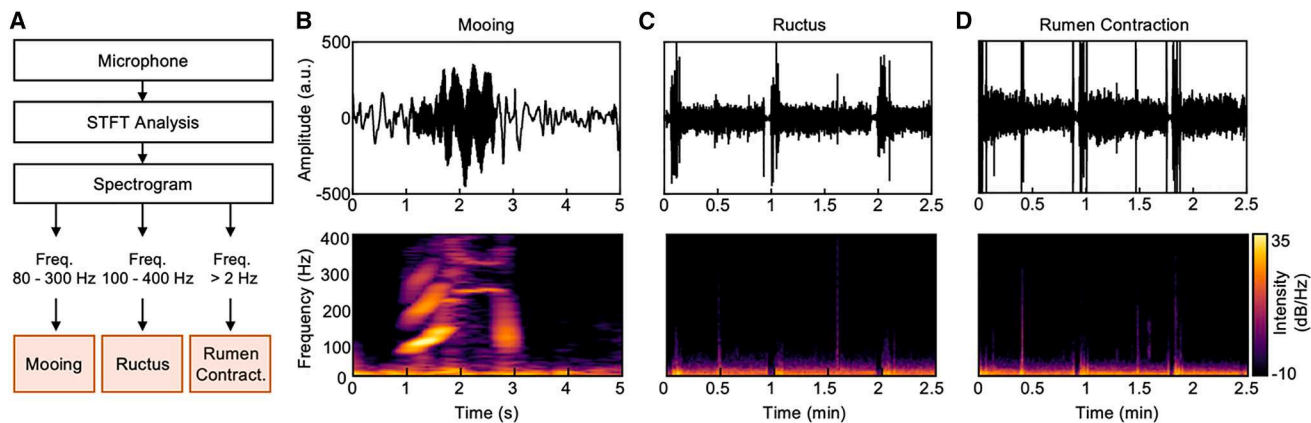


Figure 4. Flowchart for analysis of body sounds related to mooing and ructus and representative results

(A) Diagram of the approach for acoustic analysis.

(B–D) Raw microphone data and corresponding spectrograms during periods of mooing, ructus, and rumen contraction, respectively.

versions of itself, thereby enhancing repetitive patterns while suppressing random fluctuations or noise.²⁶ The result facilitates the detection of periodic physiological activities such as chewing, cardiac, and respiration even in noisy environments. The peak selected is chosen by the maximum height within the relevant range of lags for each axis. Using the corresponding peak heights as weights allows determination of weighted averages of the peak lags. The weighted average lag (samples) is inversely proportional to the sample rate. The rate in Hz follows from dividing the sample rate by the weighted lag. Multiplying the result by 60 converts the value to beats per minute (bpm). For CR, the rate is 71.5 chews per minute (cpm) from the triaxial autocorrelation data. For HR, the autocorrelation data show an HR of 55.0 bpm from the weighted average by peak height. This value corresponds to normal resting HR with no ongoing stress or environmental challenge.²⁷ RR is also consistent with a healthy resting state with no signs of respiratory disease.^{28,29} As the lag peak height in the autocorrelation is a measure of signal periodicity, and therefore signal quality for this purpose, this scheme for rate calculation is orientation robust in that it allows axes dominating rate calculations to change as the animals move throughout their environment.

Analysis of body sounds

Quantitative monitoring of mooing, ructus, and rumen contraction can aid in assessments of emotional states and rumen health, as an additional basis for early intervention strategies in dairy management. Figure 4A presents a block diagram that illustrates analysis approaches for the microphone data. Short-time Fourier transform (STFT) analysis converts time-domain signals into the frequency domain, resulting in spectrograms that visualize time variations of the signal power at different frequencies. Mooing is a form of communication and behavioral expression, and its frequency and intensity imply different emotional and physical states. For example, a sudden increase in mooing indicates environmental or social stress.³⁰ Ructus is a physiological process that allows the bovine to expel gas produced during rumen fermentation, as an indicator of rumen

health. Reduced ructus indicates ruminal acidosis, bloat, or reduced feed intake or stress, while increased ructus may follow a fiber-rich meal.³¹ Rumen contraction consists of rhythmic muscular movements that help mix and move ingested feed, promote fermentation, and aid in the release of gases, which is a critical indicator of bovine digestive health.

Figures 4B, 4C, and 4D show data and corresponding spectrograms to illustrate features corresponding to mooing, ructus, and rumen contraction. During mooing, the spectrogram exhibits fundamental frequencies in the range of 80–300 Hz, with clear harmonic structure above the fundamental frequency of ~ 100 Hz. These features, and their durations of ~ 1 s, are unique relative to other signals. Characteristic mooing of this type suggests social engagement and a healthy emotional state. Conversely, during ructus, the signal exhibits a rapid burst of less than 0.2 s with frequencies between 100 and 400 Hz, without harmonics (clear in chewing status, middle of rumination). This clean ructus signal suggests that the digestive tract is functioning properly and effectively preventing rumen distention, conducive to digestive processing. For rumen contraction, the signal shows a strong burst with a duration of less than 2 s at frequencies above 2 Hz, with a semi-periodic pattern. The bovine having rumen contractions once or twice per minute indicates that the rumen is functioning within the healthy bovine's normal physiological range.³² These behavior signatures, when abnormal, are often linked to conditions such as stress-related disorders or ruminal acidosis, illustrating their potential for early detection of health problems.

Monitoring of herd behaviors

Figures 5A and S7 present the hourly distribution of various activities for all six animals over a period from 6:30 p.m. to 6:30 p.m. the following day. The results show daily behavioral patterns and periodic trends for individual animals as well as inter-subject variability. Rumination occurs more frequently during the night and less frequently in shorter periods during daytime, while eating occurs after feed delivery, often in the morning and late afternoon. Decreases in rumination and resting periods

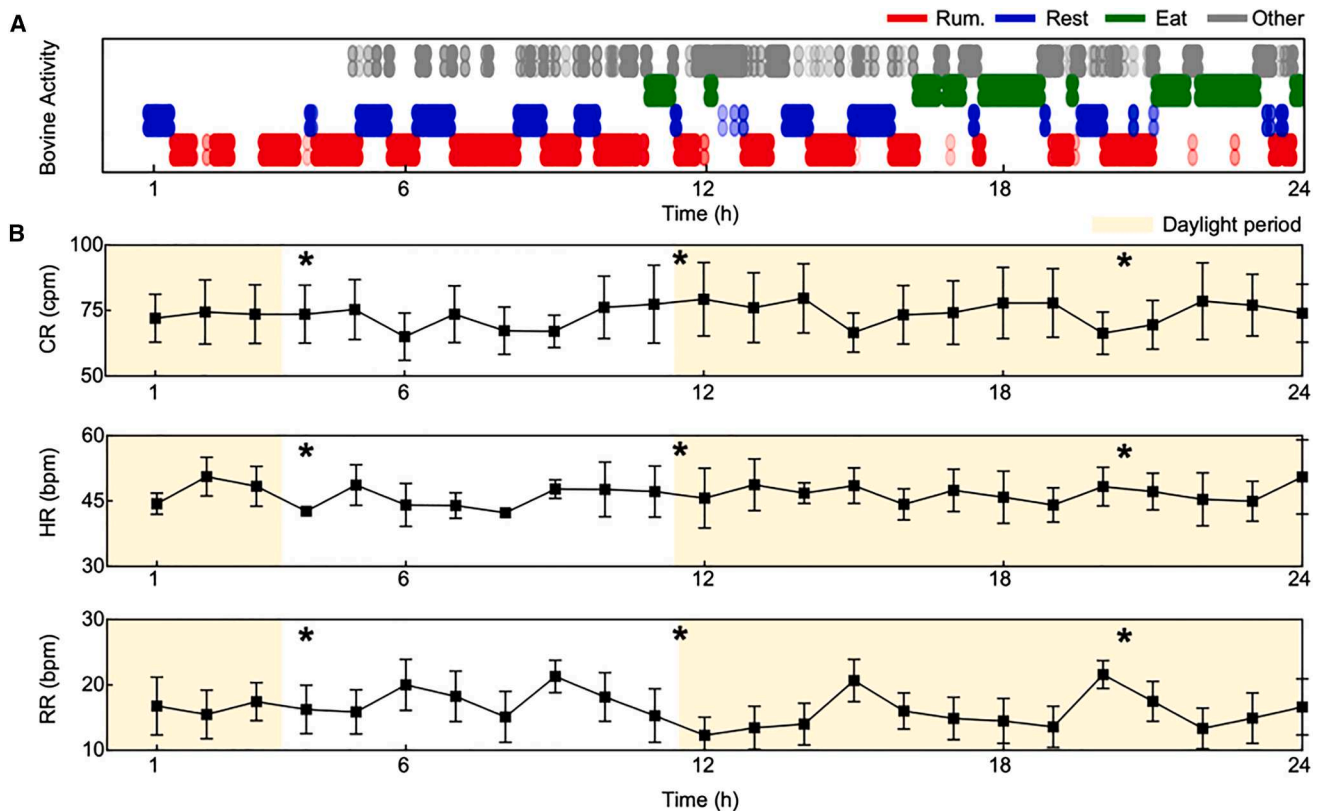


Figure 5. Representative data of episodic behavior patterns determined from a single bovine

(A) Representative hourly distribution of various activities: rumination, resting, eating, and others.

(B) Representative CR, HR, and RR over a 24-h period, with daylight hours shaded in yellow (* indicates the examination period). Error bars represent mean ± SD.

may indicate stress or illness.^{22,33} For resting periods, frequent interruptions or decreased resting time may indicate discomfort or heat stress. For CR, HR, and RR, hourly trends in episodic rate events highlight their normal health status (Figure 5B). An elevated HR occurs during clinical examinations, as it disrupts the animal's routine and involves stress and anxiety due to handling and restraint. Relatively low values of CR appear during periods between scheduled feedings or pasture rest time when the animal is not actively processing cud or feed. As expected, high CR values occur after delivery of feed or access to grazing. These 24-h distributions showcase the behavioral fingerprint of each animal and help distinguish between healthy and abnormal patterns, allowing early detection of health issues.

Conclusion and outlook

The device reported here presents a skin-interfaced wireless technology that offers cost-effective capabilities in continuous monitoring of the health status of agricultural animals with high accuracy and specificity. The system provides information for early detection of animals that should receive care, while avoiding disturbances to healthy animals. The accelerometer data enable activity classification across categories of rumination, resting, eating, and others. Frequency-based analysis provides a practical mechanism to continuously recover previously unavailable metrics, including CR, HR, and RR, as early indicators

of stressors or health anomalies. The broadband vibration microphone yields additional insights into emotional states and rumen health. The embedded temperature sensor also provides some information on the core body temperature, but with non-negligible effects of the temperature of the ambient (Figure S8). Improvements in the thermal aspects of the encapsulation design and mechanisms for body integration may improve the accuracy of temperature evaluations, with relevance to detection of fever, inflammation, thermal regulation, and other details.

Additional future directions may explore the rumen contraction rate and variability,³⁴ of interest for their potential to provide a holistic view of bovine welfare in PLF. Exploring this possibility and expanding the scale of deployments of this technology to allow for inferencing based on machine learning techniques represent areas of ongoing work. Furthermore, applications to other herd animals, including horses, sheep, goats, and others, can be considered straightforward extensions to the demonstrations reported here. Some optimization in device placement for optimal signal detection and data analytics models for accurate interpretation may be required to tailor the system to each species' unique patterns. Because most of the active components of the devices are similar to those used in commodity fitness trackers, the devices represent an attractive, affordable option for easy integration into a wide range of uses in farming.

METHODS

Animal models

Two experienced bovine veterinarians (Dr. Ruurd Jorritsma, the faculty veterinarian responsible for the dairy herd of the Veterinary faculty of Utrecht University, and Bulle Koster, the veterinarian from Animal Welfare Sensors) conducted the clinical examinations on six Holstein bovines with an average age of 3.7 (± 0.6) years. They collected each event of bovines including rumen movements, ructus, respiration, chewing, regurgitating, swallowing, coughing, and talking. All bovines stayed in the same stable during the study, separated from the rest of the herd only by a metal fence. The herd manager and milkers continued their usual routines throughout the data collection. All animal experiments were approved by the Dutch Experiments on Animals Act and EU Directive under protocol number 10803-2024-05.

Fabrication of the electronics

Autodesk Eagle was used to design the fPCB. A manufacturer (Altaflex) supplied the fPCB as a support for assembling the active and passive components. A J-Link debugger probe (SEGGER Microcontroller Systems) installed programming via Serial Wire Debug (SWD) protocols to verify and test the fPCB after manufacture. The collection of components included passives such as capacitors, inductors, and resistors, along with actives including a power management unit (nPM1100, Nordic Semiconductor), NAND flash memory (W25M02GW, Winbond), a BLE SoC (ISP1807, Insight SIP), a vibration microphone (V2S200D, Knowles), and an inertial measurement unit (LSM6DSO, STMicroelectronics).

Design of the encapsulating enclosure and assembly of the device

An ABS extruded-grade sheet (Interstate Plastics) and an aluminum mold fabricated from the milling machine (MODELA PRO II MDX-540, Roland) defined the encapsulating layer using a vacuum forming machine (Formech 450DT). Heating for 100 s at 100°C softened the ABS to yield a pliable sheet. After heating, a pneumatic bed raised the mold, and a vacuum system pulled the softened ABS over the mold, ensuring complete conformity to its shape. A CO₂ laser cutter (VLS3.50 Desktop, Universal Laser Systems) trimmed the boundary of the molded ABS layer to yield a well-formed, durable layer.

Application of a small amount of acetone to the top and bottom ABS layers temporarily softened the ABS surface, to allow seamless fusion of the layers. A brush applied a thin, even layer of acetone to the bonding surfaces, ensuring complete coverage without excessive pooling. Immediately after application, pressure applied to the two ABS layers ensured uniform contact across the entire surface. Clamps maintained consistent pressure while the acetone evaporated, and the layers fused. The bonding process required a few minutes to set, resulting in a strong and permanent encapsulation. The edges were sanded for a smooth finish. Any remaining minor gaps were filled with marine sealant, creating a durable, seamless bond between the two processed thermoplastic ABS layers.

Real-time data collection

The study conducted observations at the research facilities of the Faculty of Veterinary Medicine, Utrecht University. Six assigned animals, consisting of four healthy lactating bovines and two non-lactating bovines, were deployed for approximately 26 h. The animals wore only halters and no collars during measurements. The technicians milked all lactating bovines prior to admission. During the research, 24/24 film images and video systems operating continuously captured movements and sounds of the animals for purposes of comparisons to sensor readings by videographer Youp Kruijsdijk. Each bovine was washed, shaved, and degreased in the neck region behind the left lower jaw. Identical sensors, each with dimensions of 38 × 30 × 12 mm (l × w × h) and a weight of 7 g, were used. Each sensor was placed on the skin with a covering plaster on top of it. All bovines received two sensors, one placed behind the left lower jaw and the other positioned 10 cm higher at the left ear basis. Each bovine, numbered 1 to 6, was labeled on both sides of their plasters using coat color and pattern to enable identification by number and appearance. During the recording, 3 clinical examinations were performed at 21:30 May 29, 6:00 May 30, and 14:00 May 30. During the clinical examinations, the veterinarians confirmed activities and rates for each cow.

Data analytics and algorithms

The analysis involved extracting both time- and frequency-domain features from the accelerometer and microphone data to classify bovine behavioral activities and body sounds. A Naive Bayes classification model distinguished behavioral categories including rumination, eating, resting, and others. Synchronized video recordings derived ground truth labels, and classification was conducted on segmented time windows. Autocorrelation functions identified periodic patterns for various rates including CR, HR, and RR. FFT applied to microphone acoustic signals to extract frequency-domain features relevant to body sounds of bovines enabled identification of dominant frequency components associated with vocalization and rumen sounds. For plotting in Figures 2B and 4B–4D, the raw data were down-sampled to every 5th and 25th point, respectively. All computations were performed using Python with NumPy, SciPy, and scikit-learn libraries.

RESOURCE AVAILABILITY

Lead contact

Requests for resources and information should be directed to the lead contact, Dr. John A Rogers (jrogers@northwestern.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

The data that support the findings of this study are available at <https://github.com/qsib-cbie/study-bovine>.

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AUTHOR CONTRIBUTIONS

Conceptualization, J.Y.K., W.K., and J.A.R.; methodology, J.Y.K., W.K., J.T., and J.A.R.; formal analysis, J.Y.K., J.T., N.W., and K.H.; software, J.T., N.W., and K.H.; investigation, W.K., R.J., E.v.A., and W.P.M.L.K.; writing – original draft, J.Y.K.; writing – review & editing, J.Y.K., W.K., J.T., J.-Y.Y., J.W.K., C.L., P.N., and J.A.R.; visualization, J.Y.K., J.T., and J.W.K.; funding acquisition, A.B. and J.A.R.; supervision, A.B. and J.A.R.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

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