Information Technologies in Feeding Behavior Livestock Monitoring

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Keywords

Cattle behavior monitoring · Jaw movements identification · Sound sensor · Accelerometer sensor · Machine learning · Signal processing

Definition

Precision livestock farming is a set of information technology tools (electronic devices and algorithms) used to monitor the behaviors of individuals within a cattle. It is based on the recording and analysis of four parameters: the location, the posture, and the movements of the animal, as well as its jaw movements. Several techniques have been developed to discriminate and quantify individual feeding behavior (grazing and rumination) providing valuable tools to improve the quality and general safety, animal farming that is efficient but also sustainable, animal health and well-being, and a small ecological footprint of livestock production.

Introduction

The need to produce more food for a rapidly growing population is creating pressure on crop and animal production, generating a negative impact on the environment. Therefore, smart farming technologies are becoming increasingly common in modern farming to assist farmers in optimizing livestock production and minimizing the wastes and costs. Precision livestock farming (PLF) is used for monitoring animal behavior and the detection of diseases to optimize animal growth and milk production, among others. It relies on advanced sensors, communications protocols, and embedded processors, developed in the last decades, that enable the real-time monitoring of individual animal behavior.

Measuring such variables requires trade-offs between upstream data acquisition, while preserving battery life and taking into account processor resources, and downstream output accuracy obtained using adequate data processing techniques (le Rou et al. 2019). In this respect, sensors can be used individually or in combination to track, detect, and classify animal behaviors. For example, monitoring rumination and grazing behavior is a key to understanding how animals fulfill their requirements in pasture-based systems

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by grazing to achieve optimal plant production, animal forage intake, and performances. In this way, PLF opens new perspectives in both intensive pasture and extensive rangeland management by focusing on the individual instead of the whole herd.

Characterizing individual foraging behavior on pasture means the monitoring of grazing, rumination, and resting behaviors, which altogether occupy 90–95% of the daily time budget. Hence, the real-time characterization of animal behaviors is essential for the development of pervasive real-time monitoring of cattle on pastures. This task must address other components like jaw movements, which are of utmost importance to assess animal grazing strategies, and methods to accurately estimate their intake, among other issues.

Forage Intake Mechanism

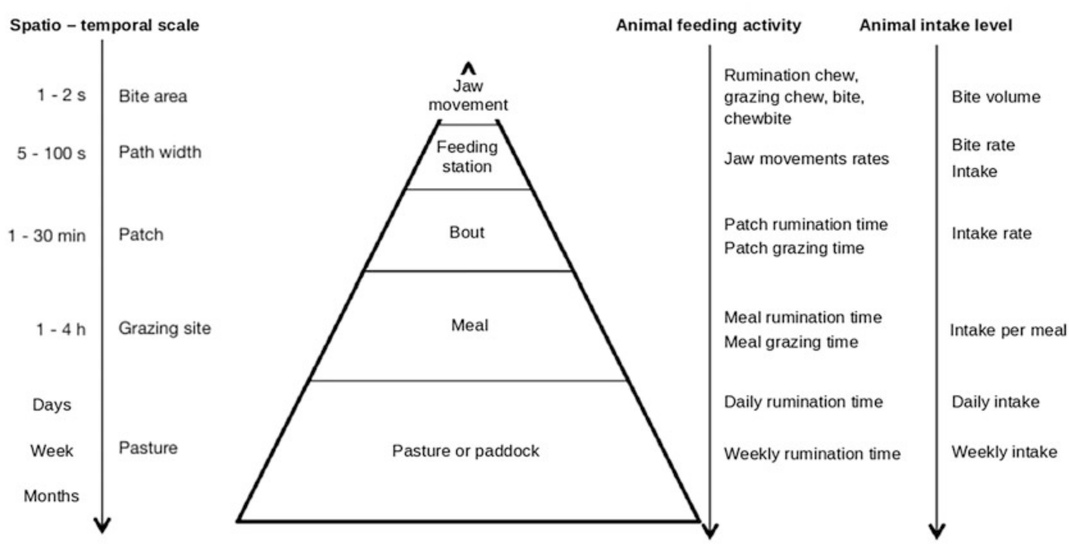
The feeding process for grazing cattle involves two main activities: grazing and rumination. Each one of these activities is a complex combination of several tasks that require movements performed by the animal at different temporal and spatial scales (see Fig. 1).

The elementary component of feeding activities is the **jaw movement**. Several jaw movements performed in a row by an animal on a **feeding station** without interruption compose a **bout** that will cover a few square meters and lasts between 5 and 100 s.

Several bouts are performed during each **meal** that occur each day for several hours during which a portion of the **paddock** is explored. Finally, the paddock is occupied for some days to several months (Gibb 1996).

Grazing requires body movements to search for herbage as well as jaws and tongue movements to apprehend, crush, and swallow it. It can be broken down into four phases (Andriamandroso et al. 2016), corresponding to three jaw movements (Fig. 2a):

- The first three phases involve the **apprehension**, cows use their tongue and lips to take the grass into their mouth, followed by the **grabbing**, the grass is captured between the jaws, and ends with the grass **cutting** by a sudden movement of jaws and head. This jaw movement is known as **bite**. Its sound is characterized by a high amplitude and a short duration,



Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 1 Spatiotemporal components of feeding behavior. (Adapted from Andriamandroso et al. (2016))

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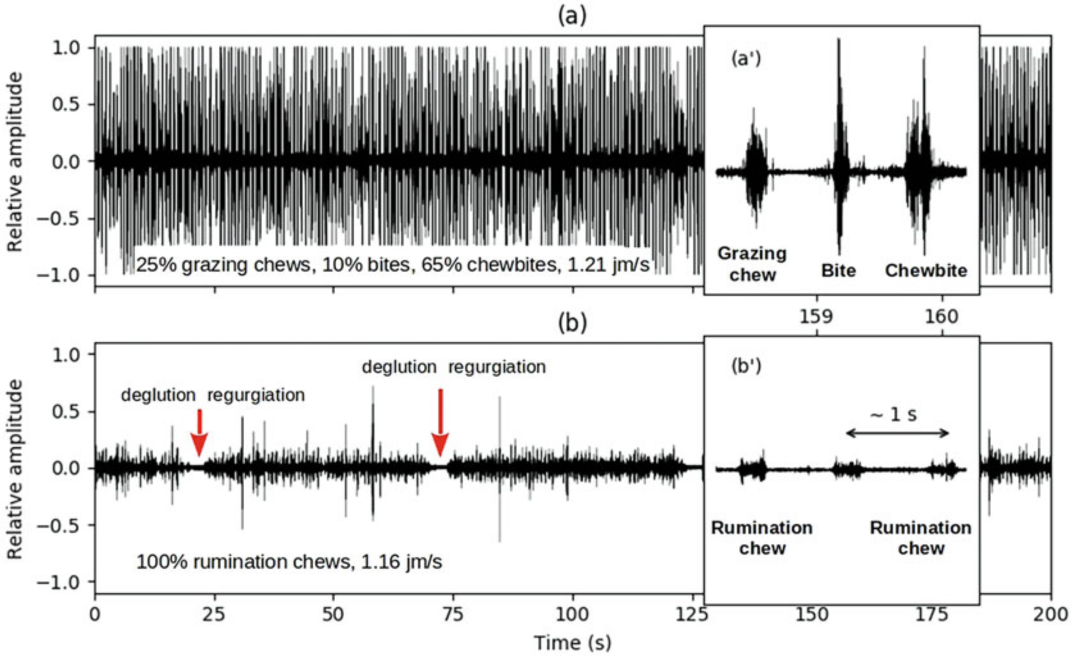

Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 2 Sound recorded during (**a**) grazing and (**b**) rumination activities. Typical percentages and JM rate (jm/s) by activity. (Adapted from Chelotti et al. (2020))

which are associated with the grass grubbing and cutting (Fig. 3c).

- The final phase of foraging involves the grass **chewing and swallowing**. This jaw movement is known as **grazing chew**. Its sound has a high energy and a moderate amplitude since grass fibers are untouched and they only have the moisture of the plant (Fig. 3b).

These two jaw movements are usually combined into one to improve the efficiency of the grazing process, known as **chewbite**. Its sound combines the features of a bite and a grazing chew, resulting in a sound of great amplitude and duration (Fig. 3d).

Rumination requires only jaw movements to crush a rumino-reticular bolus. It can be broken down into three phases (Fig. 2b): **regurgitation,** when the animal regurgitates a bolus to the mouth; **jumbling and grinding,** when the animal chews and insalivates the bolus; and **deglutition,** when the animal swallows the bolus. During the second phase, the animal performs jaw movements known as **rumination chew**. Its sound has a low energy and amplitude since grass fibers have incorporated extra water during its dwell in the rumen and they are already crushed (Fig. 3a). During the regurgitation and deglutition, there is no sound (Fig. 2b).

Grazing bouts are composed of approximately 25% of grazing chews, 10% of bites, and 65% of chewbites with a rate ranging from 0.75 to 1.2 jaw movements per second. Rumination bouts last between 45 and 70 s, and they are composed of 100% of ruminating chews with a rate of 1.16 jaw movements per second.

Animal Monitoring

The wearable sensors used for monitoring the feeding behavior can be classified into three groups depending on the physical variables they measured (Fig. 4):

- **Pressure sensors:** Directly measure the jaw movements by sensing changes in pressure or length of a sensor around the nose (see Nydegger et al. 2010; Rutter et al. 1997).

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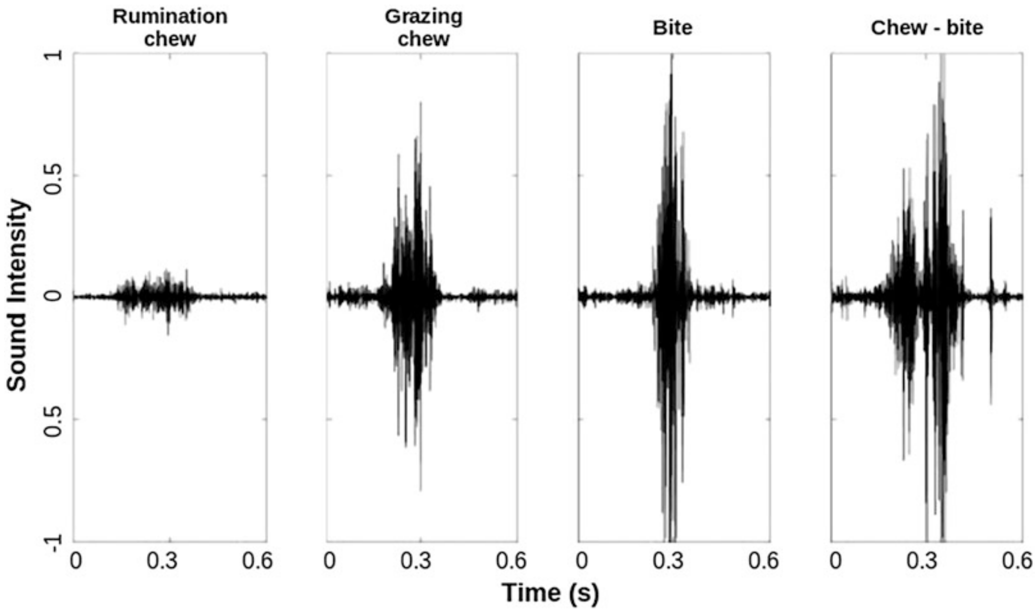


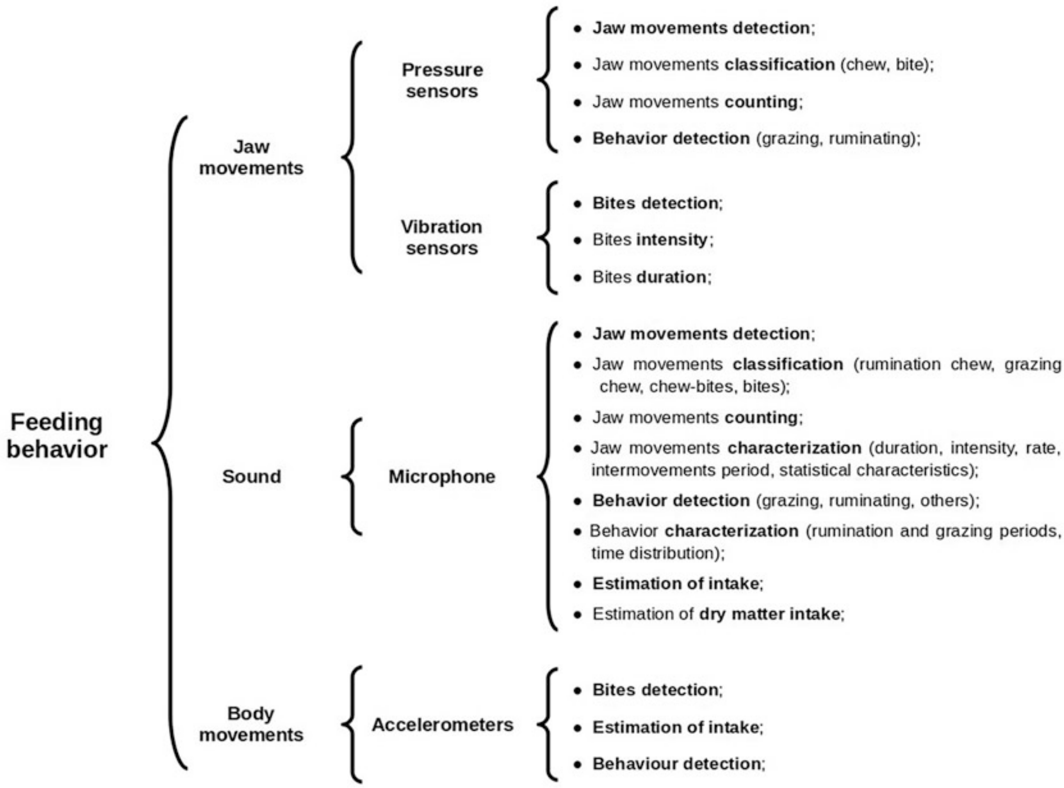
Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 3 Time series of typical mouth opening and sound signals produced by jaw movements

- **Microphones:** Indirectly measure the jaw movements by sensing the **sound** patterns produced during feeding activities (see (Chelotti et al. 2016, 2018, 2020; Clapham and Fedders 2011; Milone et al. 2012; Navon et al. 2013; Vanrell et al. 2018), among others).
- **Accelerometers:** Indirectly measure the feeding activities by sensing **body movements and postures** (see Brennan et al. 2021; Brown et al. 2013) as well as **jaw movements** (see Tani et al. 2013).

Pressure sensors only recognize basic jaw movements (chew and bites), they are robust against environmental conditions (weather and noises), and their sampling frequency is low (around 20 Hz). However, the information registered by them does not allow a detailed characterization of feeding behavior, and they can only determine whether the animal is grazing or ruminating behaviors (Fig. 4). For additional information, these sensors require an accelerometer that measures the position of the head and body movements.

Several algorithms have been developed to process the information provided by these sensors to monitor the feeding behavior of ruminants. They are pattern recognition systems that aim at classifying input data (pressure, sound, and accelerations) into a set of specific classes of jaw movements (ruminating chew, grazing chew, bite, and chewbite) and feeding behaviors (grazing, ruminating, others) using its properties and features. A classical pattern recognition system can be described by a series of generic stages (Fig. 5) that allow (i) the description and analysis of the input signal through distinctive features that simplifies (ii) their recognition and classification into classes, enabling the identification of patterns (Duda et al. 2012).

The first stage is the **signal conditioning**, which prepares the input signal $d(t)$ to meet the requirements of the system. It uses analog and digital signal processing techniques to transform $d(t)$ into $d^*(k)$, which is transformed by **signal preprocessing**. This stage processes $d^*(k)$ to simplify the extraction of features $X(k)$ and to reduce the computational load by transforming $d^*(k)$ into the segmented signal $m(k)$. The goal of **feature**



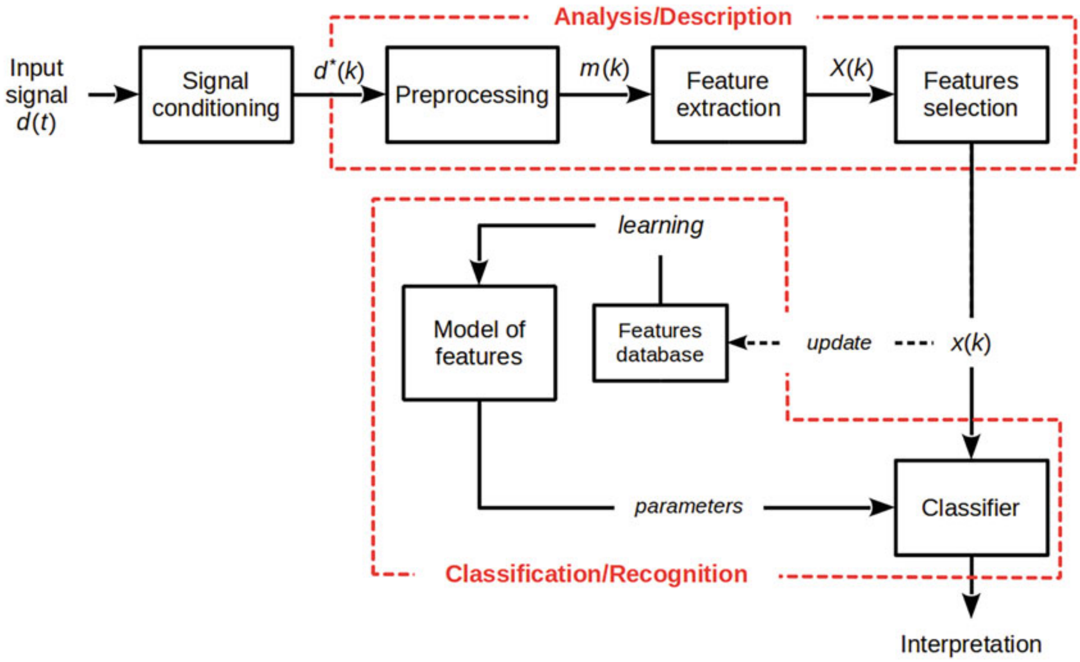
Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 4 Sensors used to characterize feeding behaviors. (Adapted from Andriamandroso et al. (2016))

extraction is to characterize events using features $X(k)$ to arrange the events into classes. This idea leads to the seeking of features $X(k)$ that univocally characterize $d^*(k)$. Finally, **features selection** optimizes $X(k)$ to improve and simplify the classification task. Features that improve discrimination ($x(k)$) are retained and the others are discarded. This transformation of $d^*(k)$ into $x(k)$ can be "continuous" (window based) or can be triggered by specific events (event based).

During the classification task, the system uses $x(k)$ to evaluate the model of features constructed during the learning stage. The learning process recognizes patterns and regularities in features $x(k)$ and organizes them into categories or classes. The sets of features employed to build the model are extracted from a database during the learning process. If the database and model are created before each query occurs, the learning process is performed offline. In the other case, the database and model are updated in real time and the learning process is performed online. These approaches have their own advantages and drawbacks; therefore, their applicability depends on the characteristic of the problem that is addressed: if the features change over a long time, the only option is the online learning that allows us to track the changes. In the other case, if the features are time-invariant, the best option is offline learning.

Signal Conditioning

This task prepares the input signal $d(t)$ to meet the requirements of the system and removes noise and artifacts, generating a new discrete-time signal $d^*(k)$. Signal conditioning includes discretization, normalization, range matching, cleaning, and removing noise from $d(t)$. These tasks are performed using analog and digital signal processing techniques.



Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 5 Block diagram of a general pattern recognition system

Problems during data acquisition, like sensor malfunction or data retrieving issues, frequently results in missing samples or outliers within the input signal, in addition to system and measurement noises. Outliers are often removed using a threshold based on quantiles or standard deviations of the input signal while missing samples are replaced using interpolation. Noises are removed using moving average or low-pass filtering, while trends and biases are removed using adaptive filtering.

Preprocessing

This task manipulates the conditioned signal $d^*(k)$ to simplify the extraction of features $X(k)$ and reduce the computational load by transforming $d^*(k)$ into an intermediate signal $m(k)$, which is segmented into windows or events for further processing (feature extraction and classification). Depending on the sensor employed, different intermediate signals are computed:

- **Pressure sensors:** Algorithms based on pressure sensors use the conditioned signal $d^*(k)$ without any preprocessing to identify the jaw movements since $d^*(k)$ provides enough information to detect them. The only task performed for this type of sensor is the segmentation into events, which is performed by detecting peaks above a given threshold.
- **Microphones:** Algorithms based on sound use a wide range of signal processing techniques ranging from computing time-domain signals (the envelope of the sound and/or the envelope of instantaneous energy, among others) to frequency-domain signals (Fourier transform on specific bands or the entire bandwidth). The algorithms that use time-domain signals usually perform a demodulation process (computing the absolute value followed by low-pass filtering) on $d^*(k)$, or an energy signal, to generate the envelope of the signals (Chelotti et al. 2016, 2018, 2020). On the other hand, the algorithms that use frequency-domain signals usually perform a discrete Fourier transform over a time window of fixed duration to generate a short-time amplitude

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spectrogram (Clapham and Fedders 2011; Milone et al. 2012; Navon et al. 2013).

- **Accelerometers:** Algorithms based on jaw and body movements use a wide range of signal processing techniques. One approach is based on computing signals independent of the sensor orientation (Benaissa et al. 2017) computing like

$$ac_{mag} = \sqrt{ac_x^2(k) + ac_y^2(k) + ac_z^2(k)}.$$

Another approach is based on computing signals related to the two main components of the acceleration, such that $m(k)$ provides an approximation for the energy expended during animal movement (Benaissa et al. 2017; Lush et al. 2018). They are usually obtained by subtracting the running mean from $d^*(k)$ or high-pass filtering. Some additional signals can be calculated to obtain information about the animal's body tilt during the expressed behavior (e.g., head up, head down, head tilted to the right side), such as the pitch, roll, or sway signals. All of these measures are derived from the static acceleration, which is often isolated using running means (Lush et al. 2018) or low-pass filtering. Finally, some behaviors may be related to specific frequencies; therefore, signals associated to a specific frequency band are computed using a bandpass filter. A peak observed in the selected band is then used to identify the behavior and discriminate it from others (Andriamandroso et al. 2016).

The downsampling process is performed after preprocessing by splitting $m(k)$ into segments at regular intervals usually called windows by resampling $m(k)$ at a lower sampling frequency $m(k)$ or combining both procedures (resampling and windowing). The window is the fundamental unit in subsequent analyses. Two successive windows can have an amount of data in common (overlap). The most common approach is to use no overlap between windows.

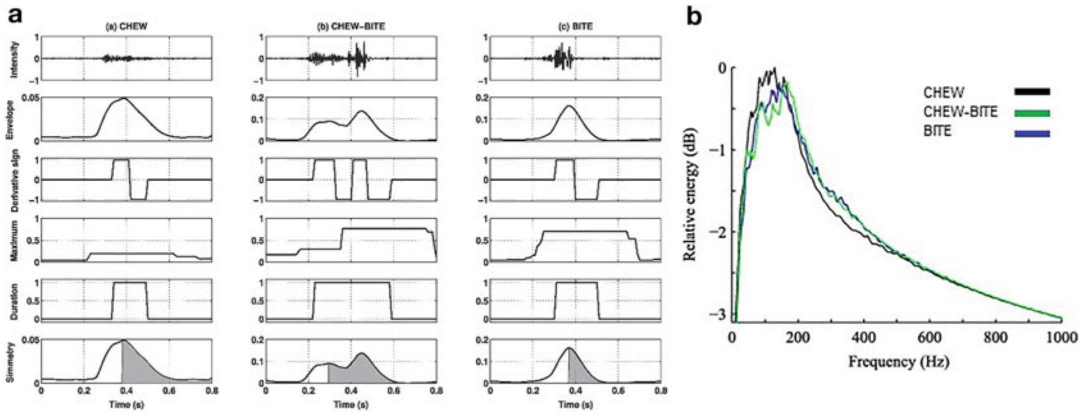
Feature Extraction

The goal of this task is to characterize jaw movements and feeding activities using a set of characteristics that allows us to unambiguously arrange them into classes. During the algorithms development, designers look for distinguishing features $x(k)$ that simplify the classification task. This transformation of $m(k)$ into x(k) can be "*continuous*" (window based) or can be "*triggered by specific events*" (event based). Depending on the sensor employed, different signals are computed:

- **Pressure sensors:** Algorithms based on pressure sensors use characteristics of the conditioned signal $d^*(k)$ to classify jaw movements and then feeding activities. To classify jaw movements (bites or chews), the algorithm analyses the peaks shape and quantity. Events are considered bites when they are a combination of a major long peak followed by a smaller subpeak or a nonsymmetrical peak in the absence of the subpeak. Conversely, a chew contains only one peak of symmetrical shape (Nadin et al. 2012). The features employed to classify jaw movements are maximum amplitude, event duration, jaw movement rate, and jaw movements count.
- **Microphones:** Algorithms based on sound use a wide variety of characteristics, ranging from time-domain features like the envelope of the sound or the envelope of instantaneous energy, among others, to frequency-domain features like Fourier transform and energy content of spectral bands.

  Algorithms that use time-domain features usually compute different characteristics that describe and quantify the jaw movements (rumination chew, grazing chew, bite, chewbite) and feeding behavior (Chelotti et al. 2018; Vanrell et al. 2018). This type of features provides information on

  Physical description of the jaw movement: It is described through the estimation physical properties that describe and quantify the jaw movement (shape, duration, rate of change, maximum intensity, symmetry and energy content, among others; Fig. 6a).



Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 6 Typical features produced by jaw movements for (**a**) time-domain features. (From Chelotti et al. (2018)) and (**b**) frequency-domain features. (Adapted from Milone et al. (2012))

Statistical description of the feeding behavior: It is described through statistical properties of detected jaw movements for different feeding behaviors (mean, bias, standard deviation, kurtosis, among others).

Algorithms that use frequency-domain features usually compute Mel-Frequency Cepstral coefficients and energy content of spectral bands (Fig. 6b). This type of feature provides information on the spectral characteristics of the sound produced by each jaw movement (chew, bite, chewbite) and the amount of herbage processed by the animal (Milone et al. 2012).

- **Accelerometers:** Features are usually extracted from each window after the preprocessing stage in order to describe each time window with local features (from the windowed signal). These features are mostly calculated in the time domain alone followed by frequency domain using the Fourier transform. Sometimes, wavelet features are also extracted in the time-frequency domain. Whatever the domain, features may provide information on.

Motion intensity: It is described through statistical properties (mean, standard deviation, movement variation, median, minimum, maximum, range and root mean square, among others) of the window (Brennan et al. 2021; Riaboff et al. 2020).

Body orientation: It is described through the mean and median of the window (Kleanthous et al. 2018).

Signal shape: It is described through statistical properties (mean, standard deviation, median, minimum, maximum, skewness, kurtosis) of the window (Lush et al. 2018).

Physical description of the body movement: It is described through a set of spectral properties (spectral flatness, spectral centroid, spectral spread, spectral kurtosis, spectral entropy, fundamental frequency, maximum and second maximum power spectral density, wavelet features) of the window (Kleanthous et al. 2018; Riaboff et al. 2020).

Classification

The goal of this stage is to build and validate a model able to classify the features *x(k)* into one of the candidate jaw movements or feeding behavior. The main categories of models employed in the literature can be classified into

- **Thresholding:** The jaw movements and behaviors are discriminated using simple rules and thresholds for each feature. They can be assigned manually, given observational data, or estimated from feature distribution (Chelotti et al. 2016; Clapham and Fedders 2011; Vanrell et al. 2018).

- **Statistical models:** It includes generalized linear models like logistic regression or models based on Markov processes. This type of models has been employed in combination with microphones and accelerometers (Milone et al. 2012; Tani et al. 2013).
- **Supervised machine learning:** It mainly includes k-nearest neighbor, linear discriminant analysis, support vector machines, decision trees, and artificial neural networks. The hyperparameters for training each model are usually found using Grid Search and validation data set. This type of model is employed in combination with microphones (Chelotti et al. 2018, 2020) and accelerometers (Benaissa et al. 2017; Brennan et al. 2021).
- **Supervised ensemble machine learning:** It involves ensemble methods for classification, such as random forest, among others. The hyperparameters for each model are found using Grid Search and validation data set. This type of model is employed mainly with accelerometers (Dutta et al. 2014; Lush et al. 2018; Riaboff et al. 2020).
- **Unsupervised machine learning:** It especially includes the k-means classification and has been employed with accelerometers (Vázquez-Diosdado et al. 2019).
- **Deep learning:** This category of classifiers includes the different types of artificial neural networks with several hierarchical layers, including multilayer perceptrons, convolutional neural networks, recurrent neural networks, and long short-term memories, among others. Although this category is somewhat marginal, its use as a classification model has increased recently because of its relative success in other applications. One distinguishing feature of this type of model is their ability to process the raw data $d(k)$ instead of the features $x(k)$. This type of model is mainly employed with microphones (Chelotti et al. 2018, 2020; Navon et al. 2013) and accelerometers (Peng et al. 2019, 2020).

The validation step aims to assess the accuracy and robustness of the developed model. This evaluation includes the three distinct substeps: firstly, a **predictive test** is performed by computing the output of the model of features using the test data set or cross-validation techniques. Then, the predicted jaw movements or behaviors are compared to the actual observed behaviors (references obtained from the observations) by **computing a confusion matrix**. A confusion matrix per behavior is used to calculate true positives, false positives, true negatives and false negatives associated with each jaw movement or behavior. Finally, the **performance of the model** is analyzed using standard metrics for model evaluation, the most common ones are F-score measure, sensitivity, specificity, and precision, among others.

Precision Livestock Farming

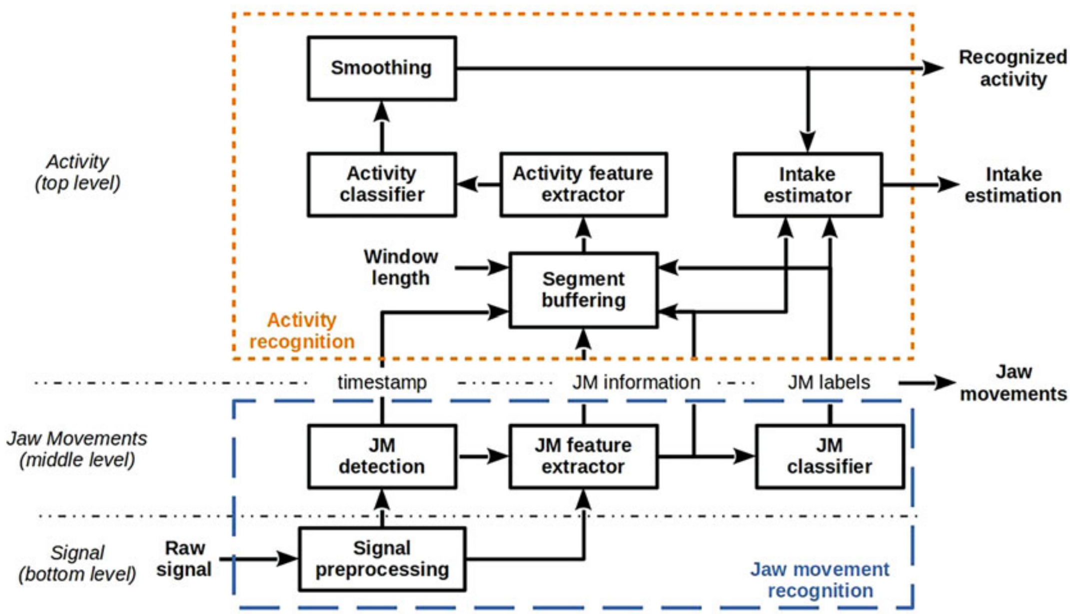
Successful herd and pasture management requires an understanding of the adjustment mechanisms behind the grazing and ruminating behaviors that enables adaptation to grazing conditions (Hostiou et al. 2017). As well as facilitating the precise herd management, the monitoring of animal position, foraging, and other behaviors can bring benefits to animal health and welfare. Any small deviation from "*normal*" behavior (for that individual animal) can be identified and flagged to the farmer (Neethirajan 2020).

The use of global navigation satellite System (GNSS) technology allows for the characterization of feeding behavior in terms of grazing patterns, paths, and favored areas. The use of GPS for livestock has opened the possibility of recording detailed position data for extended periods of time, thus allowing a more complete understanding of the habits and causes of the spatial distribution of ruminants. The position information can be stored, together with behavior and physiological data, and can be transmitted to a management center in real time or in periodical sessions (Dutta et al. 2014). For example, analyzing grazing and rumination behavior (times and rates) by means of behavior-monitoring sensors like the ones described in previous section, estrus events can be detected.

Figure 7 shows the architecture of a particular system for monitoring feeding activities of cattle (Chelotti et al. 2020). It is divided into two subsystems, each one corresponding to the timescales involved in the feeding activities: one concerned with the jaw movements and short time behaviors (jaw movement recognition) and the other concerned with the feeding activities (activity recognition). The jaw movement recognition subsystem comprises a system able to extract, from the raw signal, all the information available of short-time behaviors (jaw movements, head and body movements). It provides information about the basic elements of the feeding behavior (jaw movement information, optionally a label). The activity recognition subsystem comprises a system that concatenates the jaw movements into a feeding station, through a buffer, then it extracts the features of the window to classify activities performed by the animal. Then, the subsystem repeats this process (concatenation – feature extraction – classification) with feeding stations, bouts, meals, and paddock to estimate the feeding behavior of the animal along the different timescales (see Fig. 1).

The system for monitoring feeding activities can include a subsystem that estimates the grazing intake and/or the dry matter intake of cattle (Fig. 7). The grazing intake can be **indirectly estimated** from identified jaw movements by combining grazing duration, biting rate, and bite mass (Vallentine 2000). On the other hand, grazing intake and dry matter intake can be **directly estimated** from the sound signal produced during feeding activities. The energy of grazing chews and the number of bites during the grazing period are related to the dry matter intake, and they also provide information about the intake rate of forages and eating time (Galli et al. 2018). Since eating time can be also estimated by measuring the duration of the individual jaw movements, then intake rate can be computed by combining these variables.

The first approach is employed in systems that are able to only identify jaw movements (pressure sensors, microphones, and accelerometers). They rely on a precise determination of the individual bites (including the bite portion of the chewbite, given their significance in the grazing process, see Fig. 2) and a good estimation of the bite mass



Information Technologies in Feeding Behavior Livestock Monitoring, Fig. 7 General diagram of a top-bottom feeding activity monitoring system (or their average mass). It is given by the following formula (Vallentine 2000):

$$Forageintake[g] = Bitemass\left[gbite^{-1}\right] \cdot Biterate\left[bitemin^{-1}\right] \cdot Grazingperiod[min].$$

The accuracy of this formula depends on the precise detection of individual bites as well as the correct estimation grazing behavior and bite mass. From these variables, the more problematic is the bite mass since it depends on the size of the dental arcade and pasture characteristics like sward height, tiller density, and bulk density (Carvalho et al. 2015).

The second approach is employed in systems that are able to accurately characterize jaw movements by identifying grazing chew, bite jaw, and chewbite movements and computing their parameters like jaw movement duration, energy, and time between jaw movements, among others. Only systems that combine microphones to register sounds and algorithms based on machine learning techniques can gather this information (Galli et al. 2018). Then, linear statistical models or machine learning models are employed to estimate dry matter and forage intakes.

Conclusions

Most sensors and techniques described in this chapter have been primarily designed for research. Although some sensors such as accelerometers are already used for behavior classification in farm situations, their use as tools for jaw movements monitoring of grazing animals still requires significant hardware and software developments, to automatize process and real-time data acquisition, as well as ease of installation and use. For example, whether based on mechanical (pressure or acceleration), electrical, or acoustic signals, most sensors require the use of a halter, and the way it is mounted is extremely important in the recording of jaw movements.

A preprocessing of the signal may also be required to eliminate existing noises around the animal or during the movement. Combining different sensors, for example, accelerometers and microphones, may be a solution for a better monitoring of bites. Dedicated signal processing also requires significant development. For example, using frequency-domain signal processing approaches on acceleration data might provide useful progress.

Finally, PLF requires the system to be robust and adaptable to a wide range of situations. Most techniques presented here were applied under strictly controlled conditions for research and their implementation in the farms would also require some ability for autocalibration of the device or tools to overcome differences in individual physiological states, morphologies, or grazing conditions according to the season and pasture.

Cross-References

▶ Animal Welfare Monitoring
▶ Precision Livestock Farming: Developing Useful Tools for Livestock Farmers
▶ Sound-Based Monitoring of Livestock

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