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Review

Behavioral Fingerprinting: Acceleration Sensors for Identifying Changes in Livestock Health

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Abstract: During disease or toxin challenges, the behavioral activities of grazing animals alter in response to adverse situations, potentially providing an indicator of their welfare status. Behavioral changes such as feeding behavior, rumination and physical behavior as well as expressive behavior, can serve as indicators of animal health and welfare. Sometimes behavioral changes are subtle and occur gradually, often missed by infrequent visual monitoring until the condition becomes acute. There is growing popularity in the use of sensors for monitoring animal health. Acceleration sensors have been designed to attach to ears, jaws, noses, collars and legs to detect the behavioral changes of cattle and sheep. So far, some automated acceleration sensors with high accuracies have been found to have the capacity to remotely monitor the behavioral patterns of cattle and sheep. These acceleration sensors have the potential to identify behavioral patterns of farm animals for monitoring changes in behavior which can indicate a deterioration in health. Here, we review the current automated accelerometer systems and the evidence they can detect behavioral patterns of animals for the application of potential directions and future solutions for automatically monitoring and the early detection of health concerns in grazing animals.

Keywords: animal health; acceleration sensors; behaviors; cattle; sheep

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1. Introduction

Automatic accelerometers represent a relatively new and emerging technology to provide continuous and real-time evaluation of animal activity on-farm to support reproduction and health. In grazing ruminant livestock production systems improving animal efficiency represents large opportunities in improving environmental, animal welfare and economic outcomes. Implementing sensors and big data into livestock enterprises are proposed as an effective means for meeting many of these outcomes [1]. Various sensor technologies have been designed and implemented to provide information on a wide range of aspects of animal health and behavior. The previous reviews have described many of the links between animal physiology and different types of sensors which include wearable sensors which detect sweat, temperature, sound, movement and so on using a range of technological approaches [1,2]. The most common and widely commercialised of these technologies is the accelerometer sensor. A systematic review was conducted into the use of raw accelerometer data based on a 3-step method to predict ruminant behavior through predictive models [3]. However, those reviews were focused on behavior classification using accelerometer datasets and did not provide information on how specific behavioral changes can be for animal sickness characterized in the face of varying challenges, which remains a gap in our knowledge.

In this context, behavior could be considered an important component of animal well-being for animal welfare assessment [4]. Grazing cows with a good health status and productivity had been shown to spend less time lying down/resting and exhibit more feeding and rumination activity [5]. Further, animal behavioral changes, defined as abnormal, that are forced by the impact of an adverse environment and help the animals cope with an adverse environment, are indicators of poor welfare [6]. Animals suffering from diseases such as mastitis, metritis, metabolic disorders and ketosis, usually exhibit behavioral alterations. Cows with clinical mastitis show a decrease in feed intake and feed rate as well as fewer feeding bouts or visits to the feeder during peak feeding times [7]. Grazing dairy cows with metritic infections increased the total daily lying time the first week postpartum which simultaneously reduced physical activity and reduced feeding in the three weeks before diagnosis [8]. When cows suffer from hypocalcaemia, their feeding duration and number of visits to the feeder postpartum were shown to be reduced [9]. Ketotic cows have shown prolonged standing time and decrease feeding duration over the week before partum [10]. Behavioral responses of lying and rumination patterns of individuals exposed to environmental challenges were associated with animal welfare, indicating the balance of changeable behavioral patterns associated with the environment and similar behavioral responses on different conditions towards how to cope with health risk at different external situations at the individual level [11]. As a consequence, animal behavior can serve as an indicator of their welfare. The potential for accelerometer technology to detect changes in animal behavior associated with welfare concerns is a promising area that requires further investigation in order to link measured changes across a range of parameters to a specific disease and allow targeted individualized treatment. If successful this approach could lead to the timely diagnosis of sub-clinical disease, leading to improved welfare outcomes for farmed livestock. However, in order to detect a pattern of behavior that is indicative of a specific disease challenge, consideration needs to be given to the behavioral traits that are typically expressed when animals are in a poor welfare state. The ultimate aim may be use one or more sensors to provide a fingerprint of behavior patterns that are unique and indicative to a specific disease or welfare state.

Hence, this review aims to provide the behavioral parameters currently measured to indicate the health status of farm ruminants and their potential to be categorized via acceleration sensors used in precision livestock farming. Furthermore, revisited in this review are the current application and development of acceleration sensor technologies that have been validated to be available for accurate detection and classification of behavioral patterns.

2. Behavioral Indicators of Animal Health

Healthy ruminants spend their time in a range of behaviors which include eating, ruminating, socializing and resting. As indicated above, behavioral response to changes in health are diverse. Various behavioral changes, such as reduced grazing or ruminating time, changes in physical activity (lying, standing and posture) and expressive behaviors, could be observed and measured during the periods of different health challenges. This section will review the size of the variation in specific behaviors when the health status of an animal is compromised.

2.1. Eating

Eating behavior is a common behavioral indicator of animal welfare. The loss of appetite or a reduction in voluntary food intake is the most frequently reported symptom of infection with pathogens [12]. Although it is not always clear how anorexia provides a functional advantage to the animals during times when the nutritional demands of an immune response may be increased, infection-induced anorexia is considered to be an active behavior of systematical defense and elimination against pathogens, which is a complex mechanism of acute phase response related to immune, endocrine and central nervous system [13]. Pro-inflammatory cytokines released as part of the immunological cascade, act as a central mediator in the brain of infected animals and result in behavioral changes such as reduced eating time and fewer social activities [14–16]. Feed intake of susceptible animals can be decreased by the diseases such as metritis, mastitis, parasitism or lameness. For example, intramammary infusion with *Escherichia coli* reduced average feeding time by approximately 20% in the first day following infection compared with two days prior to infection [17]. Mastitic dairy cows had a lower feed intake and fewer feeding bouts and spent less time lying [18], while the dry matter intake (DMI) of dairy cows with mild and severe metritis was, respectively, decreased by 0.21 and 0.33 kg/d which was associated with 4.0, and 4.8 min/d reduced feeding times [19]. Further, lame dairy cows with higher locomotion scores, displaying more visible symptoms of lameness, had fewer, larger meals with shorter total feeding duration [20], with changes of feed intake and feeding time as well as feeder visits suggested as indicators to detect health disorders of dairy cows [21]. Similar observations have been reported during infection with multi-cellular organisms. In young ruminants, the maximum reduced feed intake of calves on pasture for the first season was observed at day 42, 37 and 25 for groups with low, medium and high infection levels of *Ostertagia ostertagi*, respectively [22]. Voluntary feed intake of lambs infected artificially with *Teladorsagia circumcincta* and/or *Trichostrongylus colubriformis* has frequently been reported to be reduced with the extent directly proportional to larval challenge. Voluntary feed intake of ewe lambs infected artificially with 1500 or 7000 *T. circumcincta* larvae in two doses per week for 6 weeks, was reduced by approximately 10% [23], and voluntary daily food intake of susceptible lambs dosed with 7000 *T. circumcincta* larvae 3 times per week for 12 weeks, was decreased by 13% compared with the control group [24]. Furthermore, dry matter intake of lambs receiving 3000 *T. circumcincta* and 3000 *T. colubriformis* larvae per day for 18 weeks was reduced by 60% [25]. In general, the changes of voluntary feed intake of animals confronted with stressful conditions is typically considered an adaptive behavioral alteration, although the functional advantage that this provides to the animal is yet to fully elucidated. Nevertheless, alterations to feed intake, feeding frequency and a general grazing behavior have the potential to provide useful indicators of the status of animal health and welfare associated with disease. A major obstacle has been the difficulty in assessing these parameters, particularly assessment of feed intake, of animals when grazing.

2.2. Ruminating

Ruminating behavior is a subcategory of feeding behavior pattern, defined as regurgitating a bolus, chewing the cud or moving the head and jaw in a circular motion and then swallowing the masticated cud. Chewing can reduce dietary particle size, promote the secretion of saliva as a buffer for lubricating the bolus swallowed and maintaining optimum rumen pH to enhance microbial digestion of forage, facilitate microbial colonization of the rumen and the clearance of small forage particles from the rumen into the lower gastrointestinal tract [26]. In general, ruminating duration can be increased by poor-quality forage with high neutral detergent fiber and cell wall content [27,28], and increased forage particle size [29]. However, reduced ruminating time is often observed during health challenges, such as heat stress [30] and metritis [31], at least some of which can be expected to be related to reductions in feed intake. Decreased rumination is usually considered to decrease in saliva flow and rumen buffering [32], which may affect the function of rumen digestion and nutrient absorption. Therefore, ruminating can serve as an indicator of the animal health and welfare. There has been limited research on changes of ruminating behavior caused by infection. For example, daily ruminating duration of dairy cows was reduced by up to 15–30% before diagnosis, due to metritis [33], mastitis [34] and lameness [35]. Reduced rumination time during calving or lactation was used as a measurement to monitor early endometritis, ketosis, lameness and mastitis disease of dairy cows [36,37]. However, ruminating time is frequently combined with other behavioral indicators to assess ruminant welfare. Cows with increased somatic cells in milk reduced both their rumination and feeding time, indicating changes in these behaviors could be considered as the indicators for udder health or a response to inflammation somewhere in the body [5]. Behavioral indicators related to sheep welfare were considered to be ruminating, feeding (DMI and water intake), lying as well as the time of standing and locating during seclusion [38], indicating rumination function is only one of a myriad of activities and behaviors than can be used in combination to assess welfare.

2.3. Physical Activity

2.3.1. Active Behavior

The physical activity of on-farm animals is normally described in forms such as lying, standing, walking and other body movements. Lying and standing can be classified as inactive behavior, while walking and body movements can be regarded as active behavior. Behavioral changes in physical activity and fever are usually simultaneous with a reduction in active behavior and an increase in inactive behavior. The reduced activity is associated with changes in body temperature when invading pathogens activate a pro-inflammatory immune reaction [39]. The subsequent reduction in activity is believed to be necessary to preserve the energetic resources of individual animals to fight infection [15,40]. Various studies have been carried out to reveal the changes of physical activity caused by infectious diseases. For instance, metritic infection increased the total daily lying duration of dairy cows with a simultaneous reduction of active behavior in 3 days before and after diagnosis [41]. Daily lying time of cows diagnosed with clinical metritis were increased compared with cows without clinical metritis (628.9 vs. 591.2 min/d, respectively) [42]. Similarly, compared with healthy cows, cows diagnosed with metritis had reduced daily physical activity (512.5 vs. 539.2 arbitrary units/d, respectively) and postpartum daily ruminating time (415.9 vs. 441.0 min/d, respectively) [31]. Further, rumination duration (36.8 vs. 39.8 min/2 h, respectively) and physical activity (27.7 vs. 30.5 units/2 h, respectively) were reduced in sick cows with ketosis, metritis, lameness and other health problems, compared with healthy cows [43]. The induced infections of mastitis result in prolonged standing duration and shortened total lying duration with increasing step count and decreased overall activity [17,44]. Sheep in pain caused by lameness or mastitis may display licking, rubbing or scratching painful areas, less movement and changes in posture to avoid contact with the painful area [45]. Some researchers found sheep infected with the degenerative scrapie disease spent less than half their time standing compared with the normal sheep and spent more time in an abnormal recumbent posture and more time in rubbing and self-biting [46]. In studies of animal with skin parasites, the infestation of mites (*Psoroptes ovis*) caused rubbing behavior of sheep, leading to a reduction in lying time and an increase in the number of lying bouts [47]. These changes in movement activity typically relate to one or more parts of the body. The previous example with mites can provide immediate and short term visual cues to the farmers through rubbing and self-biting, but over the time other changes in activity such as reduced lying time is important for welfare but less visible.

2.3.2. Inactive Behavior

Inactivity and recumbency in animals reflect a wide range of health challenges and welfare status. Mean total daily lying time and mean duration of lying bouts of dairy cows with hoof lesions were increased as locomotion score was increased, indicating the increasing severity of hoof lesions in cows [48]. On farms using deep bedded stalls, dairy cows with severe lameness tended to lie down 1.6 h longer per day, had longer lying bouts and greater variation in the duration of lying bouts with behavioral thresholds identified for severe lameness such as lying time >14.5 h/d, log bout duration > 4.5 log(min)/bout and standard deviation of log bout duration > 4.0 log (min)/bout [49]. When lactating dairy cows were in a high comfort and health state, average daily total lying time = 8.7 h/d, mean daily lying bouts = 12.1 and average duration of lying bouts = 46.1 min, showing that any changes in lying behavior of dairy cows can indicate the occurrence of health and welfare issues [50]. Activity patterns such as lying time, lying bouts and steps were measured to identify pain and stress of dairy cows suffering clinical metritis [42]. Some researchers have reported that lying comfort was a behavioral indicator associated with welfare to assess the impact of the cubicle on cattle welfare [51]. Lying behavior has also been used in combination with other behaviors for the assessment of ruminant welfare. Diseased pre-weaned dairy calves had longer daily lying (17.6 vs. 16.7 h/d, respectively), lying bout duration (74.8 vs. 56.0 min, respectively), shorter feeding time (19.3 vs. 22.8 min, respectively) and fewer feeder visits (2.1 vs. 3.2, respectively) compared with healthy calves, indicating changes in the number of lying bouts and lying time along with feeding patterns can be used to predict disease of dairy calves [52]. Moreover, lying and walking activity were recorded as behavioral indicators under the conditions of on-pasture and indoor housing to evaluate the influence of these conditions on dairy cows' well-being for comparison [53]. Behavioral indicators of lying behavior (total time and synchronization) and locomotion score have been suggested to estimate dairy cow welfare during housing [54] while lying behavior, gait score, and walking speed could be utilized as behavioral indicators to monitor hoof lesions of dairy cows [55]. In addition, standing behavior of dairy cows before calving could be considered as a parameter to detect postpartum sub-clinical ketosis [56]. Behavioral changes of dairy cows such as reduced standing (5.52 vs. 6.51 h/12 h, respectively), increased lying (6.48 vs. 5.50 h/12 h, respectively) and shorter feeding at night were recorded in dairy cows suffering claw horn lesions [57]. Furthermore, behavioral activities such as voluntary standing posture, weight shifting from one foot to another and uneven weight bearing as well as standing on the edge of stalls have been suggested to provide an indicator for lameness of cows [58]. However, not all increase in inactivity are associated with health per se. Animals respond to climatic extremes through variation in behavior with increased inactivity in both very hot or very cold conditions [59–63], and these changes in activity in response to non-disease challenges need to be accounted for.

2.3.3. Expressive Behavior

Subtle expressive behaviors, such as tail and ear position, facial expression, panting, separation from the flock and coughing, can be also regarded as the behavioral indicators to evaluate animal welfare under different circumstances. For example, behavioral reactions of dairy cows were used as the possible indicators to assess pain during the period of mastitis, which included changes of standing/lying, in addition to tail and ear position and attitude toward surroundings [64]. Sheep suffering pain induced by foot rot or mastitis can be identified to show abnormal facial expression, such as closing palpebral fissure by the eyelids, narrowing eye aperture, tightening masseter muscle with a convex shape, abnormal ear posture with ventral and caudal rotation, a concaved jaw and an abnormal "V" shape of nostril and philtrum [45]. The behavioral indicators of sheep welfare could include alertness, separation from the flock, posture, gait, panting, response to stimulation, shivering, coughing and play [65].

3. Acceleration Sensors for Measurement of Behavioral Patterns

With the many behavior cues, the ability to detect animal health issues and address them promptly offers an opportunity to improve outcomes and improve production and wellbeing. However, collection of quantifiable animal activity on pasture based on direct observation or video monitoring, are both time consuming and labor intensive, and the presence of an observer can disrupt normal behavioral patterns [66–68]. In extensive pastoral system, it is difficult to continuously monitor animal behaviour, especially for large numbers spread over long distances [69]. The development of sensor and communication technologies has improved the ability to remotely monitor activities of livestock in a broad range of environments and on a scale not previously possible. In order to decode the recorded data, it is essential to develop an analysis system to classify various behaviors and postures of animals [70]. Currently there are 22 validated accelerometers available to identify behaviors related to feeding and drinking, and/or movement and resting in cows [71]. In a meta-analysis of sensor technology, there are 129 commercially available sensors identified with only 18% having validation reports [72]. However, the relationship between the sensor analysis and the observed behavior needs to be validated to provide confidence in the technology and subsequent user adoption. 3-Dimensional (x, y and z axis) accelerometer sensors were used in ninety-seven percent of 66 relevant studies [3], measuring acceleration values within three orthogonal spatial axes capturing the animal's motion dynamics, as the x-axis corresponds to the front-back direction while the y-axis and the z-axis detect the side-to-side direction and the up-down direction, respectively [73]. Accelerometers attached below the neck of cattle measures the 3-axis inertial and gravitational accelerations with the x-axis detecting the up-down direction, the y-axis detecting the front-back and the z-axis detecting the right-left direction [74]. However, ear-mounted triaxial accelerometers in sheep detect the accelerometry datasets from x-axis, y-axis and z-axis corresponding to the directions of up-down, right-left and front-back, respectively, while the x-axis, y-axis and z-axis of collar-mounted accelerometers detect the right-left, the front-back and the up-down direction [75]. Overall, wearable 3-axis acceleration sensors have the capability to capture the accelerometry data corresponding to animal behaviors which can indicate the health status of farmed animals. 3-axis acceleration sensors with lightweight, small size, accuracy and real-time monitoring are a promising system to identify animal behaviors. Moreover, the research on behavioral changes of animals could also facilitate the diagnosis of animal diseases and offer significant information to determine treatment decisions given to animals. Behavioral changes may lead to the occurrence of abnormal statistics from the collected 3D-accelerometry datasets. Hence, the processing and analysis of accelerometry data from a wearable 3-Dimensional accelerometer sensors can provide information related to animal health state. Among previous studies, various acceleration sensors attached to ears, jaws, collars, legs or noses, have already been validated on characteristics of behavioral activities of animals, shown in Table 1. These acceleration sensors were validated using a range of statistical parameters including correlation coefficient, coefficient of determination, accuracy, sensitivity, specificity, precision, Kappa, concordance correlation coefficient or/and *F*-score during previous studies.

Table 1. The accelerometer systems used for the validation of behavioral activities. r = correlation coefficient (Pearson or Spearman's rank), Acc = accuracy, Se = sensitivity, Sp = specificity, Pr = precision, Kappa = κ, *F*-score, CCC = concordance correlation coefficient, and R^2 = coefficient of determination.

Accelerometer	Placement	Parameter	Measurement of Validity	NO. Animals
CowManager SensOor (Agis Automatisering BV, Harmelen, The Netherlands)	Ear (cow)	Percentage of eating time in 6 h recording	r = 0.88, κ = 0.77 [76]	15
		Percentage of eating time in about 20 h recording	r = 0.88, CCC = 0.99 [77]	24
		Percentage of ruminating time in 6 h recording	r = 0.93, κ = 0.85 [76]	15
		Percentage of eating time in about 20 h recording	r = 0.72, CCC = 0.99 [77]	24
		Percentage of eating/ruminating time in 40 h recording	r = 0.83 [78]	10
Allflex® eSense™ (SCR Engineers Ltd., Netanya, Israel)	Ear (heifer)	Minute-level panting for 10 days	Se = 0.30–0.33, Sp > 0.70 [79]	99
SMARTBOW (Smartbow GmbH, Weibern, Austria)	Ear (cow)	Hourly rumination time in 4 h recording	r= 0.97, CCC = 0.96 [80]	48
	Ear (calf)	Hourly rumination time in 20 h recording	r > 0.99 [81]	10
		Total ruminating time in 4 h recording	Se = 89.4%, Sp = 94.9%, Acc = 93.9%, Pr = 78.5%, F1 score = 83.6%, Kappa = 0.80 [82]	15
		Total time of postures (lying, standing, locomotion) in 4 h recording	Se = 94.4%, Sp = 94.3%, Pr = 95.8%, Acc = 94.3% [82]	
HOBO Pendant G data loggers (Onset Computer Corporation, Pocasset, MA, USA)	Ear (cow)	Grazing time in 30 min recording	Se = 85.47%, Sp = 82.08%, Pr = 77.63% for the intervals of 5 min [67]	20
	Jaw (cow)	Grazing time in 30 min recording	R^2 = 0.96 [83]	7
		Rumination time in 30 min recording	R^2 = 0.91 [83]	
	Neck (cow)	Feeding time in 3 h recording	Se = 0.789, Sp = 0.937, R^2 = 0.90 [84]	12
	Leg (ewe and ram)	Walking, trotting and galloping duration in 15 min recording	Overall Acc = 87% [85]	13
		Standing and lying duration in 15 min recording	Acc = 99.95% and 99.50%, respectively [85]	
GCDC X16-mini MEMS accelerometers (Gulf Coast Data Concepts, Waveland, MS, USA)	Ear (ewe)	Total grazing, standing and walking number in 10 s epochs sampling	Acc = 94%, 96% and 99%, respectively [86] Se, Sp, Acc and Pr from 92% to 100% [86]	10
DairyCheck system (BITSz engineering GmbH, Zwickau, Germany)	Jaw (cow)	Total feeding time in 311–422 min recording	r = 0.86, R^2 = 0.74 [87]	14
		Total rumination time in 311–422 min recording	r = 0.87, R^2 = 0.75 [87]	

Table 1. *Cont.*

Accelerometer	Placement	Parameter	Measurement of Validity	NO. Animals
AML prototype V1.0 (AerobTec, Bratislava, Slovakia)	Lower jaw (sheep)	Total grazing, lying, running, standing and walking at 3, 5, 10 s epochs sampling	Acc = 81.5–85.5% [88]	10
ADXL335 (Analog Devices, One Technology Way, Norwood, MA, USA)	Lower jaw (ewe)	Total grazing duration in 675 min recording	Se = 96%, Sp = 97%, Pr = 95%, Acc = 96% [89]	3
		Total ruminating duration in 675 min recording	Se = 89%, Sp = 97%, Pr = 89%, Acc = 95% [89]	
		Total resting duration in 675 min recording	Se = 93%, Sp = 95%, Pr = 94%, Acc = 94% [89]	
BEHARUM device (Analog Devices, One Technology Way, Wilmington, MA, USA)	Lower jaw (ewe)	Grazing acceleration values per min for 20-25 min in the 30 s epoch sampling	Se = 94.8%, Sp = 93.0%, Pr = 94.1%, Acc = 94.0%, κ = 0.9 [90]	48
		Ruminating acceleration values per min for 20-25 min in the 30 s epoch sampling	Se = 80.4%, Sp = 94.7%, Pr = 88.1%, Acc = 90.0%, κ = 0.8 [90]	
Hr-Tag (Allflex SCR Engineers Ltd., Netanya, Israel)	Neck (cow)	Rumination times per 2 h recording	r = 0.93, R^2 = 0.87 [91]	27
Actiwatch Mini® (CamNtech, Cambridge, UK)	Neck (ewe)	Total counts of high, medium and low activity per min in 20 min sampling	Overall Acc = 79.98% for high/medium activity and 74.56% for low activity [92]	9
Bosch BMI160 (Bosch-sensortec, Reutlingen, Germany)	Neck (sheep)	Grazing behavior points in 2 h recording with a window discretization	Sp = 98%, Pr = 96%, *F*-score = 95% [75]	6
		Ruminating behavior points in 2 h recording with a window discretization	Sp = 97%, Pr = 92%, *F*-score = 89% [75]	
MooMonitor+ (Dairymaster, Co. Kerry, Ireland)	Neck (cow)	Total feeding time in 4 h recording	r = 0.93, R^2 = 0.85, CCC = 0.80 [93]	24
		Total ruminating time in 4 h recording	r = 0.99, R^2 = 0.97, CCC = 0.95 [93]	
		Total resting time in 4 h recording	r = 0.94, R^2 = 0.88, CCC = 0.82 [93]	
		Hourly grazing time in daily 4 h recording	r = 0.94, CCC = 0.97 [94]	12
		Hourly ruminating time in daily 4 h recording	r = 0.97, CCC = 0.98 [94]	
Omnisense Series 500 Cluster Geolocation System (Omnisense Ltd., Elsworth, UK)	Neck (cow)	Feeding bouts, feeding bout duration, and total feeding time (daily, morning/afternoon/night)	Sp = 93.0%, Pr = 83.5%, Acc = 83.2% [95]	19
		Total feeding duration in 36 h recording	Se = 98.78%, Pr = 93.10% [96]	6
ADXL330 (Analog Devices, Norwood, MA 02062, USA)	Neck (cow)	Total feeding duration during 30 d	Se = 75%, Pr = 81%, Acc = 96% [97]	30
		Total ruminating duration during 30 d	Se = 75%, Pr = 86%, Acc = 92% [97]	
Axivity AX3 (Axivity Ltd., Newcastle, UK)	Neck (cow)	Minute-level feeding/rumination in 6 h recording	Overall Acc = 93% [98]	10
	Ear (ewe)	Total number of grazing behavior at 10 s epoch Support Vector Machine test	Acc = 76.9%, Se = 90.3%, Sp = 98.1%, Pr = 96.8%, κ = 0.6 [99]	12
		Total number of active or inactive behaviors at 30 s epoch Classification and Regression Tree test	Acc = 98.1%, Se, Sp, Pr from 96.9% to 98.6%, κ = 1.0 [99]	
H30CD (Hitachi Metals, Ltd., Tokyo, Japan)	Neck (cow)	Minute-level eating, ruminating, lying in 6 h recording	Pr = 99.2% by a 10-fold cross-validation, Se = 100%, Sp = 100% [100]	38
Kenz Lifecorder Plus device (LCP, Suzuken Co., Ltd., Nagoya, Japan)	Neck (cow)	Minute-level grazing in daily 4 h recording for 12 d	R^2 = from 0.97 to 0.99 [101]	6
GENEActiv (Activinsights Ltd., Kimbolton, Cambridgeshire, UK)	Neck (ewe and lamb)	Data points of standing and lying in ewes for 39 d	Average Acc = 83.7% [102]	116
		Data points of standing and lying in lambs for 39 d	Average Acc = 85.9% [102]	
		Data points of activities in ewes for 39 d	Average Acc = 70.9% [102]	
		Data points of activities in lambs for 39 d	Average Acc = 80.8% [102]	
ActiGraph wGT3X-BT® (ActiGraph, LLC, Pensacola, FL, USA)	Neck (lamb)	5s epoch counts of grazing during 4 d recording	Acc = 91%, Se = 94%, Sp = 88%, Pr = 86% [103]	6
		5s epoch counts of resting during 4 d recording	Acc = 93%, Se = 89%, Sp = 96%, Pr = 96% [103]	
		5s epoch counts of walking during 4 d recording	Acc = 95%, Se = 72%, Sp = 97%, Pr = 76% [103]	
InvenSense MPU-9250 (no mentioned provider)	Neck (lamb)	Confusion matrix for grazing activity in 22.5 h recording at the 5 s, 10 s and 15s epoch	Pr, Sp, Se, Acc between 92.6% to 98.9% [104]	3

Table 1. *Cont.*

Accelerometer	Placement	Parameter	Measurement of Validity	NO. Animals
Track A Cow (ENGS, Rosh Pina, Israel)	Leg (cow)	Minute-level feeding time in 4 h recording per day	r = 0.93; CCC = 0.79 [80]	48
		Minute-level lying time in daily 4 h recording	r > 0.99; CCC > 0.99 [80]	
ADXL345 (Analog Devices, Norwood, MA 02062, USA)	Leg (cow)	Feeding duration at second-level window	Se = 52%, Pr = 55%, Acc = 80% [105]	5
		Active walking duration at second-level window	Se = 94%; Pr = 89%; Acc = 99% [105]	
		Lying duration at second-level window	Se = 93%; Pr = 82%; Acc = 92% [105]	
		Standing up duration at second-level window	Se = 74%; Pr = 85%; Acc = 99% [105]	
AfiAct Pedometer Plus (Afimilk, Kibbutz Afikim, Israel)	Leg (cow)	Hourly lying time in 4 h recording	r > 0.99; CCC > 0.99 [80]	48
IceQube (IceRobotics Ltd., Edinburgh, Scotland)	Leg (cow)	Hourly lying time in 4 h recording	r > 0.99; CCC > 0.99 [80]	48
	Leg (lamb)	Second-level durations of standing, lying in daily 1 h recording for 40 h	Positive predictive value > 92%, sensitivity > 88% [106]	10
IceTag3D-accelerometer (IceRobotics Ltd., Edinburgh, UK)	Leg (lamb)	Second-level durations of standing, lying in daily 1 h recording for 40 h	Sensitivity and specificity > 91.5% [106]	10
		Second-level lying bouts in daily 1 h recording for 40 h	Positive predictive value > 44%, sensitivity > 91% [106]	
FEDO (ENGS, Rosh Pina, Israel)	Leg (calf)	Daily step counts, the number of lying bouts, lying time, the visits to feed bunk	Se = 68.8%, Sp = 72.4%, Acc = 71.5% [107]	325
RumiWatch system (ITIN + HOCH GmbH, Liestal, Switzerland)	Noseband (beef cattle)	Hourly feeding time at 10 min interval sampling in daily 6 h recording for 6 d	Pr = 88%, Acc = 89%, r = 0.81 [108]	8
		Hourly rumination time at 10 min interval sampling in daily 6 h recording for 6 d	Pr = 76%, Acc = 91%, r = 0.75 [108]	
	Leg (cow)	Lying duration over 24 h recording	r = 1 [109]	18
		Standing and walking time over 10 min recording	r = 0.96 [109]	21

3.1. Ear-Attached Accelerometers

As presented in Table 1, ear- attached accelerometers are a category of acceleration sensors that are generally small in size and lightweight. The Cowmanager SensOor is an example of an ear-attached accelerometer that has been used to simultaneously identify the animals' behaviors of eating, rumination, resting and active behavior for which validation data exists. It has been concluded that there are moderate correlations for eating (r = 0.88) and high correlations for rumination (r = 0.93) between the sensors and observations [76]. However, some researchers found moderate correlations for eating/ruminating time (r = 0.83) between the sensors and observations [78]. There were good correlations of rumination (r = 0.72) and eating (r = 0.88) between sensor data and direct visual observations [77]. As for illness monitoring, ear-mounted accelerometers have been used to identify the behavioral changes of beef steers induced by the challenge of lipopolysaccharide injection, with the results showing that steers infected with lipopolysaccharide spent less time on highly active behaviors, eating and ruminating than the control [110]. From this perspective, this technology has the promising advantages of simultaneously detecting a range of animal activities and conditions. In addition, other ear-attached accelerometers have been validated to accurately identify specific behaviors. The ear-attached sensor FDX-ISO 11784/11785 demonstrated Se = 99.9%, Sp = 99.6% for feeding in cattle [111]. The SMARTBOW has been tested to record the ruminating behavior and posture of cows and there were high correlations with observations for rumination time (r = 0.97, concordance correlation coefficient, CCC = 0.96) [80], and high correlations for rumination time (r > 0.99) [81], and high correlations for rumination (89% sensitivity, 95% specificity and 94% accuracy) and posture (lying, standing and locomotion) (94% sensitivity, 94% specificity, 95% precision and 94% accuracy) [82]. The GCDC X16-mini MEMS accelerometers attached to the ear of ewes were used to remotely classify behavioral activities of grazing, standing and walking with high prediction accuracies (94%, 96% and 99%, respectively) and sensitivity, specificity, accuracy and precision all being from 92% to 100% for all the observed activities in comparison with the collar deployed accelerometer and the front leg mounted accelerometer [86]. While the aforementioned examples may not be a complete list of the validation work that has been undertaken, regardless of the technology platform, reliable estimates of various animal behaviors can be obtained through the use of ear-mounted accelerometers.

3.2. Jaw-Mounted Accelerometers

Jaw-mounted accelerometers are acceleration sensors that can provide valuable information for research on grazing behavior patterns, although these may be limited for commercial applications on-farm. These accelerometers have already been validated to detect grazing behavior with a high degree of accuracy. The HOBO Pendant G data logger is an acceleration sensor that can be attached to the jaws of cows to monitor grazing time, rumination time and feeding time as well as lying time. It has been reported the HOBO Pendant G data loggers fixed to the medial-lateral jaws of dairy cows could identify grazing time and rumination time with the variance of the prediction R^2 = 0.961 and 0.945, respectively, compared with visual observations [83]. Dairy Check is another jaw-attached acceleration sensor that has a high accuracy when used in dairy cows; r = 0.86 for feeding duration and r = 0.87 for rumination duration between the sensor system and visual observations [87]. Differentiating feeding behavior of free-ranging ruminants have been shown to improve production efficiency, with the logger AML prototype V1.0 tri-axial accelerometer attached onto the under-jaw of the ewe to identify and classify the grazing, lying, running, standing and walking activities of sheep at pasture with the results showing the 81.5–85.5% accuracy for all five behaviors [88]. Some researchers even suggested a tri-axial accelerometer sensor of the ADXL335 placed under the lower jaw, to automatically classify grazing, ruminating, and resting activities of dairy sheep [89], reporting 96% sensitivity, 97% specificity, 95% precision and 96% accuracy for grazing, a 89% sensitivity, 97% specificity, 89% precision and 95% accuracy for ruminating and a 93% sensitivity, 95% specificity, 94% precision and 94% accuracy for resting with a 93% overall accuracy for the three behaviors. The BEHARUM device (ADXL335 MEMS) attached under the lower jaw of sheep, including a three-axial accelerometer sensor and a force sensor, has been used to accurately validate and identify behavior of grazing, rumination and other activities of lambs at pasture, and the results demonstrated were the optimized accuracies of 94.0% for grazing, 90.0% for ruminating and 95.5% for other activities with the peak overall accuracy of 89.7% in the 30s epoch [90].

3.3. Collar-Mounted Accelerometers

Neck-mounted accelerometers are common sensors which can simultaneously identify activities related to feeding, ruminating and physical behaviors. Some neck-mounted sensors have been proposed for validation in cattle and sheep. For instance, It's been found that the ruminating times recorded by the neck-mounted Hr-Tag loggers, provided by Allflex SCR Engineers Ltd. (Rahway, NJ, USA), had a high correlation with that recorded through visual observations (r = 0.93, R^2 = 0.87) [91]. Furthermore, Hr-Tag was used to detect the differences of feeding and ruminating between sick and healthy dairy cows [112]. They found pre-calving cows with subclinical ketosis or subclinical ketosis and metritis spent less feeding and ruminating. Hr-Tags have been validated to monitor rumination and activity of dairy cows for identifying health disorders such as displaced abomasum, ketosis, indigestion, mastitis and metritis [33,34,113]. Other researchers have used Hr-tags to categorize patterns of activity and ruminating of beef cattle for the early detection of cattle respiratory disease and lameness which facilitates targeted treatment [114]. As a consequence, Hr-Tag is regarded as a reliable sensor to remotely monitor animal health.

Some other accelerometers have also been validated in cattle. For example, the MooMonitor+ had been validated with an r = 93% of feeding time, an r = 0.94 of resting time for cows [93] and an r = 0.94 and CCC = 0.97 of grazing time for cows [94]. The Xtrinsic MMA8451Q 3-Axis was able to detect cattle's feeding activity that was highly correlated with observations with a 98.78% sensitivity and 93.10% precision [96] and a 93.0% specificity, 83% precision and 83% accuracy [95]. The ADXL330 had a moderate correlation between sensors and observations for feeding (75% sensitivity, 81% precision and 96% accuracy) and for lying (80% sensitivity, 83% precision and 84% accuracy) in cows [97]. There were a 85% sensitivity, 95% specificity and 92% precision of feeding and a 92% sensitivity, 96% specificity and 88% precision of rumination for support vector machine approach by using Axivity AX3 to record the behavioral activities of cows' feeding and ruminating [98].

Collar-mounted sensors can also identify sheep behaviors, such as Actiwatch Mini®, GENEActiv, ActiGraph wGT3X-BT®, AXY-3, and InvenSense MPU-9250, Gulf Coast X-16-4 Accelerometer. The sensors of Actiwatch Mini® activity monitor attached to the necks of the ewes when used in combination with the activity scores to record behaviors with an overall accuracy of 79.98% and 74.56% for active and inactive, respectively [92]. The accelerometer GENEActiv has a 83.7% average accuracy of standing and lying and a 80.8% average accuracy of grazing, rumination, inactive and walking in ewes, a 85.9% average accuracy of standing and lying and a 85.9% average accuracy of inactive, suckling, walking in lambs by random forest decision tree [102], while the accelerometer ActiGraph can detect the grazing, walking and resting behaviors of lambs on pasture with a classification accuracy of 89.6% [103]. The neck-mounted devices of AXY-3 accelerometer were used along with fractal methods to record temporal sequences of behavioral activity patterns of parasitized sheep which spent 66.03% $\pm$ 24.49% of the day and 18.30% $\pm$ 8.58% of the night active during the experimental periods, indicating an accurate description of the activity/inactivity patterns of sheep although the activity/inactivity patterns of parasitized sheep rely on long-term activity events and gastrointestinal parasite infection [115]. As the neck-mounted accelerometers, InvenSense MPU-9250 has a precision, specificity, sensitivity, accuracy between 92.6% to 98.9% for grazing activity and non-grazing behaviors [104], and Gulf Coast X-16-4 Accelerometer can be used to remotely detect perennial ryegrass staggers of sheep grazing on endophyte-infected grass [116].

3.4. Leg-Mounted Accelerometers

Leg-attached accelerometers are typically used to identify lying, standing and walking patterns of animals. The IceTag and IceQube 3D-accelerometers commercially available for identifying the behavioral activities are validated to accurately record standing and lying time of growing lambs, with all sensitivity and specificity > 91.5% of the IceTag for standing and lying, and sensitivity > 91% and >88% of IceTag and IceQube for lying bouts [106]. Further, IceTag and/or IceQube have been used to remotely identify activity patterns of cattle and/or lambs exposed to nematode parasitism [117–119], opioid involvement [120] and neuronal ceroid lipofuscinosis [121]. As a result, IceTag and IceQube are promising tools to monitor animal health problems.

There are other validated acceleration sensors proposed with high accuracy used in cattle and sheep, including Track A Cow, ADXL345, AfiAct Pedometer Plus and The HOBO Pendant G accelerometer. Track A Cow and AfiAct Pedometer Plus were simultaneously examined to determine feeding and lying and all of them had been validated with the high correlations of recorded data for feeding time (r = 0.93; CCC = 0.79) and lying time (r > 0.99; CCC > 0.99), respectively, compared with observations [80]. The ADXL345 accelerometer was reported to have 92% accuracy, 93% sensitivity, 82% precision for lying, 99% accuracy, 82% sensitivity, 86% precision for lying down, 99% accuracy, 74% sensitivity, 85% precision for standing up, and 99% accuracy, 94% sensitivity, 89% precision for active walking, but poor accuracy, sensitivity and precision for feeding and standing [105]. The HOBO Pendant G acceleration data logger, mounted on the left lateral side of the hind leg of sheep, had the highest accuracy for walking and running and showed the highest discriminatory values of 99.95% for standing and 99.50% for lying [85].

3.5. Noseband-Mounted Accelerometers

Though noseband-attached accelerometers may have limited practical use and are not widely used, they can provide scientific solutions and valuable information for research purposes. A nose-attached accelerometer RumiWatch system has been validated to identify the eating behavior patterns of cows. There were moderate correlations for feeding time with 88% precision, 89% accuracy and r = 0.81, and rumination time with 76% precision, 91% accuracy and r = 0.75 between the RumiWatch system and visual observations [108], whereas the RumiWatch system mounted to the leg had an r = 1 of lying time, an r = 0.96 of standing, an r = 0.96 of walking time and an r = 0.98 of stride number with r = 0.75 for stride duration and r = 0.81 for stride length [109], indicating that it has the capability of monitoring animal health and welfare on farms.

3.6. Other Accelerometers-Related Sensors

In order to accurately classify animal activity, some other 3-axis acceleration-related sensors that may not be included in Table 1, have been also used or developed, such as Silent Herdsman [122,123], ProMove-mini [124], iFarmTec [125], MPU9250 9-axis micro-electromechanical system [73], MinIMU-9V2 IMU [126], Digitanimal Livestock GPS [127], GPS collar [128], Bosch BMI160 [75,129] and Bosch BMA400 micro electromechanical system [130]. Further, these sensors are utilized in combination with additional sensors or/and approaches of data processing and analysis for predicting animal behaviors.

Neck-mounted Afimilk Silent Herdsman collar and tail-mounted AX3 3-axis logging accelerometer were simultaneously attached to beef and cows, together with machine learning random forest algorithms developed for predicting calving based on single-sensor variables and multiple sensor-data [123]. Convolutional Neural Network was developed to classify ruminating, eating and other behaviors of cattle using the motion-related data captured by Silent Herdsman collars and Rumiwatch halters, achieving an overall *F*1 score, precision and recall of 82%, 83% and 82%, respectively for validation performance [122]. The ProMove-mini containing a 3-axis accelerometer and 3-axis gyroscope, was attached to the neck of goats within independent different orientations to collect real-world datasets and had a 94%accuracy for all the data through a simple Naive Bayes classifier based on a single feature [124]. An existing monitoring platform iFarmTec composed of A Wireless Sensor Network, a Computational Platform and a User Interface, was used to fetch the data from sheep motions together with a video camera used for recording sheep behaviors and machine learning Decision Trees algorithms applied within multiple features to achieve an overall accuracy over 91% [125].

In addition, a MinIMU-9V2 IMU integrated with a LSM303DLHC 3-axis accelerometer, a L3GD20 3-axis gyroscope, and a 3-axis magnetometer, was used as a collar sensor together with a GPS to measure the movement dynamics of horse gaits with achieving up to 97.96 $\pm$ 1.42% accuracy and an efficient energy consumption under Artificial Neural Network model using cross validation [126], and MPU9250 9-axis micro-electromechanical system was integrated with battery pack and solar panels into a collar tags to collect 3D-accelerometry data corresponding to grazing, ruminating, resting and other behaviors of cattle using several different machine-learning algorithms via cross-validation, with results showing the algorithms multilayer perceptron (MLP) with a single hidden layer, logistic regression (LR) with an one-versus-one reduction scheme and support vector machine (SVM) with an one-versus-one reduction scheme, yielded the highest overall accuracies of approximately 93% [73]. Moreover, the same MPU9250 9-axis micro-electromechanical system, mounted to the neck of cattle to fetch the 3D-accelerometry data related to cattle behaviors using an end-to-end deep learning algorithm, had an overall Matthews correlation coefficient values between 80.34–95.68%.

GPS sensors have also been also combined with 3-axis acceleration sensors to capture the 3D-accelerometry datasets corresponding to animal behaviors. The Digitanimal Livestock GPS device is integrated with a 3-D micro-electromechanical-system accelerometer and a GPS sensor, which was attached to the neck of cattle to obtain the accelerometer raw data at a sampling frequency of 10 Hz together with video recording on the durations of grazing, ruminating, laying and steady standing, and a random forest machine learning algorithm was used to classify cattle behaviors matched to accelerometer records with good accuracies of 0.93, 0.907. 0.881, and 0.922 for grazing, ruminating, laying and steady standing, respectively [127]. A lab-constructed GPS collar, which is comprised of an iGotU GT-120 GPS logger and a 3-axis X16 mini accelerometer, was mounted to the bottom of the cattle's neck to classify grazing and non-grazing behaviors using random forest (RF), linear discriminant analysis (LDA), quadratic discriminate analysis (QDA), and support vector machines (SVM) for comparison [128]. Moreover, a CSIRO collar sensor containing a 3-axis accelerometer and a 3-axis magnetometer in its piezoelectric micro-electromechanical system (MEMS) chip, was attached below cattle's neck in combination with a GPS sensor on top of cattle's neck to classify the foraging, ruminating, resting, travelling and other active behaviors of grazing cattle by mixture models and decision tree [74]. The results of these trials showed good classification accuracy of identifying behaviors of grazing cattle.

Both Bosch BMI160 and Bosch BMA400 are integrated with a 16 bit triaxial gyroscope and a 16 bit triaxial accelerometer. Machine learning random forest algorithm for classifying grazing and ruminating behavior of sheep yielded the highest overall accuracies of 92% and 91% for collar and ear sensors, respectively, using the raw data collected by Bosch BMI at 16 Hz sampling frequency [75]. Similarly, using Bosch BMI160 together with the random forest approach to identify lying, standing and walking in sheep yielded the best performance with 95% accuracy and 91–97% $F1$ score at 32 Hz frequency, 7 s window and 32 Hz frequency, 5 s window for collar and ear sensors compared with 91–93% accuracy and F-score 88–95% at 16 Hz frequency, 7 s window [129]. The recurrent neural network (RNN) models within gated recurrent unit (GRU) architecture was utilized to analyze 3D-accelerometry data associated with cattle behavior captured by Bosch BMA400, showing better classification accuracy and less complexity than the ones with long short-time memory (LSTM) architecture [130].

4. Considerations around Sensor Choice

Acceleration sensors provide a means to accurately record and classify the behavioral patterns of on-farm animals and have the potential to provide valuable behavioral indicators to measure animal welfare and health status from which management decisions under different infection challenges can be made. As outlined above, there already exists a multitude of different sensor technologies, and it can be expected that more will be developed in the future. However, it needs to be considered how a farmer may make a suitable choice over the right acceleration sensor systems for it to be implemented commercially on a large scale. The real time monitoring systems of acceleration sensors should fulfill some requirements to reach the level of practical applications on-farm and would be considered a necessary function of any accelerometer. The accelerometer devices should also have the attribute of being cost-effective, light weight and tolerant of different conditions during practical application without impacting animal behavior. For many farmers the adoption of a new digital technology depends on how easily it can be integrated with current digital platforms [131]. The application site of acceleration sensors over an animal body should also be taken into consideration as an important factor affecting accuracy of remote detection and should be considered, especially in the context of what information is captured and for what purpose. As mentioned in Section 3, 3-Dimensional accelerometer sensors can be mounted to different positions over animals, which may influence their predictive performance. It has been suggested that ear, neck and jaw-mounted sensors had better capability for monitoring feeding behavior, while leg-mounted sensors exhibited better results on behavioral activities such as walking and resting than collar-mounted sensors [71]. Accurate detection of animal behavior may depend on the categories of behavioral patterns on the condition of infection challenges, though behavioral changes can be used as the indicators of animal health. For instance, lameness can lead to abnormality of active behaviors such as walking and posture while parasitic infection induces anorexia, detected through a decrease in eating time. The behavioral alterations of an animal wearing a triaxial accelerometer sensor lead to changes of 3-axis accelerometry directions where the accelerometry datasets with abnormality are then generated. Accelerometer sensors transform static or dynamic acceleration due to gravity or animal motions into the voltage outputs as the measurements of animal activities [2]. As a consequence, accelerometry data captured via a wearable 3D accelerometer sensor can indicate the health status of an animal.

Sensor technologies have the potential to perform early detection of behavioral changes due to animal diseases. There has been multiple biosensors such mechanical sensors, acoustic sensors, electromyography sensors and acceleration sensors as proposed to quantify physiological and behavioral responses of animals exposed to different diseases and real-time monitoring animal behaviors using wireless sensors to acquire data can provide detailed and precise information on animals' activity and wellbeing [2]. Further, among the motion-detection sensors, acceleration sensors are capable of monitoring any changes in an animal' behavioral patterns for predicting the sickness induced by infection. However, appropriate accelerometer sensors need to be chosen to detect the information from the behavioral changes of sick animals with sub-clinical signs. In general, the symptoms of sick animals with sub-clinical infection are subtle, making it more difficult to monitor changes in animal behavior by direct observation. For instance, grazing time can be affected by different factors, such as animal age, breed, physiological status, health/disease, vegetation, weather, season and environment [132]. Although the occurrence of abnormal behavioral patterns may indicate a decrease in animal health or wellbeing, most behavioral indicators cannot be specific for a particular issue of animal health. Some signs of different sub-clinical infections in cattle and sheep may be similar and subtle, but with detailed investigations into the extent and pattern of changes in behaviors this approach of utilizing sensors can potentially provide sufficient evidence that animal health is impaired leading to diagnosis and appropriate treatment. The behaviors such as expressive activities mentioned in Section 2.3.3 may be hardly detected using a single sensor. Therefore, additional sensors or/and monitoring approaches are suggested for implementation, including a GPS and video recording. Moreover, two or more sensors, such as ProMove-mini [124] and MinIMU-9V2 IMU [126], can be integrated into a whole monitoring system to facilitate the collection of accelerometry data. The value of real time data from acceleration sensor recordings can be considered as an early diagnostic signal to timely detect changes in particular behaviors that relate to health. However, the designed infrastructure of a 3D-acceleration sensor is an important aspect that needs to be considered for enabling the transmission, transformation and acquisition of real time data. The eGrazor collar tags [133] is an example that consists of an artificial intelligence device, battery pack, and solar panels. Further, the sampling frequency of an acceleration sensor associated with energy consumption should be appropriately selected to capture the accelerometer data for predicting behaviors. The results of validation performance varied based on the sampling frequencies [129]. The balance between sampling rate and an efficiency of energy consumption also needs to be obtained for validation performance to prolong the battery life. The sufficient Wi-Fi connection or direct line of site to the transmitter for an acceleration sensor, which may facilitate the applications in certain environments, should be taken into consideration as well as a long battery life with sustainable supply of electrical power and a data storage and management system that enables viewing, storing and downloading real time data. Already a smart ear tag containing a microcontroller, a triaxial accelerometer, satellite communication interface, an on-board memory, a solar panel and a battery has been developed [130], which can provide new perspectives for future research. In current studies related to the detection of behavioral patterns, the total time spent on specific behavior during a day or a period is often measured for evaluating the impact of some diseases or adverse conditions. However, diurnal patterns of activities may be more sensitive and useful for early identification of animal welfare concerns, particularly when seeking to identify which challenge the animal may be facing. The diurnal duration of lying, diurnal lying bouts and diurnal steps as well as diurnal motion index of grazing cattle have been evaluated under the parasitic infection using the collected 3D-accelerometry data [119]. This approach of developing a behavioral fingerprint which of diurnal patterns of animal behaviors that are unique to a specific challenge is a promising area for future studies and applications, although there has been limited research on this area. However, a major consideration may be the processing and analysis of accelerometry data for predictive performance and how much this needs to rely on the comparison with visual observations, which themselves may contain error. Nevertheless, the raw accelerometer data need to be preprocessed by cleaning noise in the raw time-series, calculating additional time-series, segmenting the time-series into time-windows, calculating features from each time-window and splitting datasets, and then machine learning algorithms are carried out to classify different behaviors [3]. Predicting sickness behaviors of animals using 3D-accelerometer data is promising for early diagnosis of animal diseases, although there are still limitations for practical utilization. In order to strengthen the potential of acceleration sensor technology, different behavioral parameters should be integrated for analysis at the same time, and the sensor system needs to be added with different functions and has the capability of comparing and recognizing simultaneous changes of behavioral patterns [71].

5. Future Considerations

Acceleration sensor systems are an efficient and reliable way that can make it much easier to record the activity status of an animal at pasture and have the potential to provide valuable insights as to their welfare state. However, acceleration sensor technologies cannot replace people and good management, due to that there may be similar behavioral changes under a number of different conditions, just helping identify individual animals who are suffering from infections and need appropriate targeted treatments. Therefore, specific behavioral changes can be considered as indicators for animal health and welfare. As the early diagnostic tools for animal diseases, sensor technologies can measure characteristic variables related to those behavioral indicators. A number of commercial acceleration sensors have been increasingly available for livestock management and many of these have been shown to have high accuracies and sensitivities for detecting animal behaviors such as feeding, ruminating and physical activities. The acceleration sensor technology selected according to the purposes which it is being intended and how the information provided may contribute to the development of precision livestock farming. As the sensor technologies are being developed, new detection technologies are constantly emerging, providing alternatives to identify the status of animals health under the impaired infection challenges. It is also important to improve the detection capability of behaviors and expand the current application of sensor technologies and integrate these into existing farm management. The integrated application of different sensor technologies can have the potential of to better monitor animal diseases, allowing for more timely diagnosis and treatment and facilitate animal performance. However, further research on the ability of sensors to assess animal welfare, including the diurnal patterns of activity, is necessary. Sensors can rapidly provide data, but there is still a gap in our understanding of how this data can best be managed and utilized to provide optimum benefit. The notion put forward here of utilizing changes in animals behavior to identify subclinical disease is an exciting prospect, where not only gross changes but the pattern of change may allow behavioral fingerprinting to be a means of optimizing animal productivity and wellness.

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References

1. Neethirajan, S. The role of sensors, big data and machine learning in modern animal farming. *Sens. Bio-Sens. Res.* **2020**, *29*, 100367. [CrossRef]
2. Neethirajan, S.; Tuteja, S.K.; Huang, S.-T.; Kelton, D. Recent advancement in biosensors technology for animal and livestock health management. *Biosens. Bioelectron.* **2017**, *98*, 398–407. [CrossRef] [PubMed]
3. Riaboff, L.; Shalloo, L.; Smeaton, A.F.; Couvreur, S.; Madouasse, A.; Keane, M.T. Predicting livestock behaviour using accelerometers: A systematic review of processing techniques for ruminant behaviour prediction from raw accelerometer data. *Comput. Electron. Agric.* **2022**, *192*, 106610. [CrossRef]
4. Temple, D.; Manteca, X.; Velarde, A.; Dalmau, A. Assessment of animal welfare through behavioural parameters in Iberian pigs in intensive and extensive conditions. *Appl. Anim. Behav. Sci.* **2011**, *131*, 29–39. [CrossRef]
5. Jaeger, M.; Brügemann, K.; Brandt, H.; König, S. Associations between precision sensor data with productivity, health and welfare indicator traits in native black and white dual-purpose cattle under grazing conditions. *Appl. Anim. Behav. Sci.* **2019**, *212*, 9–18. [CrossRef]
6. Broom, D.M. Abnormal behavior and the self-regulation of motivational state. *J. Vet. Behav.* **2019**, *29*, 1–3. [CrossRef]
7. Sepúlveda-Varas, P.; Proudfoot, K.L.; Weary, D.M.; von Keyserlingk, M.A.G. Changes in behaviour of dairy cows with clinical mastitis. *Appl. Anim. Behav. Sci.* **2016**, *175*, 8–13. [CrossRef]
8. Ingvartsen, K.L.; Dewhurst, R.J.; Friggens, N.C. On the relationship between lactational performance and health: Is it yield or metabolic imbalance that cause production diseases in dairy cattle? A position paper. *Livest. Prod. Sci.* **2003**, *83*, 277–308. [CrossRef]
9. Jawor, P.E.; Huzzey, J.M.; LeBlanc, S.J.; von Keyserlingk, M.A.G. Associations of subclinical hypocalcemia at calving with milk yield, and feeding, drinking, and standing behaviors around parturition in Holstein cows. *J. Dairy Sci.* **2012**, *95*, 1240–1248. [CrossRef]
10. Goldhawk, C.; Chapinal, N.; Veira, D.M.; Weary, D.M.; von Keyserlingk, M.A.G. Prepartum feeding behavior is an early indicator of subclinical ketosis. *J. Dairy Sci.* **2009**, *92*, 4971–4977. [CrossRef]
11. de Arcipreste, N.C.F.; Mancera, K.F.; Miguel-Pacheco, G.G.; Galindo, F. Plasticity and consistency of lying and ruminating behaviours of heifers exposed to different cubicle availability: A glance at individuality. *Appl. Anim. Behav. Sci.* **2018**, *205*, 1–7. [CrossRef]
12. Kyriazakis, I. Pathogen-induced anorexia: A herbivore strategy or an unavoidable consequence of infection? *Anim. Prod. Sci.* **2014**, *54*, 1190–1197. [CrossRef]
13. Exton, M.S. Infection-induced anorexia: Active host defence strategy. *Appetite* **1997**, *29*, 369–383. [CrossRef]
14. Kelley, K.W.; Bluthé, R.-M.; Dantzer, R.; Zhou, J.-H.; Shen, W.-H.; Johnson, R.W.; Broussard, S.R. Cytokine-induced sickness behavior. *Brain Behav. Immun.* **2003**, *17*, 112–118. [CrossRef]
15. Tizard, I. Sickness behavior, its mechanisms and significance. *Anim. Health Res. Rev.* **2008**, *9*, 87–99. [CrossRef]
16. Dantzer, R.; O'Connor, J.C.; Freund, G.G.; Johnson, R.W.; Kelley, K.W. From inflammation to sickness and depression: When the immune system subjugates the brain. *Nat. Rev. Neurosci.* **2008**, *9*, 46–56. [CrossRef]
17. Fogsgaard, K.K.; Røntved, C.M.; Sørensen, P.; Herskin, M.S. Sickness behavior in dairy cows during Escherichia coli mastitis. *J. Dairy Sci.* **2012**, *95*, 630–638. [CrossRef]
18. Fogsgaard, K.K.; Bennedsgaard, T.W.; Herskin, M.S. Behavioral changes in freestall-housed dairy cows with naturally occurring clinical mastitis. *J. Dairy Sci.* **2015**, *98*, 1730–1738. [CrossRef]
19. Huzzey, J.M.; Veira, D.M.; Weary, D.M.; von Keyserlingk, M.A.G. Prepartum Behavior and Dry Matter Intake Identify Dairy Cows at Risk for Metritis. *J. Dairy Sci.* **2007**, *90*, 3220–3233.
20. Palmer, M.A.; Law, R.; O'Connell, N.E. Relationships between lameness and feeding behaviour in cubicle-housed Holstein–Friesian dairy cows. *Appl. Anim. Behav. Sci.* **2012**, *140*, 121–127. [CrossRef]
21. González, L.A.; Tolkamp, B.J.; Coffey, M.P.; Ferret, A.; Kyriazakis, I. Changes in Feeding Behavior as Possible Indicators for the Automatic Monitoring of Health Disorders in Dairy Cows. *J. Dairy Sci.* **2008**, *91*, 1017–1028. [CrossRef] [PubMed]
22. Berk, Z.; Bishop, S.C.; Forbes, A.B.; Kyriazakis, I. A simulation model to investigate interactions between first season grazing calves and Ostertagia ostertagi. *Vet. Parasitol.* **2016**, *226*, 198–209. [CrossRef] [PubMed]
23. Valderrábano, J.; Delfa, R.; Uriarte, J. Effect of level of feed intake on the development of gastrointestinal parasitism in growing lambs. *Vet. Parasitol.* **2002**, *104*, 327–338. [CrossRef]
24. Zaralis, K.; Tolkamp, B.; Houdijk, J.; Wylie, A.; Kyriazakis, I. Changes in food intake and circulating leptin due to gastrointestinal parasitism in lambs of two breeds. *J. Anim. Sci.* **2008**, *86*, 1891–1903. [CrossRef] [PubMed]
25. Bown, M.D.; Poppi, D.P.; Sykes, A.R. The effects of a concurrent infection of Trichostrongylus colubriformis and Ostertagia circumcincta on calcium, phosphorus and magnesium transactions along the digestive tract of lambs. *J. Comp. Pathol.* **1989**, *101*, 11–20. [CrossRef]

26. Beauchemin, K. Invited review: Current perspectives on eating and rumination activity in dairy cows. *J. Dairy Sci.* **2018**, *101*, 4762–4784. [CrossRef]
27. Welch, J.; Smith, A. Forage quality and rumination time in cattle. *J. Dairy Sci.* **1970**, *53*, 797–800. [CrossRef]
28. Welch, J.; Smith, A. Influence of forage quality on rumination time in shee. *J. Anim. Sci.* **1969**, *28*, 813–818. [CrossRef]
29. Yansari, A.T.; Valizadeh, R.; Naserian, A.; Christensen, D.; Yu, P.; Shahroodi, F.E. Effects of alfalfa particle size and specific gravity on chewing activity, digestibility, and performance of Holstein dairy cows. *J. Dairy Sci.* **2004**, *87*, 3912–3924. [CrossRef]
30. Soriani, N.; Panella, G.; Calamari, L. Rumination time during the summer season and its relationships with metabolic conditions and milk production. *J. Dairy Sci.* **2013**, *96*, 5082–5094. [CrossRef]
31. Liboreiro, D.N.; Machado, K.S.; Silva, P.R.; Maturana, M.M.; Nishimura, T.K.; Brandão, A.P.; Endres, M.I.; Chebel, R.C. Characterization of peripartum rumination and activity of cows diagnosed with metabolic and uterine diseases. *J. Dairy Sci.* **2015**, *98*, 6812–6827. [CrossRef]
32. Andreen, D.M.; Haan, M.M.; Dechow, C.D.; Harvatine, K.J. Relationships between milk fat and rumination time recorded by commercial rumination sensing systems. *J. Dairy Sci.* **2020**, *103*, 8094–8104. [CrossRef]
33. Stangaferro, M.L.; Wijma, R.; Caixeta, L.S.; Al-Abri, M.A.; Giordano, J.O. Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part III. Metritis. *J. Dairy Sci.* **2016**, *99*, 7422–7433. [CrossRef]
34. Stangaferro, M.L.; Wijma, R.; Caixeta, L.S.; Al-Abri, M.A.; Giordano, J.O. Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part II. *Mastitis. J. Dairy Sci.* **2016**, *99*, 7411–7421. [CrossRef]
35. King, M.; LeBlanc, S.; Pajor, E.; Wright, T.; DeVries, T. Behavior and productivity of cows milked in automated systems before diagnosis of health disorders in early lactation. *J. Dairy Sci.* **2018**, *101*, 4343–4356. [CrossRef]
36. Calamari, L.; Soriani, N.; Panella, G.; Petrera, F.; Minuti, A.; Trevisi, E. Rumination time around calving: An early signal to detect cows at greater risk of disease. *J. Dairy Sci.* **2014**, *97*, 3635–3647. [CrossRef]
37. Cocco, R.; Canozzi, M.E.A.; Fischer, V. Rumination time as an early predictor of metritis and subclinical ketosis in dairy cows at the beginning of lactation: Systematic review-meta-analysis. *Prev. Vet. Med.* **2021**, *189*, 105309. [CrossRef]
38. De, K.; Saxena, V.K.; Balaganur, K.; Kumar, D.; Naqvi, S.M.K. Effect of short-term seclusion of sheep on their welfare indicators. *J. Vet. Behav.* **2018**, *27*, 1–7. [CrossRef]
39. Dittrich, I.; Gertz, M.; Krieter, J. Alterations in sick dairy cows' daily behavioural patterns. *Heliyon* **2019**, *5*, e02902. [CrossRef]
40. Hart, B. Beyond fever: Comparative perspectives on sickness behavior. *Encycl. Anim. Behav.* **2010**, *1*, 205–210.
41. Titler, M.; Maquivar, M.; Bas, S.; Gordon, E.; Rajala-Schultz, P.; McCullough, K.; Schuenemann, G. Effect of metritis on daily activity patterns in lactating Holstein dairy cows. *J. Dairy Sci* **2013**, *96*, 647.
42. Barragan, A.A.; Piñeiro, J.M.; Schuenemann, G.M.; Rajala-Schultz, P.J.; Sanders, D.E.; Lakritz, J.; Bas, S. Assessment of daily activity patterns and biomarkers of pain, inflammation, and stress in lactating dairy cows diagnosed with clinical metritis. *J. Dairy Sci.* **2018**, *101*, 8248–8258. [CrossRef] [PubMed]
43. Steensels, M.; Maltz, E.; Bahr, C.; Berckmans, D.; Antler, A.; Halachmi, I. Towards practical application of sensors for monitoring animal health: The effect of post-calving health problems on rumination duration, activity and milk yield. *J. Dairy Res.* **2017**, *84*, 132–138. [CrossRef] [PubMed]
44. Siivonen, J.; Taponen, S.; Hovinen, M.; Pastell, M.; Lensink, B.J.; Pyörälä, S.; Hänninen, L. Impact of acute clinical mastitis on cow behaviour. *Appl. Anim. Behav. Sci.* **2011**, *132*, 101–106. [CrossRef]
45. Manteca, X.; Temple, D.; Mainau, E.; Llonch, P. Assessment of pain in sheep. *Farm Anim. Welf. Fact Sheet. FAWEC-Farm Anim. Welf. Educ. Cent.* **2017**, *17*, 1–2.
46. Healy, A.M.; Hanlon, A.J.; Weavers, E.; Collins, J.D.; Doherty, M.L. A behavioural study of scrapie-affected sheep. *Appl. Anim. Behav. Sci.* **2002**, *79*, 89–102. [CrossRef]
47. Berriatua, E.; French, N.P.; Broster, C.E.; Morgan, K.L.; Wall, R. Effect of infestation with Psoroptes ovis on the nocturnal rubbing and lying behaviour of housed sheep. *Appl. Anim. Behav. Sci.* **2001**, *71*, 43–55. [CrossRef]
48. Thomsen, P.T.; Munksgaard, L.; Sørensen, J.T. Locomotion scores and lying behaviour are indicators of hoof lesions in dairy cows. *Vet. J.* **2012**, *193*, 644–647. [CrossRef]
49. Ito, K.; von Keyserlingk, M.A.G.; LeBlanc, S.J.; Weary, D.M. Lying behavior as an indicator of lameness in dairy cows. *J. Dairy Sci.* **2010**, *93*, 3553–3560. [CrossRef]
50. Mattachini, G.; Antler, A.; Riva, E.; Arbel, A.; Provolo, G. Automated measurement of lying behavior for monitoring the comfort and welfare of lactating dairy cows. *Livest. Sci.* **2013**, *158*, 145–150. [CrossRef]
51. Gieseke, D.; Lambertz, C.; Gauly, M. Effects of cubicle characteristics on animal welfare indicators in dairy cattle. *Animal* **2020**, *14*, 1934–1942. [CrossRef]
52. Duthie, C.-A.; Bowen, J.; Bell, D.; Miller, G.; Mason, C.; Haskell, M. Feeding behaviour and activity as early indicators of disease in pre-weaned dairy calves. *Animal* **2021**, *15*, 100150. [CrossRef]
53. Crump, A.; Jenkins, K.; Bethell, E.J.; Ferris, C.P.; Arnott, G. Pasture access affects behavioral indicators of wellbeing in dairy cows. *Animals* **2019**, *9*, 902. [CrossRef]
54. Fregonesi, J.A.; Leaver, J.D. Behaviour, performance and health indicators of welfare for dairy cows housed in strawyard or cubicle systems. *Livest. Prod. Sci.* **2001**, *68*, 205–216. [CrossRef]
55. Chapinal, N.; de Passille, A.M.; Weary, D.M.; von Keyserlingk, M.A.; Rushen, J. Using gait score, walking speed, and lying behavior to detect hoof lesions in dairy cows. *J. Dairy Sci.* **2009**, *92*, 4365–4374. [CrossRef]

56. Rodriguez-Jimenez, S.; Haerr, K.J.; Trevisi, E.; Loor, J.J.; Cardoso, F.C.; Osorio, J.S. Prepartal standing behavior as a parameter for early detection of postpartal subclinical ketosis associated with inflammation and liver function biomarkers in peripartal dairy cows. *J. Dairy Sci.* **2018**, *101*, 8224–8235. [CrossRef]
57. Nechanitzky, K.; Starke, A.; Vidondo, B.; Müller, H.; Reckardt, M.; Friedli, K.; Steiner, A. Analysis of behavioral changes in dairy cows associated with claw horn lesions. *J. Dairy Sci.* **2016**, *99*, 2904–2914. [CrossRef]
58. Villettaz Robichaud, M.; Rushen, J.; de Passillé, A.M.; Vasseur, E.; Haley, D.; Pellerin, D. Associations between on-farm cow welfare indicators and productivity and profitability on Canadian dairies: II. On tiestall farms. *J. Dairy Sci.* **2019**, *102*, 4352–4363. [CrossRef]
59. Allen, J.; Hall, L.; Collier, R.; Smith, J. Effect of core body temperature, time of day, and climate conditions on behavioral patterns of lactating dairy cows experiencing mild to moderate heat stress. *J. Dairy Sci.* **2015**, *98*, 118–127. [CrossRef]
60. Herbut, P.; Hoffmann, G.; Angrecka, S.; Godyń, D.; Vieira, F.M.C.; Adamczyk, K.; Kupczyński, R. The effects of heat stress on the behaviour of dairy cows–a review. *Ann. Anim. Sci.* **2021**, *21*, 385–402. [CrossRef]
61. Kaygusuz, E.; Akdağ, F. Effect of cold stress on milk yield, milk composition and some behavioral patterns of simmental cows kept in open shed barns. *Kocatepe Vet. J.* **2021**, *14*, 351–358. [CrossRef]
62. Tucker, C.B.; Rogers, A.R.; Schütz, K.E. Effect of solar radiation on dairy cattle behaviour, use of shade and body temperature in a pasture-based system. *Appl. Anim. Behav. Sci.* **2008**, *109*, 141–154. [CrossRef]
63. Webster, J.; Stewart, M.; Rogers, A.; Verkerk, G. Assessment of welfare from physiological and behavioural responses of New Zealand dairy cows exposed to cold and wet conditions. *Anim. Welf.* **2008**, *17*, 19–26.
64. de Boyer des Roches, A.; Faure, M.; Lussert, A.; Herry, V.; Rainard, P.; Durand, D.; Foucras, G. Behavioral and patho-physiological response as possible signs of pain in dairy cows during Escherichia coli mastitis: A pilot study. *J. Dairy Sci.* **2017**, *100*, 8385–8397. [CrossRef] [PubMed]
65. Phythian, C.J.; Michalopoulou, E.; Jones, P.H.; Winter, A.C.; Clarkson, M.J.; Stubbings, L.A.; Grove-White, D.; Cripps, P.J.; Duncan, J.S. Validating indicators of sheep welfare through a consensus of expert opinion. *Animal* **2011**, *5*, 943–952. [CrossRef] [PubMed]
66. Müller, R.; Schrader, L. A new method to measure behavioural activity levels in dairy cows. *Appl. Anim. Behav. Sci.* **2003**, *83*, 247–258. [CrossRef]
67. Nielsen, P.P. Automatic registration of grazing behaviour in dairy cows using 3D activity loggers. *Appl. Anim. Behav. Sci.* **2013**, *148*, 179–184. [CrossRef]
68. Trénel, P.; Jensen, M.B.; Decker, E.L.; Skjøth, F. Technical note: Quantifying and characterizing behavior in dairy calves using the IceTag automatic recording device. *J. Dairy Sci.* **2009**, *92*, 3397–3401. [CrossRef]
69. Dobos, R.C.; Taylor, D.B.; Trotter, M.G.; McCorkell, B.E.; Schneider, D.A.; Hinch, G.N. Characterising activities of free-ranging Merino ewes before, during and after lambing from GNSS data. *Small Rumin. Res.* **2015**, *131*, 12–16. [CrossRef]
70. Moreau, M.; Siebert, S.; Buerkert, A.; Schlecht, E. Use of a tri-axial accelerometer for automated recording and classification of goats' grazing behaviour. *Appl. Anim. Behav. Sci.* **2009**, *119*, 158–170. [CrossRef]
71. Chapa, J.M.; Maschat, K.; Iwersen, M.; Baumgartner, J.; Drillich, M. Accelerometer systems as tools for health and welfare assessment in cattle and pigs–A review. *Behav. Process.* **2020**, *181*, 104262. [CrossRef] [PubMed]
72. Stygar, A.H.; Gómez, Y.; Berteselli, G.V.; Dalla Costa, E.; Canali, E.; Niemi, J.K.; Llonch, P.; Pastell, M. A systematic review on commercially available and validated sensor technologies for welfare assessment of dairy cattle. *Front. Vet. Sci.* **2021**, *8*, 634338. [CrossRef] [PubMed]
73. Arablouei, R.; Currie, L.; Kusy, B.; Ingham, A.; Greenwood, P.L.; Bishop-Hurley, G. In-situ classification of cattle behavior using accelerometry data. *Comput. Electron. Agric.* **2021**, *183*, 106045. [CrossRef]
74. González, L.A.; Bishop-Hurley, G.J.; Handcock, R.N.; Crossman, C. Behavioral classification of data from collars containing motion sensors in grazing cattle. *Comput. Electron. Agric.* **2015**, *110*, 91–102. [CrossRef]
75. Mansbridge, N.; Mitsch, J.; Bollard, N.; Ellis, K.; Miguel-Pacheco, G.G.; Dottorini, T.; Kaler, J. Feature selection and comparison of machine learning algorithms in classification of grazing and rumination behaviour in sheep. *Sensors* **2018**, *18*, 3532. [CrossRef]
76. Bikker, J.P.; van Laar, H.; Rump, P.; Doorenbos, J.; van Meurs, K.; Griffioen, G.M.; Dijkstra, J. Technical note: Evaluation of an ear-attached movement sensor to record cow feeding behavior and activity. *J. Dairy Sci.* **2014**, *97*, 2974–2979. [CrossRef]
77. Pereira, G.M.; Heins, B.J.; Endres, M.I. Technical note: Validation of an ear-tag accelerometer sensor to determine rumination, eating, and activity behaviors of grazing dairy cattle. *J. Dairy Sci.* **2018**, *101*, 2492–2495. [CrossRef]
78. Zambelis, A.; Wolfe, T.; Vasseur, E. Technical note: Validation of an ear-tag accelerometer to identify feeding and activity behaviors of tiestall-housed dairy cattle. *J. Dairy Sci.* **2019**, *102*, 4536–4540. [CrossRef]
79. Islam, M.; Lomax, S.; Doughty, A.; Islam, M.; Thomson, P.; Clark, C. Revealing the diversity in cattle behavioural response to high environmental heat using accelerometer-based ear tag sensors. *Comput. Electron. Agric.* **2021**, *191*, 106511. [CrossRef]
80. Borchers, M.R.; Chang, Y.M.; Tsai, I.C.; Wadsworth, B.A.; Bewley, J.M. A validation of technologies monitoring dairy cow feeding, ruminating, and lying behaviors. *J. Dairy Sci.* **2016**, *99*, 7458–7466. [CrossRef]
81. Reiter, S.; Sattlecker, G.; Lidauer, L.; Kickinger, F.; Öhlschuster, M.; Auer, W.; Schweinzer, V.; Klein-Jöbstl, D.; Drillich, M.; Iwersen, M. Evaluation of an ear-tag-based accelerometer for monitoring rumination in dairy cows. *J. Dairy Sci.* **2018**, *101*, 3398–3411. [CrossRef]
82. Roland, L.; Schweinzer, V.; Kanz, P.; Sattlecker, G.; Kickinger, F.; Lidauer, L.; Berger, A.; Auer, W.; Mayer, J.; Sturm, V.; et al. Technical note: Evaluation of a triaxial accelerometer for monitoring selected behaviors in dairy calves. *J. Dairy Sci.* **2018**, *101*, 10421–10427. [CrossRef]

83. Rayas-Amor, A.A.; Morales-Almaráz, E.; Licona-Velázquez, G.; Vieyra-Alberto, R.; García-Martínez, A.; Martínez-García, C.G.; Cruz-Monterrosa, R.G.; Miranda-de la Lama, G.C. Triaxial accelerometers for recording grazing and ruminating time in dairy cows: An alternative to visual observations. *J. Vet. Behav.* **2017**, *20*, 102–108. [CrossRef]
84. Mattachini, G.; Riva, E.; Perazzolo, F.; Naldi, E.; Provolo, G. Monitoring feeding behaviour of dairy cows using accelerometers. *J. Agric. Eng.* **2016**, *47*, 54–58. [CrossRef]
85. Radeski, M.; Ilieski, V. Gait and posture discrimination in sheep using a tri-axial accelerometer. *Animal* **2017**, *11*, 1249–1257. [CrossRef]
86. Barwick, J.; Lamb, D.W.; Dobos, R.; Welch, M.; Trotter, M. Categorising sheep activity using a tri-axial accelerometer. *Comput. Electron. Agric.* **2018**, *145*, 289–297. [CrossRef]
87. Büchel, S.; Sundrum, A. Technical note: Evaluation of a new system for measuring feeding behavior of dairy cows. *Comput. Electron. Agric.* **2014**, *108*, 12–16. [CrossRef]
88. Alvarenga, F.A.P.; Borges, I.; Palkovič, L.; Rodina, J.; Oddy, V.H.; Dobos, R.C. Using a three-axis accelerometer to identify and classify sheep behaviour at pasture. *Appl. Anim. Behav. Sci.* **2016**, *181*, 91–99. [CrossRef]
89. Giovanetti, V.; Decandia, M.; Molle, G.; Acciaro, M.; Mameli, M.; Cabiddu, A.; Cossu, R.; Serra, M.G.; Manca, C.; Rassu, S.P.G.; et al. Automatic classification system for grazing, ruminating and resting behaviour of dairy sheep using a tri-axial accelerometer. *Livest. Sci.* **2017**, *196*, 42–48. [CrossRef]
90. Decandia, M.; Giovanetti, V.; Molle, G.; Acciaro, M.; Mameli, M.; Cabiddu, A.; Cossu, R.; Serra, M.G.; Manca, C.; Rassu, S.P.G.; et al. The effect of different time epoch settings on the classification of sheep behaviour using tri-axial accelerometry. *Comput. Electron. Agric.* **2018**, *154*, 112–119. [CrossRef]
91. Schirmann, K.; von Keyserlingk, M.A.; Weary, D.; Veira, D.; Heuwieser, W. Validation of a system for monitoring rumination in dairy cows. *J. Dairy Sci.* **2009**, *92*, 6052–6055. [CrossRef] [PubMed]
92. McLennan, K.M.; Skillings, E.A.; Rebelo, C.J.B.; Corke, M.J.; Pires Moreira, M.A.; Morton, A.J.; Constantino-Casas, F. Technical note: Validation of an automatic recording system to assess behavioural activity level in sheep (Ovis aries). *Small Rumin. Res.* **2015**, *127*, 92–96. [CrossRef]
93. Grinter, L.; Campler, M.; Costa, J. Validation of a behavior-monitoring collar's precision and accuracy to measure rumination, feeding, and resting time of lactating dairy cows. *J. Dairy Sci.* **2019**, *102*, 3487–3494. [CrossRef] [PubMed]
94. Werner, J.; Umstatter, C.; Leso, L.; Kennedy, E.; Geoghegan, A.; Shalloo, L.; Schick, M.; O'brien, B. Evaluation and application potential of an accelerometer-based collar device for measuring grazing behavior of dairy cows. *Animal* **2019**, *13*, 2070–2079. [CrossRef] [PubMed]
95. Barker, Z.; Diosdado, J.V.; Codling, E.; Bell, N.; Hodges, H.; Croft, D.; Amory, J. Use of novel sensors combining local positioning and acceleration to measure feeding behavior differences associated with lameness in dairy cattle. *J. Dairy Sci.* **2018**, *101*, 6310–6321. [CrossRef]
96. Diosdado, J.A.V.; Barker, Z.E.; Hodges, H.R.; Amory, J.R.; Croft, D.P.; Bell, N.J.; Codling, E.A. Classification of behaviour in housed dairy cows using an accelerometer-based activity monitoring system. *Anim. Biotelemetry* **2015**, *3*, 1–14.
97. Martiskainen, P.; Järvinen, M.; Skön, J.-P.; Tiirikainen, J.; Kolehmainen, M.; Mononen, J. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. *Appl. Anim. Behav. Sci.* **2009**, *119*, 32–38. [CrossRef]
98. Benaissa, S.; Tuyttens, F.A.; Plets, D.; Cattrysse, H.; Martens, L.; Vandaele, L.; Joseph, W.; Sonck, B. Classification of ingestive-related cow behaviours using RumiWatch halter and neck-mounted accelerometers. *Appl. Anim. Behav. Sci.* **2019**, *211*, 9–16. [CrossRef]
99. Fogarty, E.S.; Swain, D.L.; Cronin, G.M.; Moraes, L.E.; Trotter, M. Behaviour classification of extensively grazed sheep using machine learning. *Comput. Electron. Agric.* **2020**, *169*, 105175. [CrossRef]
100. Tamura, T.; Okubo, Y.; Deguchi, Y.; Koshikawa, S.; Takahashi, M.; Chida, Y.; Okada, K. Dairy cattle behavior classifications based on decision tree learning using 3-axis neck-mounted accelerometers. *Anim. Sci. J.* **2019**, *90*, 589–596. [CrossRef]
101. Delagarde, R.; Lamberton, P. Daily grazing time of dairy cows is recorded accurately using the Lifecorder Plus device. *Appl. Anim. Behav. Sci.* **2015**, *165*, 25–32. [CrossRef]
102. Price, E.; Langford, J.; Fawcett, T.W.; Wilson, A.J.; Croft, D.P. Classifying the posture and activity of ewes and lambs using accelerometers and machine learning on a commercial flock. *Appl. Anim. Behav. Sci.* **2022**, *251*, 105630. [CrossRef]
103. Ikurior, S.J.; Marquetoux, N.; Leu, S.T.; Corner-Thomas, R.A.; Scott, I.; Pomroy, W.E. What are sheep doing? Tri-axial accelerometer sensor data identify the diel activity pattern of ewe lambs on pasture. *Sensors* **2021**, *21*, 6816. [CrossRef]
104. Guo, L.; Welch, M.; Dobos, R.; Kwan, P.; Wang, W. Comparison of grazing behaviour of sheep on pasture with different sward surface heights using an inertial measurement unit sensor. *Comput. Electron. Agric.* **2018**, *150*, 394–401. [CrossRef]
105. Wang, J.; He, Z.; Zheng, G.; Gao, S.; Zhao, K. Development and validation of an ensemble classifier for real-time recognition of cow behavior patterns from accelerometer data and location data. *PLoS ONE* **2018**, *13*, e0203546. [CrossRef]
106. Högberg, N.; Höglund, J.; Carlsson, A.; Saint-Jeveint, M.; Lidfors, L. Validation of accelerometers to automatically record postures and number of steps in growing lambs. *Appl. Anim. Behav. Sci.* **2020**, *229*, 105014. [CrossRef]
107. Belaid, M.A.; Rodríguez-Prado, M.; Rodríguez-Prado, D.V.; Chevaux, E.; Calsamiglia, S. Using behavior as an early predictor of sickness in veal calves. *J. Dairy Sci.* **2020**, *103*, 1874–1883. [CrossRef]
108. Poulopoulou, I.; Lambertz, C.; Gauly, M. Are automated sensors a reliable tool to estimate behavioural activities in grazing beef cattle? *Appl. Anim. Behav. Sci.* **2019**, *216*, 1–5. [CrossRef]

109. Alsaaod, M.; Niederhauser, J.J.; Beer, G.; Zehner, N.; Schuepbach-Regula, G.; Steiner, A. Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows. *J. Dairy Sci.* **2015**, *98*, 6236–6242. [CrossRef]
110. VanValin, K.R.; Carmichael-Wyatt, R.N.; Deters, E.L.; Messersmith, E.M.; Heiderscheit, K.J.; Hochmuth, K.G.; Jackson, T.D.; Peschel, J.M.; Johnson, A.K.; Hansen, S.L. Dietary zinc concentration and lipopolysaccharide injection affect circulating trace minerals, acute phase protein response, and behavior as evaluated by an ear-tag–based accelerometer in beef steers. *J. Anim. Sci.* **2021**, *99*, skab278. [CrossRef]
111. Chizzotti, M.; Machado, F.; Valente, E.; Pereira, L.; Campos, M.; Tomich, T.; Coelho, S.; Ribas, M. Validation of a system for monitoring individual feeding behavior and individual feed intake in dairy cattle. *J. Dairy Sci.* **2015**, *98*, 3438–3442. [CrossRef] [PubMed]
112. Schirmann, K.; Weary, D.; Heuwieser, W.; Chapinal, N.; Cerri, R.; Von Keyserlingk, M. Rumination and feeding behaviors differ between healthy and sick dairy cows during the transition period. *J. Dairy Sci.* **2016**, *99*, 9917–9924. [CrossRef] [PubMed]
113. Stangaferro, M.; Wijma, R.; Caixeta, L.; Al-Abri, M.; Giordano, J. Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part I. Metabolic and digestive disorders. *J. Dairy Sci.* **2016**, *99*, 7395–7410. [CrossRef] [PubMed]
114. Marchesini, G.; Mottaran, D.; Contiero, B.; Schiavon, E.; Segato, S.; Garbin, E.; Tenti, S.; Andrighetto, I. Use of rumination and activity data as health status and performance indicators in beef cattle during the early fattening period. *Vet. J.* **2018**, *231*, 41–47. [CrossRef] [PubMed]
115. Burgunder, J.; Petrželková, K.J.; Modrý, D.; Kato, A.; MacIntosh, A.J.J. Fractal measures in activity patterns: Do gastrointestinal parasites affect the complexity of sheep behaviour? *Appl. Anim. Behav. Sci.* **2018**, *205*, 44–53. [CrossRef]
116. Trieu, L.L.; Bailey, D.W.; Cao, H.; Son, T.C.; Scobie, D.R.; Trotter, M.G.; Hume, D.E.; Sutherland, B.L.; Tobin, C.T. Potential of Accelerometers and GPS Tracking to Remotely Detect Perennial Ryegrass Staggers in Sheep. *Smart Agric. Technol.* **2022**, *2*, 100040.
117. Högberg, N.; Hessle, A.; Lidfors, L.; Baltrušis, P.; Claerebout, E.; Höglund, J. Subclinical nematode parasitism affects activity and rumination patterns in first-season grazing cattle. *Animal* **2021**, *15*, 100237. [CrossRef]
118. Högberg, N.; Hessle, A.; Lidfors, L.; Enweji, N.; Höglund, J. Nematode parasitism affects lying time and overall activity patterns in lambs following pasture exposure around weaning. *Vet. Parasitol.* **2021**, *296*, 109500. [CrossRef]
119. Högberg, N.; Lidfors, L.; Hessle, A.; Arvidsson Segerkvist, K.; Herlin, A.; Hoglund, J. Effects of nematode parasitism on activity patterns in first-season grazing cattle. *Vet Parasitol X* **2019**, *1*, 100011. [CrossRef]
120. Verbeek, E.; Ferguson, D.; de Monjour, P.Q.; Lee, C. Opioid control of behaviour in sheep: Effects of morphine and naloxone on food intake, activity and the affective state. *Appl. Anim. Behav. Sci.* **2012**, *142*, 18–29. [CrossRef]
121. Cronin, G.M.; Beganovic, D.F.; Sutton, A.L.; Palmer, D.J.; Thomson, P.C.; Tammen, I. Manifestation of neuronal ceroid lipofuscinosis in Australian Merino sheep: Observations on altered behaviour and growth. *Appl. Anim. Behav. Sci.* **2016**, *175*, 32–40. [CrossRef]
122. Pavlovic, D.; Davison, C.; Hamilton, A.; Marko, O.; Atkinson, R.; Michie, C.; Crnojević, V.; Andonovic, I.; Bellekens, X.; Tachtatzis, C. Classification of cattle behaviours using neck-mounted accelerometer-equipped collars and convolutional neural networks. *Sensors* **2021**, *21*, 4050. [CrossRef]
123. Miller, G.; Mitchell, M.; Barker, Z.; Giebel, K.; Codling, E.; Amory, J.; Michie, C.; Davison, C.; Tachtatzis, C.; Andonovic, I. Using animal-mounted sensor technology and machine learning to predict time-to-calving in beef and dairy cows. *Animal* **2020**, *14*, 1304–1312. [CrossRef]
124. Kamminga, J.W.; Le, D.V.; Meijers, J.P.; Bisby, H.; Meratnia, N.; Havinga, P.J. Robust sensor-orientation-independent feature selection for animal activity recognition on collar tags. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* **2018**, *2*, 1–27. [CrossRef]
125. Nóbrega, L.; Gonçalves, P.; Antunes, M.; Corujo, D. Assessing sheep behavior through low-power microcontrollers in smart agriculture scenarios. *Comput. Electron. Agric.* **2020**, *173*, 105444. [CrossRef]
126. Dominguez-Morales, J.P.; Duran-Lopez, L.; Gutierrez-Galan, D.; Rios-Navarro, A.; Linares-Barranco, A.; Jimenez-Fernandez, A. Wildlife monitoring on the edge: A performance evaluation of embedded neural networks on microcontrollers for animal behavior classification. *Sensors* **2021**, *21*, 2975. [CrossRef]
127. Cabezas, J.; Yubero, R.; Visitación, B.; Navarro-García, J.; Algar, M.J.; Cano, E.L.; Ortega, F. Analysis of Accelerometer and GPS Data for Cattle Behaviour Identification and Anomalous Events Detection. *Entropy* **2022**, *24*, 336. [CrossRef]
128. Brennan, J.; Johnson, P.; Olson, K. Classifying season long livestock grazing behavior with the use of a low-cost GPS and accelerometer. *Comput. Electron. Agric.* **2021**, *181*, 105957. [CrossRef]
129. Walton, E.; Casey, C.; Mitsch, J.; Vázquez-Diosdado, J.A.; Yan, J.; Dottorini, T.; Ellis, K.A.; Winterlich, A.; Kaler, J. Evaluation of sampling frequency, window size and sensor position for classification of sheep behaviour. *R. Soc. Open Sci.* **2018**, *5*, 171442. [CrossRef]
130. Wang, L.; Arablouei, R.; Alvarenga, F.A.; Bishop-Hurley, G.J. Animal Behavior Classification via Accelerometry Data and Recurrent Neural Networks. *arXiv preprint* **2021**, arXiv:2111.12843.
131. Groher, T.; Heitkämper, K.; Umstätter, C. Digital technology adoption in livestock production with a special focus on ruminant farming. *Animal* **2020**, *14*, 2404–2413. [CrossRef] [PubMed]

132. Forbes, A. Ruminant behaviour in subclinical parasitic gastroenteritis. *Livestock* **2021**, *26*, 78–85. [CrossRef]
133. Arablouei, R.; Wang, L.; Currie, L.; Alvarenga, F.A.; Bishop-Hurley, G.J. Animal Behavior Classification via Deep Learning on Embedded Systems. *arXiv preprint* **2021**, arXiv:2111.12295.