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Summary

Sustainable and competitive milk production is highly dependent on securing the performance potential, health and fertility of dairy cows. Therefore, farmers can benefit from sensor data of animal monitoring systems to improve health management and work processes in dairy farming. The research during this PhD thesis aimed to contribute to the development and evaluation of a scientifically validated, sensor-based animal monitoring system that comprises a device for measurement of ingestive behavior and a device for measurement of movement behavior in cattle that interact as a system with system-specific software. Further aim of this thesis was to evaluate application potentials for this animal monitoring system by means of calving prediction in dairy cows and measurement of chewing activity in horses. The underlying experimental work was structured into four separate studies. The aim of the first study was to develop and validate a novel scientific monitoring device for automated measurement of rumination and eating behavior in dairy cows. Research works for this study aimed to provide a complete and detailed technical specification of the functionality of this device and to perform a validation under field conditions in stable-fed cows. The objective of the second study was to develop and validate a novel algorithm to monitor lying, standing, and walking behavior based on the output of a triaxial accelerometer collected from loose-housed dairy cows. The third study aimed to use automated measurements of ingestive behavior obtained from the developed sensor device to develop and validate a predictive model for calving in dairy cows. The aim of the fourth study was to investigate the suitability and validity of the developed sensor system for automated measurement of chewing activity in horses.

The RumiWatch noseband sensor (Agroscope, Ettenhausen, Switzerland and Itin+Hoch GmbH, Liestal, Switzerland) developed in the first study incorporates a noseband pressure sensor, a data logger with online data analysis, and software. Automated measurements of behavioral parameters are based on generic algorithms without animal-specific learning data. Thereby, the system records and classifies the duration of chewing activities and enables users to quantify individual ruminating and eating jaw movements performed by the animal. During the course of the development, two releases of the system-specific software RumiWatch Converter (RWC) were created and taken into account for the validation study. The results generated by the two software versions, RWC V0.7.2.0 and RWC V0.7.3.2, were compared with direct behavioral observations. Direct observations of cow behavior were conducted on 14 Swiss dairy farms with an observation time of 1 hour per animal, resulting in a total sample of 60 dairy cows. Agreement of sensor measurement and direct observation was expressed as Spearman correlation coefficients (r_s) for the pooled sample. For consolidated classification of sensor data (1-hour resolution), correlations for rumination time were $r_s = 0.91$ (RWC V0.7.2.0) and $r_s = 0.96$ (RWC 0.7.3.2), and for eating time $r_s = 0.86$ (RWC 0.7.2.0) and $r_s = 0.96$ (RWC V0.7.3.2). Both software versions provide a high standard of validity and measuring performance for ruminating and eating behavior. The high to very high correlations between direct observation and sensor data demonstrate that the RumiWatch noseband sensor was successfully developed and validated as a scientific monitoring device for automated measurement of ruminating and eating activity in stable-fed dairy cows. Further research is needed to allow for the differentiation of total eating jaw movements, as the described state of the analysis routines does not enable a separate classification of chews, bites, and chew-bites during eating.

The objective of the second study was to develop and validate a novel algorithm to monitor extended parameters of lying, walking, and standing behavior of loose-housed dairy cows based on the output of the RumiWatch pedometer (Itin+Hoch GmbH, Liestal, Switzerland). Data of locomotion were acquired by simultaneous accelerometer measurements at a sampling rate of 10 Hz and video recordings for manual observation later. The study consisted of 3 independent experiments with a total of 55 dairy cows. Experiment 1 was carried out to develop and validate the algorithm for lying behavior (n = 18 cows), Experiment 2 for walking and standing behavior (n = 21 cows), and Experiment 3 for stride duration and stride length (n = 16 cows). The final version was validated, using the raw data, collected from cows not included in the development of the algorithm. Spearman correlation coefficients were calculated between accelerometer variables and respective data derived from the video recordings (gold standard). Dichotomous data were expressed as the proportion of correctly detected events, and the overall difference for continuous data was expressed as the relative measurement error. The proportions for correctly detected events or bouts were 1 for stand ups, lie downs, standing bouts, and lying bouts and 0.99 for walking bouts. The relative measurement error and Spearman correlation coefficient for lying time were 0.09% and 1; for standing time, 4.7% and 0.96; for walking time, 17.12% and 0.96; for number of strides, 6.23% and 0.98; for stride duration, 6.65% and 0.75; and for stride length, 11.92% and 0.81, respectively. The strong to very high correlations of the variables between visual observation and converted pedometer data indicate that the novel RumiWatch algorithm may markedly improve automated livestock management systems for efficient health monitoring of dairy cows. Using the new pedometer software, further research is intended to study in more detail the normal locomotor activity of healthy dairy cows and to evaluate the suitability of the newly described parameters of walking behavior for early detection of lameness.

In the third study, measurement data of the RumiWatch noseband sensor (Agroscope, Ettenhausen, Switzerland and Itin+Hoch GmbH, Liestal, Switzerland) of 35 dairy cows were used for the development and validation of a predictive model for calving time based on variables of ingestive behavior. Sensor data obtained from calving events on three farms were used as one training dataset (n = 11 cows) and two independent validation datasets (n = 11 and n = 13 cows, respectively) to evaluate the predictive performance of a Naïve Bayes classifier model for calving prediction at 1 hour before the start of calving. The model performance was evaluated on an hourly basis for 168 hours prior to the start of calving. Thereby, different noseband sensor variables as best individual predictors were identified for the two validation datasets. These were ruminating chews for Validation Dataset 1 (sensitivity = 0.82, specificity = 0.79, positive predictive value = 0.02), and other chews, i.e., non-ingestive related jaw movements, for Validation Dataset 2 (sensitivity = 0.69, specificity = 0.81, positive predictive value = 0.02). Combinations of sensor variables were most useful in calving prediction, as they improved predictive performance and decreased the number of false positive alerts in comparison with individual sensor variables. The best combination of calving predictors consisted of ruminating chews, ruminating boluses, and eating chews for Validation Dataset 1 (sensitivity = 0.82, specificity = 0.87, positive predictive value = 0.04), and ruminating chews per bolus, ruminating chews per minute, eating chews, other activity time, and other chews for Validation Dataset 2 (sensitivity = 0.69, specificity = 0.86, positive predictive value = 0.03). These results indicate, that the sensitivity and specificity of the predictive model were satisfactory, but the positive predictive value was low and the amount of false positive alerts was considerably high. Although the developed model is therefore not suitable for application in practice, the analyses showed that particularly variables of rumination behavior have predictive value and should be taken into consideration for future research on calving prediction models. The findings of this study demonstrate that specifically for predictive models in livestock production, an assessment limited to the terms of sensitivity and specificity may be misleading, as these variables may achieve high values and suggest adequate performance, while the model is not appropriate in the light of its expected use.

In the fourth study, it was successfully demonstrated that it is feasible to apply the RumiWatch noseband sensor (Agroscope, Ettenhausen, Switzerland and Itin+Hoch GmbH, Liestal, Switzerland) to horses. In order to investigate the measuring performance, 10 horses (5 mares, 5 stallions) were equipped with the device. Additionally, direct observations were conducted as a reference method, while feeding three different feeds (hay, haylage and concentrate). The results of direct observation compared with the automatic measurement showed an overall agreement of the observed and automatically measured chews per minute of 93% within all feedstuffs. The agreement between automated measurements and direct observations was high for all analyzed feed types, amounting to 92.4% for hay, 96.8% for

haylage, and 91.4% for concentrate, respectively. The analysis indicated that the differentiation between chews and other muzzle and lip movements could improve the overall measuring performance of the device, as horses tend to display a high amount of lip movements towards the end of the concentrate intake. However, the constituents and software of the measurement system were not specifically adapted to horses so far and can be optimized in order to improve accuracy. Consequently, the noseband sensor has a high potential to become a reliable tool for research and practical use.

In conclusion, the RumiWatch noseband sensor and pedometer that were developed and validated in the current project represent a suitable measuring instrument for automated recording of ingestive and locomotor behavior in dairy cows. The system-specific software is suitable for research purposes and shows a high performance for classification of extended parameters of rumination, eating, lying, standing, and walking behavior. The achieved validation results indicate that the measuring performance satisfies scientific requirements. Further application potentials were demonstrated by means of automated calving prediction in dairy cows and automated measurement of chewing activity in horses. The development and validation of a predictive model for calving time using measurements of the RumiWatch noseband sensor revealed a high amount of false positive alerts that was prohibitive for application of the model in farming practice. However, the analyses showed that particularly parameters of ruminating behavior have predictive value and should be taken into consideration for future research on calving prediction models. Furthermore, it was successfully demonstrated that it is feasible to apply the RumiWatch noseband sensor to horses. The results of direct observation compared with the automatic measurement showed a very high overall agreement of the observed and automatically measured data and, after minor refinements, this measuring device has the potential to become a valuable and easy-to-use tool for equine research and management.

Zusammenfassung

Eine nachhaltige und wettbewerbsfähige Milchproduktion erfordert in hohem Masse die Sicherstellung des Leistungspotentials, der Gesundheit und der Fruchtbarkeit von Milchkühen. Sensordaten, die durch technische Monitoringsysteme für die Überwachung des Tierverhaltens generiert werden, können hierbei einen wichtigen Beitrag für die Verbesserung der Arbeitsprozesse und des Gesundheitsmanagement in der Milchviehhaltung leisten. Die Zielsetzung dieses Dissertationsprojekts stellte einen Beitrag zur Entwicklung und wissenschaftlichen Evaluation eines technischen Monitoringsystems für die Tieraktivität dar. Im Rahmen der Forschungsvorhaben sollten Messinstrumente für die Erfassung des Ingestionsverhaltens und des Bewegungsverhaltens entwickelt und wissenschaftlich validiert werden, die unter Hinzunahme einer systemspezifischen Software zum nicht-invasiven, systematischen Gesundheitsmonitoring bei Milchkühen dienen. Zudem sollten Anwendungspotentiale für dieses Monitoringsystem anhand der Abkalbungsvorhersage bei Milchkühen und der Messung der Kauaktivität bei Pferden evaluiert werden. Die zugrundeliegenden experimentellen Arbeiten waren in vier separate Studien unterteilt. Die erste Studie beinhaltete die Entwicklung und Validierung eines neuartigen wissenschaftlichen Messinstruments für die automatisierte Erfassung des Wiederkau- und Futteraufnahmeverhaltens bei Milchkühen. Die Forschungsarbeiten im Rahmen dieser Studie umfassten die Bereitstellung eines umfassenden technischen Funktionsbeschriebs dieses Messinstruments und die Durchführung einer Validierungsstudie unter Praxisbedingungen bei stallgefütterten Milchkühen. Die Zielsetzung der zweiten Studie war die Entwicklung und Validierung eines neuartigen Algorithmus zur Erfassung des Geh-, Steh- und Liegeverhaltens von Milchkühen in Laufstallhaltung basierend auf den Messdaten eines triaxialen Accelerometers. In der dritten Studie wurde die Nutzung von Messdaten des Ingestionsverhaltens zur Entwicklung und Validierung eines Modells für die automatisierte Kalbungsvorhersage beabsichtigt. Ziel der vierten Studie war die Untersuchung der Eignung und Validität des entwickelten Sensorsystems für die automatisierte Erfassung des Kauverhaltens von Pferden.

Die Zielsetzung der ersten Studie dieses Dissertationsprojektes war es, ein neuartiges wissenschaftliches Messinstrument für die automatisierte Erfassung des Wiederkau- und Futteraufnahmeverhaltens von stallgefütterten Milchkühen zu entwickeln und zu validieren. Der Forschung soll hierdurch eine technische Lösung für das Aktivitäts- und Gesundheitsmonitoring zur Verfügung gestellt werden. Der im Rahmen dieser Studie entwickelte RumiWatch-Nasenbandsensor (Agroscope, Ettenhausen, Schweiz und Itin+Hoch GmbH, Liestal, Schweiz) umfasst einen Drucksensor im Nasenband eines Halfters, einen Datenlogger mit Echtzeit-Datenanalyse sowie eine systemspezifische Software. Die automatisierte Erfassung der Verhaltensparameter basiert auf generischen Algorithmen ohne tierspezifische Lerndaten. Hierdurch kann das Messsystem die Dauer von Kauaktivitäten aufzeichnen und klassifizieren. Zudem können die individuellen Wiederkau- und Fresskauschläge des Tieres aufgezeichnet werden. Im Verlauf der Entwicklung wurden zwei Versionen der der systemspezifischen Software RumiWatch Converter (RWC) erarbeitet und zur Validierung verwendet. Die Resultate der automatischen Auswertung durch die beiden Software-Versionen, RWC V0.7.2.0 und RWC 0.7.3.2, wurden jeweils mit den Ergebnissen einer zeitgleichen Direktbeobachtung verglichen. Die Direktbeobachtungen wurden auf 14 Schweizerischen Milchviehbetrieben mit einer Beobachtungsdauer von 1 Stunde pro Tier durchgeführt. Zur Auswertung stand eine Gesamtstichprobe von 60 Kühen zur Verfügung. Die Übereinstimmung der Ergebnisse von Sensormessungen und Direktbeobachtungen wurde durch den Spearman-Korrelationskoeffizient (r_s) für die Gesamtstichprobe wiedergegeben. Für die zusammengefasste Auswertung der Sensormessdaten in 1-Stunde-Auflösung betrugen die Korrelationen für die gemessenen Wiederkauzeiten $r_s = 0.91$ (RWC V0.7.2.0) und $r_s = 0.96$ (RWC 0.7.3.2) sowie für die gemessenen Fresszeiten $r_s = 0.86$ (RWC 0.7.2.0) und $r_s = 0.96$ (RWC V0.7.3.2). Beide Software-Versionen stellen einen hohen Standard der Validität und Messgenauigkeit für die Erfassung des Wiederkau- und Futteraufnahmeverhaltens dar. Die hohen bis sehr hohen Korrelationen zwischen den Ergebnissen der Direktbeobachtung und der Sensormessung verdeutlichen die erfolgreiche Entwicklung und Validierung eines wissenschaftlichen Monitoringsystems für die automatisierte Erfassung des Wiederkau- und Futteraufnahmeverhaltens für stallgefütterte Milchkühe. Weitere Forschungsarbeiten sind für die genauere Differenzierung des Kauverhaltens während der Futteraufnahme erforderlich, da der beschriebene Stand der Auswertungsroutinen noch keine separate Klassierung von Fresskauschlägen, Fressbissen und Kau-Fressbissen ermöglicht.

Zielsetzung der zweiten Studie war die Entwicklung und Validierung eines neuartigen Algorithmus zur Erfassung erweiterter Parameter des Geh-, Steh- und Liegeverhaltens von Milchkühen in Laufstallhaltung, der auf den Messwerten des RumiWatch-Pedometers (Itin+Hoch GmbH, Liestal, Schweiz) basiert. Daten des Bewegungsverhaltens wurden durch Accelerometer-Messungen mit einer Aufzeichnungsrate von 10 Hz und eine zeitgleiche Videobeobachtung zur späteren Auswertung bei einer Gesamtzahl von 55 Milchkühen akquiriert. Die Studie war hierbei in 3 unabhängige Experimente unterteilt. Zur Entwicklung und Validierung eines Algorithmus wurde Experiment 1 für das Liegeverhalten (n = 18 Kühe), Experiment 2 für das Geh- und Stehverhalten (n = 21 Kühe) und Experiment 3 für die Schrittdauer und Schrittlänge (n = 16 Kühe) durchgeführt. Die finale Version des Algorithmus wurde mit Rohdaten von Kühen validiert, die nicht für die Entwicklung verwendet wurden. Hierzu wurde der Spearman-Korrelationskoeffizient zwischen den Pedometer-Messwerten und den jeweiligen Aufzeichnungen der Videobeobachtung (Goldstandard) berechnet. Für dichotome Variablen wurde die Übereinstimmung als Anteil korrekt detektierter Ereignisse bestimmt. Für kontinuierliche Variablen wurde die Differenz als relativer prozentualer Messfehler wiedergegeben. Der Anteil korrekt detektierter Ereignisse oder Phasen betrug 1 für Aufsteh- und Abliegevorgänge sowie für Steh- und Liegephasen bzw. 0.99 für Gehphasen. Der relative Messfehler und Spearman-Korrelationskoeffizient betrug für Liegezeit 0.09% und 1, Stehzeit 4.7% und 0.96, Gehzeit 17.12% und 0.96, Schrittanzahl 6.23% und 0.98, Schrittdauer 6.65% und 0.75 sowie für Schrittlänge 11.92% und 0.81. Die hohen bis sehr hohen Korrelationen zwischen der visuellen Erfassung und der Pedometer-Messung verdeutlichen das hohe Potential des neu entwickelten RumiWatch-Algorithmus für die Verbesserung der automatisierten Erfassung des Tierverhaltens und für ein effizienteres Gesundheitsmonitoring bei Milchkühen. Bei weiterführenden Forschungen können die neuartigen Auswertungsroutinen des RumiWatch-Pedometers für eine genauere Untersuchung des Bewegungsverhaltens gesunder Milchkühe genutzt werden. Zudem soll die Möglichkeit einer Früherkennung von Lahmheiten basierend auf den neu beschreibenden Auswertungsparametern des Bewegungsverhaltens eruiert werden.

In der dritten Studie wurden Messdaten des RumiWatch-Nasenbandsensors (Agroscope, Ettenhausen, Schweiz und Itin+Hoch GmbH, Liestal, Schweiz) von 35 Milchkühen zur Entwicklung und Validierung eines Vorhersagemodells für den Kalbezeitpunkt basierend auf Parametern des Ingestionsverhaltens verwendet. Sensordaten von Abkalbungen auf drei verschiedenen Milchviehbetrieben wurden als ein Trainingsdatensatz (n = 11 Kühe) und zwei unabhängige Validierungsdatensätze (n = 11 bzw. n = 13 Kühe) verwendet, um die Vorhersageleistung eines Naiven Bayes Klassifikators für die Bestimmung des Zeitpunktes 1 Stunde vor Beginn der Kalbung zu evaluieren. Die Modelleistung wurde auf stündlicher Basis für einen Zeitraum von 168 Stunden vor Beginn der Kalbung evaluiert. Hierbei wurden unterschiedliche Verhaltensparameter als beste individuelle Prädiktoren für die beiden Validierungsdatensätze identifiziert. Dies waren Wiederkauschläge für Validierungsdatensatz 1 (Sensitivität = 0.82, Spezifität = 0.79, Positiver Vorhersagewert = 0.02) und andere Kauschläge, d. h. nicht-ingestive Kieferbewegungen, für Validierungsdatensatz 2 (Sensitivität = 0.69, Spezifität = 0.81, Positiver Vorhersagewert = 0.02). Kombinationen von Sensorparametern waren am besten für die Vorhersage der Kalbung geeignet, da hierdurch im Vergleich zu individuellen Sensorparametern eine Verbesserung der Vorhersageleistung und eine Verringerung der Falsch-Positiv-Alarme festzustellen war. Die bestleistende Kombination von Kalbungsprädiktoren bestand aus Wiederkauschlägen, Wiederkauboli und Fresskauschlägen in Validierungsdatensatz 1 (Sensitivität = 0.82, Spezifität = 0.87, Positiver Vorhersagewert = 0.04) sowie Wiederkauschläge pro Bolus, Wiederkauschläge pro Minute, Fresskauschläge, Dauer anderer Aktivitäten und andere Kauschläge für

Validierungsdatensatz 2 (Sensitivität = 0.69, Spezifität = 0.86, Positiver Vorhersagewert = 0.03). Diese Ergebnisse verdeutlichen, dass die berechnete Sensitivität und Spezifität zwar zufriedenstellend war, aber gleichzeitig niedrige Positive Vorhersagewerte und eine hohe Anzahl an Falsch-Positiv-Alarmen festgestellt wurden. Obwohl das entwickelte Modell daher nicht für die praktische Anwendung geeignet ist, zeigten die Analysen, dass insbesondere Parameter des Wiederkauverhaltens für die zukünftige Erarbeitung von Vorhersagemodellen für den Kalbungszeitpunkt berücksichtigt werden sollten. Zudem zeigen die Ergebnisse dieser Studie, dass eine auf die Parameter Sensitivität und Spezifität begrenzte Modellbewertung im spezifischen Kontext einer Anwendung in der Nutztierhaltung missverständlich interpretiert werden kann, da diese Parameter zwar hohe Werte annehmen und so eine zufriedenstellende Modelleistung suggerieren können, obwohl das betreffende Modell für den erwarteten Nutzen ungeeignet ist.

In der vierten Studie wurde die erfolgreiche Anwendung des RumiWatch-Nasenbandsensors (Agroscope, Ettenhausen, Schweiz und Itin+Hoch GmbH, Liestal, Schweiz) bei Pferden demonstriert. Zur Bestimmung der Messgenauigkeit wurden 10 Pferde (5 Stuten, 5 Hengste) mit diesem Messgerät ausgestattet. Parallel zur Sensormessung wurden als Referenzmethode Direktbeobachtungen bei der Fütterung dreier Futtermittel (Heu, Heulage, Kraftfutter) durchgeführt. Ein Vergleich der Ergebnisse von Direktbeobachtung und Sensormessung zeigte eine prozentuale Übereinstimmung der erfassten Kauschläge pro Minute von 93% im Mittelwert aller Futtermittel. In einer separaten Betrachtung war für alle untersuchten Futtermittel eine hohe Übereinstimmung festzustellen, diese betrug 92.4% für Heu, 96.8% für Heulage und 91.4% für Kraftfutter. Die Analyse zeigte zudem, dass durch eine weitere Differenzierung der Kauschläge und sonstiger Maul- und Lippenbewegungen eine weitere Verbesserung der Messleistung erbracht werden könnte, da Pferde gegen Ende der Kraftfutteraufnahme eine erhöhte Anzahl von Lippenbewegungen zeigen. Die Bestandteile und Software des Messsystems waren nicht spezifisch für Pferde angepasst und können für eine Erhöhung der Messgenauigkeit weiter optimiert werden. Demzufolge kann dem Nasenbandsensor ein hohes Potential als reliables Messinstrument für Forschung und Praxis zugemessen werden.

In einer Gesamtbetrachtung ist festzustellen, dass der RumiWatch-Nasebandsensor und das RumiWatch-Pedometer erfolgreich als Messinstrumente für die Erfassung des Ingestions- und Bewegungsverhaltens von Milchkühen entwickelt wurden. Die systemspezifische Software ist für wissenschaftliche Zwecke geeignet und zeigt eine hohe Validität bei der Messung erweiterter Parameter des Wiederkau-, Futteraufnahme-, Geh-, Steh- und Liegeverhaltens. Die erzielte Messgenauigkeit bei der Validierung der beiden Messinstrumente entspricht wissenschaftlichen Ansprüchen. Weitere Anwendungspotentiale wurden anhand der automatisierten Kalbungsvorhersage bei Milchkühen und Messung der Kauaktivität bei Pferden demonstriert. Bei der Entwicklung und Validierung eines Vorhersagemodells für den Kalbezeitpunkt basierend auf Messdaten des RumiWatch-Nasenbandsensors zeigte sich eine hohe Anzahl an Falsch-Positiv-Alarmen, die prohibitiv für die Anwendung des entwickelten Modells in der landwirtschaftlichen Praxis ist. Dennoch konnte gezeigt werden, dass insbesondere Parameter des Wiederkauverhaltens für die zukünftige Erarbeitung von Vorhersagemodellen für den Kalbezeitpunkt herangezogen werden sollten. Zudem konnte der RumiWatch-Nasenbandsensor erfolgreich auch bei Pferden eingesetzt werden. Der Vergleich von Direktbeobachtungen und Sensormessungen zeigte hierbei eine hohe Übereinstimmung zwischen beobachteten und automatisch erfassten Messwerten. Nach geringfügigen Modifikationen ist dem Nasenbandsensor somit auch ein hohes Potential für den Einsatz in Forschung und Praxis bei Pferden zuzuschreiben.

1 General Introduction

Benefiting from automated detection of occurrences requiring assistance or treatment by farmers, such as calving, disease, or heat is a particular interest of large-scale dairy farming. This demand is driven by structural changes towards intensified production and growing herds in the dairy industry that affect health and welfare of dairy cows (Barkema et al. 2015). Accordingly, technical monitoring tools to support health management on dairy farms are a major focus in the development and marketing of dairy technology (Rutten et al. 2013). Using an automated health monitoring system may serve for early detection of changes in health-related behavioral parameters and may enable diagnosis and reactions to feeding deficiencies and metabolic diseases at an early stage. This is of particular relevance, as costs for medical treatment and losses in production may have a considerable economic impact. Fourichon et al. (2001) found that average total costs related to animal health made up 1.14 € per 100 kg milk. Thus, automated behavior monitoring systems for health management can render a contribution to secure profitability of dairy farming and to improve animal welfare. The presented thesis will therefore focus on the development and assessment of a sensor-based behavior monitoring system for ruminants.

1.1 Framework of health monitoring in dairy farming

Sustainable and competitive milk production is highly dependent on securing the performance potential, health and fertility of dairy cows. Today’s performance-oriented dairy cow nutrition aims to contribute both to adequate nutrient supply and best possible profitability of dairy farming. Rations are marked by an increased proportion of easily fermentable carbohydrates and risks for deficits in structured fiber contents. This may represent possible causes of pathological strains of forestomach digestion and facilitate occurrence of metabolic diseases. These disorders have an increased prevalence in intensive dairy farming and are highly correlated to increased milk yield and production stress (Fleischer et al. 2001). In addition, the peri-partum and early lactation represent phases of increased physiological disposition for deficiency diseases and secondary complications in dairy cows (Overton and Waldron 2004).

Studies by Gonzalez et al. (2008) and DeVries et al. (2009) revealed significant changes in rumination, eating and movement behavior as indicators for impairments of dairy cows' metabolic health. These pathophysiologic impacts may result in economic losses by decrease in milk yield and milk quality, costs for veterinary treatments, increased working time, and early culling of dairy cows (Gonzalez et al. 2008). Lameness has been specified as one of the main health problems in modern dairy herds (Kossaibati and Esslemont 1997). With increasing livestock numbers per farm, the available time per cow for individual observation of abnormalities, deficiencies and disorders will decrease, which will affect the early diagnosis of lameness and further impairments of animal health. Making use of sensor data might support the farmer in their daily management (de Mol et al. 2013).

1.2 Sensor data to support health monitoring in dairy farming

Sensor-controlled, automated processes are increasingly available also for the optimization of dairy production systems and are referred to as Precision Dairy Farming (Maltz 2010) or Smart Farming (Walter et al. 2017) solutions. On the basis of a systematic measurement and evaluation, these technologies intend to provide decision criteria or recommendations for the management of production-relevant natural, human, and technical resources. Furthermore, by considering economic, environmental and also increasingly social parameters, Precision Dairy or Smart Farming solutions intend both to improve the efficiency of production and to facilitate the work of agricultural producers. The increasing spread of automated milking systems is an exemplary case that underlines the structural change in dairy farming due to the introduction of automated solutions for farming practice. For automated animal behavior monitoring systems, development potentials have increased due to technological progress, particularly in sensor and software applications. Advantages of automated recording can be seen in a less time consuming, more continuous and objective measurement process.

Computerized applications offer improved methods for documentation and information exchange. Thus, high data and information density can be generated specifically for the individual animal. In the field of health management, an elementary goal of such sensor-based animal monitoring technology is to enable detection of critical conditions at an early stage and to suggest management measures for farmers and veterinarians in response to the detected conditions.

As one of the main challenges in animal health management, metabolic disorders in dairy cows represent a common problem in farming practice with high physiological and economic impact (Fourichon et al. 2001, Bareille et al. 2003). For early detection of metabolic problems, ruminating activity is considered an important non-invasive measurable behavioral parameter (Maekawa et al. 2002, DeVries et al. 2009, Nydegger et al. 2010). An automated measurement of ruminating and eating activity may enable the identification of feeding deficiencies and thus facilitate a decision to adjust the ration (Gonzalez et al. 2008, Weary et al. 2009, Nydegger et al. 2010). Several studies have been aiming at the development and validation of a non-invasive, automated method for measuring rumination and feed intake in ruminants (Penning 1983, Penning et al. 1984, Rutter et al. 1997, Nydegger et al. 2010). Furthermore, the development of applications for automated measurement of locomotor behavior has gained an increasing scientific and commercial interest (Champion et al. 1997, Scheibe and Gromann 2006, de Mol et al. 2009), predominantly for detection of estrus (McGowan et al. 2007, Saint-Dizier and Chastant-Maillard 2012) and lameness (Mazrier et al. 2006, Alsaaod et al. 2012). Solutions for automated recording and analysis of behavioral parameters initially had a focus on scientific and advisory purposes. Meanwhile, these technologies were further developed, consolidated, and commercialized and are increasingly used in farming practice, particularly for intensive dairy systems. The role of research is to contribute to the ongoing development of these assisting tools, to validate the technology in the light of its expected use, and to evaluate its added value for farming practice.

1.3 Rationale for the development of a novel animal monitoring system

The ultimate goal of the underlying research project was to use state-of-the-art technology to develop a sensor-based animal monitoring system for ingestive and locomotor behavior which generates a high data density of relevant behavioral parameters that indicate the health state of the animal. This animal monitoring system needed to undergo a scientific evaluation and validation during the course of the development to ensure functionality and measuring performance that satisfies scientific requirements. Therefore, we aimed to use real-time analysis of sensor signals obtained from different types of sensors in a systematic approach based on high-resolution measurement data and enabled us to classify multiple behaviors and extended parameters of these behaviors. Further requirement of the projected animal monitoring system was to enable both wireless data transmission and device-based storage of measurement data, and adequate data storage capacity and energy supply for longitudinal recordings. The functionality of the system was intended to be further expandable by additional analysis parameters and sensor types. It was also envisioned that a system-specific software for user-defined post-processing of measurement data was included. Thereby, we aimed to provide high usability for a broad field of applications in agronomic and veterinary research. The development was intended to be based on the measurement system described by Swiss Patent CH 700 494 B1 (Nydegger and Bollhalder 2010).

1.4 Aims of research

The research during this PhD thesis aimed at contributing to the development and scientific validation of a sensor-based animal monitoring system comprising a device for measuring ingestive behavior and a device for measuring movement behavior in cattle. Both devices interact as a system linked via a system-specific software. Further aim of this thesis was to evaluate application potentials for this animal monitoring system by means of calving detection in dairy cows and measurement of chewing activity in horses. The underlying experimental work was structured into four studies. The aim of the first study was to develop and validate a novel scientific monitoring device for automated measurement of ingestive behavior in dairy cows. Research works for this study provide a complete and detailed technical specification of the functionality of this device and to perform a validation under field conditions in stable-fed cows. The objective of the second study was to develop and validate a novel algorithm to monitor locomotor behavior based on the output of a triaxial accelerometer collected from loose-housed dairy cows. The third study aimed to use automated measurements of ingestive behavior obtained from the developed sensor device to create and validate a detection model for calving in dairy cows. The aim of the fourth study was to investigate the suitability and validity of the developed noseband sensor for automated measurement of chewing activity in horses.

1.5 References

Alsaaod, M., Römer, C., Kleinmanns, J., Hendriksen, K., Rose-Meierhöfer, S., Plümer, L., Büscher, W., 2012. Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. Applied Animal Behaviour Science, 142, 134–141.

Bareille, N., Beaudeau, F., Billon, S., Robert, A., Faverdin, U. P., 2003. Effects of health disorders on feed intake and milk production in dairy cows. Livestock Production Science, 83, 53–62.

Barkema, H. W., von Keyserlingk, M. A. G., Kastelic, J. P., Lam, T. J. G. M., Luby, C., Roy, J. P., LeBlanc, S. J., Keefe, G. P., Kelton, D. F., 2015. Invited review: Changes in the dairy industry affecting dairy cattle health and welfare. Journal of Dairy Science, 98, 7426–7445.

de Mol, R. M., André, G., Bleumer, E. J. B., van der Werf, J. T. N., de Haas, Y., van Reenen, C. G., 2013. Applicability of day-to-day variation in behavior for the automated detection of lameness in dairy cows. Journal of Dairy Science, 96, 3703–3712.

Champion, R. A., Rutter, S. M., Penning, P. D., 1997. An automatic system to monitor lying, standing and walking behaviour of grazing animals. Applied Animal Behaviour Science, 54, 291–305.

de Mol, R. M., Lammers, R. J. H., Pompe, J. C. A. M., Ipema, A. H., Hogewerf, P. H., 2009. Recording and analysis of locomotion in dairy cows with 3D accelerometers. In: Precision Livestock Farming ’09. Proceedings of 4th European Conference on Precision Livestock Farming, Wageningen, The Netherlands, 6–8 July 2009, Wageningen Academic Publishers, 333–342.

DeVries, T. J., Beauchemin, K. A., Dohme, F., Schwartzkopf-Genswein, K. S., 2009. Repeated ruminal acidosis challenges in lactating dairy cows at high and low risk for developing acidosis: Feeding, ruminating, and lying behavior. Journal of Dairy Science, 92, 5067–5078.

Fleischer, P., Metzner, M., Beyerbach, M., Hoedemaker, M., Klee, W., 2001. The relationship between milk yield and the incidence of some diseases in dairy cows. Journal of Dairy Science, 84, 2025–2035.

Fourichon, C., Seegers, H., Bareille, N., Beaudeau, F., 1999. Effects of disease on milk production in the dairy cow: a review. Preventive Veterinary Medicine, 41, 1–35.

Fourichon, C., Seegers, H., Beaudeau, F., Verfaille, L., Bareille, N., 2001. Health-control costs in dairy farming systems in western France. Livestock Production Science, 68, 141–156.

Gonzalez, L. A., Tolkamp, B. J., Coffey, M. P., Ferret, A., Kyriazakis, I., 2008. Changes in feeding behavior as possible indicators for the automatic monitoring of health disorders in dairy cows. Journal of Dairy Science, 91, 1017–1028.

Kossaibati, M. A., and Esslemont, R. J., 1997. The costs of production diseases in dairy herds in England. The Veterinary Journal, 154, 41–51.

Maekawa, M., Beauchemin, K. A., Christensen, D. A., 2002. Effect of concentrate level and feeding management on chewing activities, saliva production, and ruminal pH of lactating dairy cows. Journal of Dairy Science, 85, 1165–1175.

Maltz, E., 2010. Novel Technologies: Sensors, Data and Precision Dairy Farming. In: Proceedings of the First North American Conference on Precision Dairy Management, March 2–5, 2010, Toronto, Canada.

Mazrier, H., Tal, S., Aizinbud, E., Bargai, U., 2006. A field investigation of the use of the pedometer for the early detection of lameness in cattle. The Canadian Veterinary Journal, 47, 883-886.

McGowan, J. E., Burke, C. R., Jago, J. G., 2007. Validation of a technology for objectively measuring behaviour in dairy cows and its application for oestrus detection. Proceedings of the New Zealand Society of Animal Production, 67, 136–142.

Nydegger, F., Bollhalder, H., 2010. Vorrichtung zum Erfassen der Kauaktivität. Swiss Patent CH 700 494 B1, filed September 24, 2009, and issued September 15, 2010.

Nydegger, F., Gygax, L., Egli, W., 2010. Automatic measurement of rumination and feeding activity using a pressure sensor. Proceedings of AgEng Conference 2010, European Society of Agricultural Engineers. Clermont-Ferrand, France, September 6–8, 2010.

Penning, P. D., 1983. A technique to record automatically some aspects of grazing and ruminating behaviour in sheep. Grass and Forage Science, 38, 89–96.

Penning, P. D., Steel, G. L., Johnson, R. H., 1984. Further development and use of an automatic recording system in sheep grazing studies. Grass and Forage Science, 39, 345–351.

Overton, T. R., and Waldron, M. R., 2004. Nutritional Management of Transition Dairy Cows: Strategies to Optimize Metabolic Health. Journal of Dairy Science, 87, E105–E119.

Rutten, C. J., Velthuis, A. G. J., Steeneveld, W., & Hogeveen, H., 2013. Invited review: Sensors to support health management on dairy farms. Journal of Dairy Science, 96, 1928–1952.

Rutter, S. M., Champion, R. A., Penning, P. D., 1997. An automatic system to record foraging behaviour in free-ranging ruminants. Applied Animal Behaviour Science, 54, 185–195.

Saint-Dizier, M., Chastant-Maillard, S., 2012. Towards an automated detection of oestrus in dairy cattle. Reproduction in Domestic Animals, 47, 1056–1061.

Scheibe, K. M., Gromann, C., 2006. Application testing of a new three-dimensional acceleration measuring system with wireless data transfer (WAS) for behavior analysis. Behavior Research Methods, 38, 427–433.

Walter, A., Finger, R., Huber, R., Buchmann, N., 2017. Opinion: Smart farming is key to developing sustainable agriculture. Proceedings of the National Academy of Sciences, 114, 6148–6150.

Weary, D. M., Huzzey, J. M., von Keyserlingk, M. A. G., 2009. Board-invited review: Using behavior to predict and identify ill health in animals. Journal of Animal Science, 87, 770–777.

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2 System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows

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2.1 Abstract

Rumination and eating behavior are important indicators for assessing health and well-being in cattle. The objective of this study was to develop and validate a novel scientific monitoring device for automated measurement of ruminating and eating behavior in stable-fed cows to provide research with a measuring instrument for automated health and activity monitoring. The RumiWatch noseband sensor (Itin+Hoch GmbH, Liestal, Switzerland) incorporates a noseband pressure sensor, a data logger with online data analysis, and software. Automated measurements of behavioral parameters are based on generic algorithms without animal-specific learning data. Thereby, the system records and classifies the duration of chewing activities and enables users to quantify individual ruminating and eating jaw movements performed by the animal. During the course of the development, two releases of the system-specific software RumiWatch Converter (RWC) were created and taken into account for the validation study. The results generated by the two software versions, RWC V0.7.2.0 and RWC V0.7.3.2, were compared with direct behavioral observations. Direct observations of cow behavior were conducted on 14 Swiss dairy farms with an observation time of 1 hour per animal, resulting in a total sample of 60 dairy cows. Agreement of sensor measurement and direct observation was expressed as Spearman correlation coefficients (r_s) for the pooled sample. For consolidated classification of sensor data (1-hour resolution), correlations for rumination time were $r_s = 0.91$ (RWC V0.7.2.0) and $r_s = 0.96$ (RWC 0.7.3.2), and for eating time $r_s = 0.86$ (RWC 0.7.2.0) and $r_s = 0.96$ (RWC V0.7.3.2). Both software versions provide a high standard of validity and measuring performance for ruminating and eating behavior. The high to very high correlations between direct observation and sensor data demonstrate that the RumiWatch noseband sensor was successfully developed and validated as a scientific monitoring device for automated measurement of ruminating and eating activity in stable-fed dairy cows.

Key words: Precision Dairy Farming, health monitoring, dairy cow, RumiWatch, chewing activity

2.2 Introduction

Research in the field of Precision Livestock Farming has put a major effort on development and evaluation of technologies allowing early recognition of pathological and management-relevant behavioral changes and assessment of the individual health state in dairy cows (cf. review by Rutten et al. 2013). Hence, sensor devices for automated detection of health impairments in livestock are increasingly available and can provide effective management support in various types of farming systems. In dairy cattle nutrition, chewing activity has been identified as an important parameter to assess the adequate composition of a diet and the risk of ruminal acidosis (Yang and Beauchemin 2007). Furthermore, ruminating activity may provide meaningful information on calving time and subclinical diseases or health disorders (Goff and Horst 1997, Soriani et al. 2012).

Accordingly, continuous measurements of cow feeding variables enable us to develop a more complete understanding of the dietary effects on digestive function and performance (Dado and Allen 1993). The timeline and intensity of feeding activity provide information on the diurnal pattern of the behavior of ruminants, and identification of deviations may be used for detection of health impairments (Weary et al. 2009, Braun et al. 2014). Direct observation for measurement of ruminating and eating behavior is labor intensive, error-prone and hardly applicable for continuous observations on several animals simultaneously (Penning 1983).

For these reasons, several methods have been developed for automated, non-invasive measurement of chewing activity in ruminants. The working principle of these devices is mainly based on detection of jaw movements via strain or pressure sensors fitted to a halter (Luginbuhl et al. 1987, Matsui and Okubo 1991, Dado and Allen 1993). The best known approach is the IGER Behaviour Recorder (Penning 1983, Penning et al. 1984, Rutter et al. 1997, Rutter 2000). However, continuous recording is hereby limited to approximately 24 hours and Nydegger et al. (2010) reported frequent damages of the IGER Behaviour Recorder when applied in loose housing systems, as the recorder’s dimensions impeded the animals, particularly on entering and leaving the feed rack. Therefore, Nydegger et al. (2010) developed a compact-built pressure sensor system integrated into a halter (ART-MSR Jaw Movement Sensor, MSR Electronics GmbH, Seuzach, Switzerland), which allowed individual jaw movements to be recorded but required animal-specific learning data. The necessity of creating learning datasets for classification of the activities before starting the measurement is laborious, and recording time of this device was limited to a maximum of 40 hours due to storage capacity and power supply (Nydegger et al. 2012).

Meanwhile, technological progress in electronics led to increased battery lifetime, storage capacity, continuous recording time, and accuracy of automated measurements. Considering both scientific and commercial requirements for detailed analysis of the behavior and activity of ruminants, automated measurement technologies should generate information on the duration, intensity and diurnal pattern of chewing activities. Furthermore, a suitable method for automated recording of jaw movements needs to allow classification and quantification of individual jaw movements for a long operating time (i.e., weeks to several months) at a high resolution and with satisfactory measuring performance.

The aim of this study was to develop and validate a novel scientific monitoring device for automated health and activity monitoring in dairy cows. The presented RumiWatch noseband sensor was developed by Agroscope Institute for Sustainability Sciences (Ettenhausen, Switzerland) in collaboration with Itin+Hoch GmbH and InnoClever GmbH (both Liestal, Switzerland) and enables automated measurements of ruminating, eating, and drinking behavior.

Our aim in this paper was twofold. Firstly, to provide a complete and detailed technical specification of the functionality of this device and, secondly, to perform a validation focusing on the system’s ability to quantify the duration of chewing activity and the number of jaw movements during rumination and eating. As the algorithms have undergone successive development, two releases of the device-specific software for behavior classification are currently available that allow repeated analysis of previously recorded noseband sensor data. Hence, a further aim of this study was to validate these two commercially available versions of the software applied to the same data set recorded by the RumiWatch noseband sensor in comparison with direct observation under field conditions in stable-fed cows.

2.3 Materials and methods

2.3.1 RumiWatch noseband sensor

The RumiWatch noseband sensor (Nydegger and Bollhalder 2010, Swiss Patent CH 700 494 B1, Agroscope, Ettenhausen, Switzerland; manufactured and distributed by Itin+Hoch GmbH, Liestal, Switzerland) is a non-invasive sensor-based system enabling automated measurement of rumination, eating, drinking, movement and posture of the head in cattle. It comprises a noseband sensor, a data logger with online data analysis, and evaluation software. The noseband sensor consists of a glycol-filled silicone pressure tube with a built-in pressure sensor placed in the casing of a fully adjustable polyethylene halter over the bridge of the cow's nose (Figure 2.1). Adjustable straps provide a proper fit of the padded halters to the dimensions of the animal's head, in order to ensure wearing comfort, correct positioning of the sensor unit, and collection of valid data. The total weight of the noseband sensor including all components is approximately 700 grams.

The pressure sensor is connected to a data logger placed in a protective casing on the right side of the halter. A second, identically constructed casing on the left side of the halter stores two 3.6-V lithium-ion batteries (Tadiran SL-761, Tadiran Batteries Ltd., Kiryat Ekron, Israel) for power supply of the electronic components. The data logger registers the pressure changes in the noseband sensor, triaxial accelerations of the halter, and ambient temperature at a constant logging rate of 10 Hz and saves the raw data as a binary file to a specific microSD memory card (Swissbit AG, Bronschhofen, Switzerland). Online data analysis with preliminary classification of measurement data is conducted via the device firmware that is operated by the onboard 16-bit CPU (MSP430, Texas Instruments Inc., Dallas, Texas, USA). During chewing activity, the curvature of the noseband is altered by the cow's jaw movement, exerting a pressure change in the pressure tube. Thus, the pressure sensor allows individual jaw movements to be recorded.

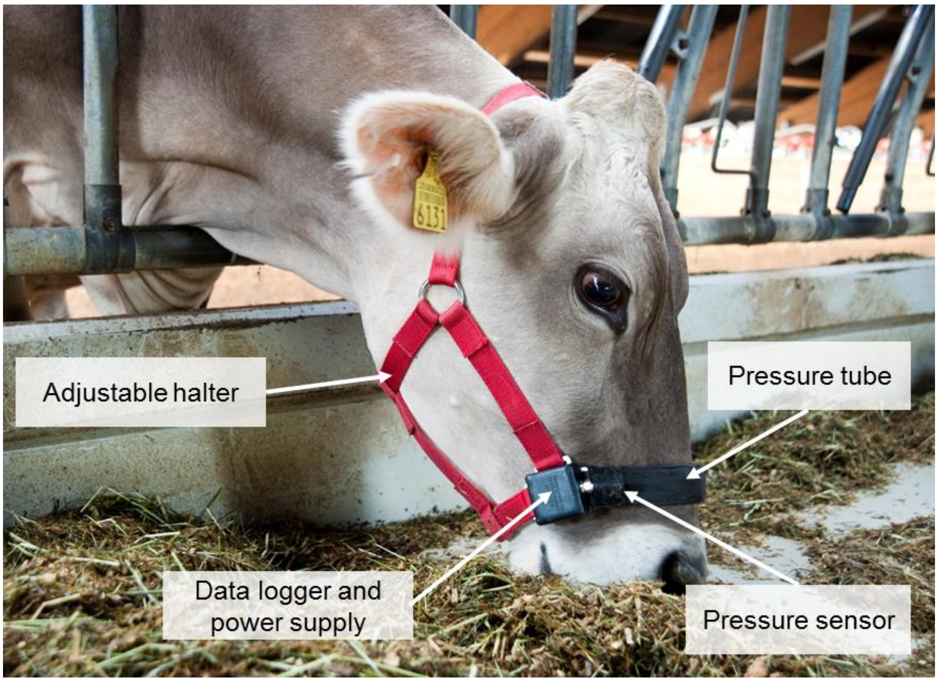

Figure 2.1. Technical components of the RumiWatch noseband sensor.

Automatic classification and quantification of chewing activity is based on the logging of individual pressure peaks, whereby every peak above a detection threshold of 28 mbar is counted as a chew. Absolute peak height is not considered for classification of chewing activity, as the pressure head inside the silicone tube is not standardized. In consequence, chewing activity is classified according to the frequency of peaks, as characteristic peak rates and peak intervals during rumination, eating, drinking, and other activity (e.g., idling) allow distinguishing between jaw movements of these behaviors. Peak frequencies recorded by the noseband sensor during measurement of ruminating, eating, and drinking behavior are shown in Figure 2.2a–c. The diagrams show that rumination is clearly distinguishable from eating activity. Homogeneous phases of jaw movements interrupted by bolus regurgitation cause the significant peak profile of ruminating activity. Peak rates during eating are more heterogeneous with irregular interruptions and altering peak frequencies due to the animal's partly increased bite rate and feed selecting behavior. A specific peak profile during drinking activity recorded by the noseband sensor is clearly distinguishable from those of rumination and eating (Figure 2.2a–c). The shown diagrams represent typical measures that are obtained from noseband sensor recordings under normal operating conditions.

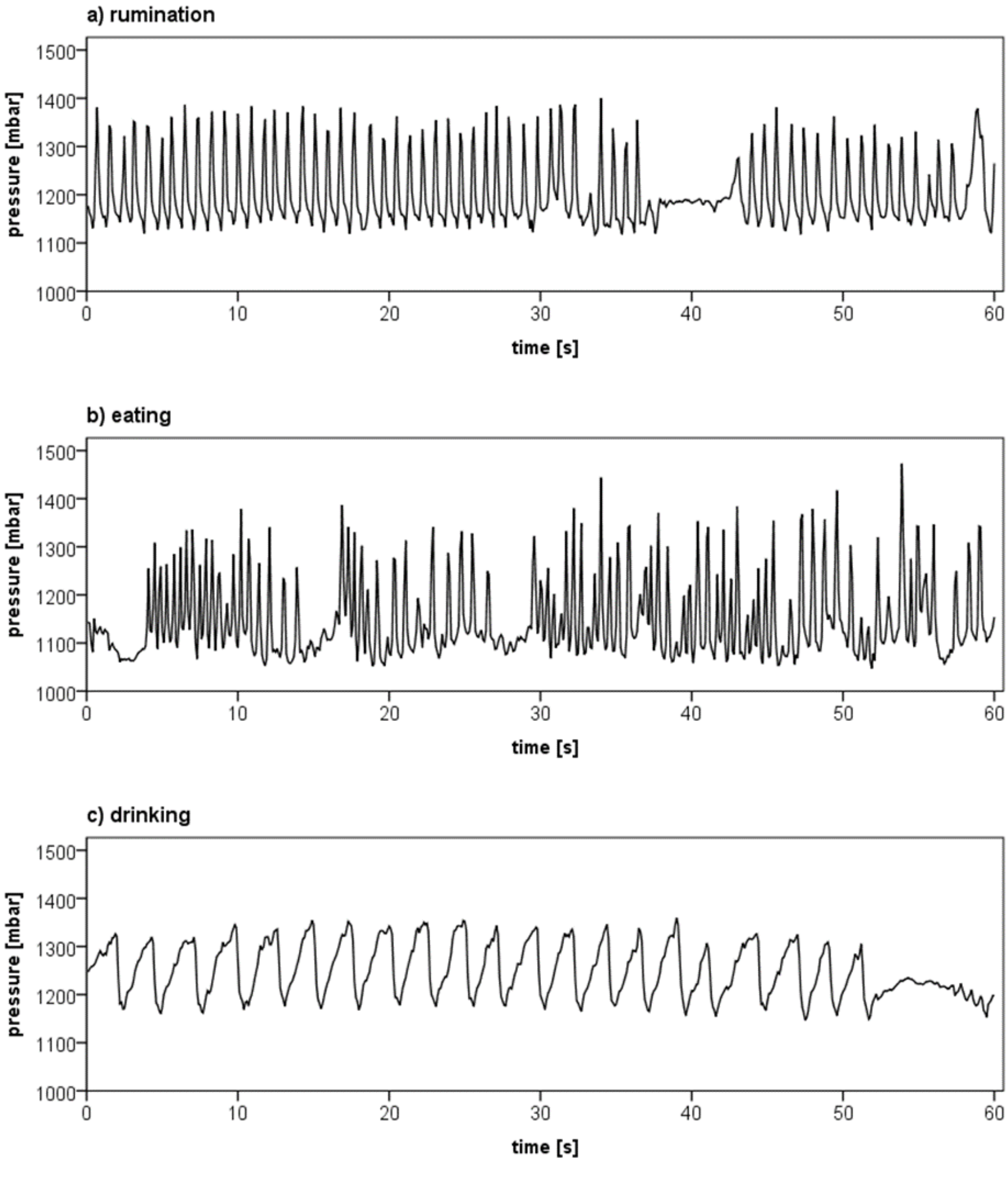

Figure 2.2a–c. Peak profiles over a period of 60 seconds during a) rumination, b) eating, and c) drinking, obtained from the same animal and noseband sensor.

The raw data files of noseband sensor recordings contain all information logged at 10 Hz, comprising the date and time of measurement, pressure value, triaxial acceleration values, ambient temperature value, time of last pressure peak detection, and preliminary classification of the detected behavior. They can be transferred to a PC and processed as Comma-Separated Values (CSV) files for further evaluation.

2.3.2 RumiWatch Converter software

The RumiWatch Converter (referred to hereafter as RWC; Itin+Hoch GmbH, Liestal, Switzerland) is a specific software application for user-defined post-processing of RumiWatch measurement data. It executes the analysis algorithms and serves for conversion of recorded pressure data into classified measurement data of animal activity. The basic concept of the RumiWatch algorithm is to generate four classifications for parameters of ingestive behavior based on the noseband sensor pressure data (Figure 2.3).

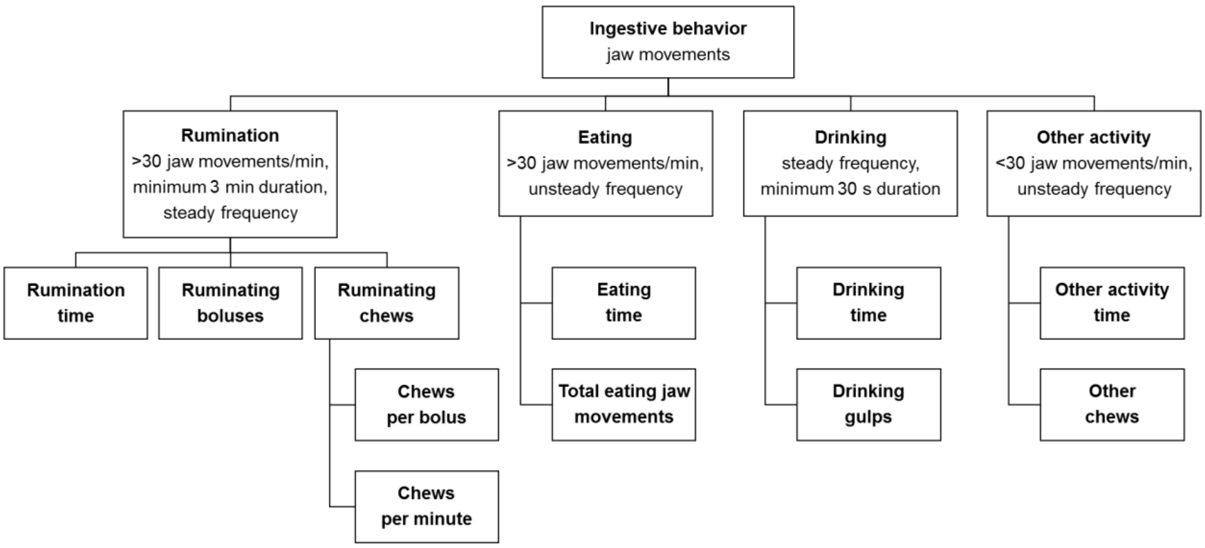

Figure 2.3. Classification tree of ingestive behaviors applied by the RumiWatch noseband sensor algorithm.

Classification and quantification of jaw movements is based on generic algorithms without animal-specific learning data. During the conversion and classification process, recorded pressure data first undergo a raw classification procedure. Thereby, the analysis algorithm classifies pressure data according to the frequency of jaw movements, e.g., 50-70 chews per minute during rumination, and occurrence of systematic interruptions of jaw movements, e.g., during regurgitation of ruminating boluses, within an analysis period (Figure 2.2a). An interval between two pressure peaks that is longer than 3.2 seconds, is registered as a ruminating bolus. The total analysis period for raw classification of pressure data is 60 seconds. A classification update is made every 10 seconds. Three consecutive 10-second intervals of the same behavior classification are needed for final classification of the analyzed minute according to the prevailing activity, i.e., either rumination, eating, drinking, or other activity (any other activity not covered by the previously mentioned behaviors). The output of this procedure contains raw classification summaries in 1-minute resolution. As a further conversion and classification option in the software, consolidated summaries of animal activity can be created e.g. with a resolution of one hour. Thereby, the recorded sensor data additionally undergo validity checks contained in the analysis algorithm in order to avoid invalid and defective interpretation of measured values. These validity checks require a minimum resolution of 10 minutes and can only be applied to consolidated classification data. Hence, they are not effective in the raw classification procedure for data in 1-minute resolution. The output of the consolidated classification procedure contains measurement results that represent percentages of behavior time and quantification of jaw movements and boluses within a 1-hour interval.

As the analysis algorithms have undergone successive development, two releases of the device-specific software for behavior classification are currently available. Software versions used in this validation study were RWC V0.7.2.0 and the subsequently developed RWC V0.7.3.2. Improved validity of detected ruminating activity has been a major focus in the development of RWC V0.7.3.2 due to its high relevance as a health and welfare indicator. The parameters and criteria of the executed validity checks, comparing RWC V0.7.2.0 and RWC V0.7.3.2, are shown in Table 2.1.

Table 2.1. Parameters and criteria for validity checks integrated into RumiWatch Converters V0.7.2.0 and V0.7.3.2.

Parameter	Validity criterion	Converter version
Ruminating classification	• If bouts of classified ruminating activity are less than a duration of 3 minutes, this analysis interval is classified as eating activity	V0.7.2.0, V0.7.3.2
Ruminating classification	• Double peaks (peak interval < 0.2 seconds) are ignored for chew count to achieve higher validity of ruminating classification	V0.7.3.2
Bolus detection	• Bolus detection is only activated if current classification is rumination • Ruminating chews between two detected boluses are counted (chews per bolus) • After detection of a new bolus, counted chews per bolus assist to validate the detection of the respective bolus, executed in the following manner: - < 20 chews per bolus: insufficient number of chews, detected bolus is ignored for classification - ≥ 20 chews per bolus: valid bolus count - ≥ 90 chews per bolus: detection of latest bolus failed, so bolus count is doubled for classification - ≥ 150 chews per bolus: detection of last 2 boluses failed, so bolus count is tripled for classification	V0.7.2.0, V0.7.3.2
Bolus detection	• Minimum of one counted bolus per minute is required for ruminating classification of the analyzed minute	V0.7.3.2

2.3.3 Experimental procedures

The validation of the RumiWatch noseband sensor was conducted as a field study on commercial dairy farms to investigate the device's and software's suitability for automated behavior classification.

2.3.3.1 Data collection

The study was performed on 14 Swiss commercial dairy farms. A varying number of experimental animals was randomly selected per farm (range 2 to 18), resulting in a total number of 60 cows of various breeds (9 Holstein Friesian, 6 Red Holstein, 2 Jersey, 34 Brown Swiss, 5 Fleckvieh, 3 Original Braunvieh, 1 Crossbred). The sample consisted of 11 primiparous and 49 multiparous cows with an average of 3.2 (standard deviation 2.1) lactations. The cows were on average 141.4 (standard deviation 97.1) days in milk. The measurements were undertaken during 15 days in August and September. Date and time of observations were chosen randomly. During each observation day, 4 cows were observed. All 60 cows were housed in loose housing systems with cubicles and fed a mixed ration with different proportions of concentrate and forage. In all farms, cows were continuously housed and did not have access to pasture for grazing.

Direct observations were performed using a tablet computer (Dell Latitude 10, Dell Inc., Round Rock, Texas, USA). Jaw movements were entered and counted in a spreadsheet (Microsoft Excel 2013, Microsoft Corporation, Redmond, Washington, USA) with a macro for time stamps in tenth of a second resolution (Visual Basic for Applications, Microsoft Corporation, Redmond, Washington, USA). Each jaw movement was registered with its classification of behavior, date and time to a tenth of a second. The beginning and end of ruminating, eating, drinking, and other activity were also registered and, thus, used to determine total duration of these behaviors during the observation periods. All direct observations in this study were done by the same observer (first author) with observational routine based on previous studies. Each cow's behavior was observed continuously for the duration of 1 hour, adding up to 3,600 observed minutes in total. Direct observation was done according to a pre-defined ethogram for all registered behaviors (Table 2.2).

Table 2.2. Ethogram for the classification of behaviors registered during observations.

Behavior	**Description**
Ruminating	Chewing and swallowing of a ruminating bolus
Bolus regurgitation	Process of regurgitating a ruminating bolus
Eating	Intake, chewing, and swallowing of feed
Drinking	Putting mouth in water bowl and swallowing water
Other activity	Non-ingestive related activities

In order to allow for time of habituation and to avoid impairments of the animals' normal behavior, direct observations were started approximately 1 hour after newly equipping an animal with a RumiWatch noseband sensor. The tablet PC and noseband sensors were time synchronized. Animal behavior could be observed at any location, including feed rack, cubicles, and concrete-floored loafing area, as the observer was able to move freely in order to follow the target animals.

2.3.3.2 Data preparation

RumiWatch data were converted into 1-minute classification summaries (raw classification, i.e., without validity checks) and 1-hour classification summaries (consolidated results, i.e., with validity checks, cf. Table 2.1) using both RWC V0.7.2.0 and RWC V0.7.3.2 for each animal-specific data file. For 1-minute raw classification data, the activity within 1 minute was summarized and classified according to the dominant activity (either rumination, eating, drinking, or other activity), with simultaneous count of chews and boluses during the respective behavior. Within the 1-hour consolidated classification data, measurement results represent percentages of behavior time per hour and quantification of jaw movements and boluses. Recordings of observation protocols were summarized for the same analysis intervals and resolutions to allow comparison with sensor data.

2.3.3.3 Statistical analysis

All statistical analyses were conducted in IBM SPSS Statistics 23 (IBM Corporation, Armonk, New York, USA). According to graphical examination and Kolmogorov–Smirnov test of analyzed variables, none of the defined variables was normally distributed ($p < 0.05$); thus, nonparametric tests were used. For evaluation of the raw classification performance, the classification cases shown in Table 2.3 were defined.

Table 2.3. Definition of classification cases for the types of ingestive behavior (either ruminating, eating, drinking, or other activity).

	Actual classification (direct observation)	
Predicted classification (RumiWatch Converter)	Behavior type present	Behavior type not present
Behavior type present	True Positive	False Positive
Behavior type not present	False Negative	True Negative

Data in 1-minute resolution (raw classification, i.e., without validity checks) were analyzed by calculating sensitivity, specificity, positive predictive value, and accuracy, comparing results of direct observation and sensor data classified by RWC V0.7.2.0 and RWC V0.7.3.2. The parameters included in the analysis were the four different classifications of jaw movements (i.e., either rumination, eating, drinking, or other activity). A confusion matrix approach (Stehman 1997) was used for classification accuracy assessment of the RWC versions. This specific matrix layout allows visualization of the classification performance, whereby each row of the matrix represents the occurrences in the predicted classification according to the RWC, whereas each column represents the occurrences in the actual classification according to direct observations. Based on the created confusion matrices, the statistical parameters listed in Table 2.4 were calculated for classifications of the RWC versions.

Table 2.4. Statistical parameters for classification accuracy assessment of the RumiWatch Converter.

Parameter	**Equation**
Sensitivity	$\text{Sensitivity} = \frac{\text{True Positives}}{\text{Positives}} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Negatives})}$
Specificity	$\text{Specificity} = \frac{\text{True Negatives}}{\text{Negatives}} = \frac{\text{True Negatives}}{(\text{True Negatives} + \text{False Positives})}$
Positive predictive value	$\text{Positive predictive value} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Positives})}$
Accuracy	$\text{Accuracy} = \frac{(\text{True Positives} + \text{True Negatives})}{(\text{True Positives} + \text{False Positives} + \text{False Negatives} + \text{True Negatives})}$

Thereby, sensitivity describes the proportion of positives that are correctly identified as such. Specificity indicates the proportion of negatives that are correctly identified, whereas the positive predictive value evaluates the proportion of true positives against all positive results. Accuracy is defined as the proportion of true results (both true positives and true negatives) among all obtained results. The Spearman nonparametric correlation coefficient (r_s) was used to analyze the concordance of sensor data in summarized 1-hour resolution (consolidated classification, i.e., with validity checks, cf. Table 2.1) and direct observation. According to Taylor (1990), correlation coefficients were rated as weak ($r_s \leq 0.35$), moderate (r_s = 0.36–0.67), strong or high (r_s = 0.68–0.89), and very high correlation ($r_s \geq 0.9$). A graphical analysis was conducted by using the Bland–Altman plot (Bland and Altman 1986). This method evaluates the agreement between two measurement methods, here of behavior classification by direct observation and RWC software. Agreement was expressed as the mean difference between the paired results of software classifications and direct observations (minutes or chews classified by software − minutes or chews classified by direct observation) and plotted against the mean of the paired values ([minutes or chews classified by software + minutes or chews classified by direct observation]/2). Additionally, the upper and lower limits of agreement for the 95% confidence interval (CI) were calculated.

2.4 Results

2.4.1 Raw classification (1-minute resolution)

Raw classification data in 1-minute resolution represent the results of the raw classification process exerted by the RWC. The results of counted jaw movements per minute during rumination and eating measured by RumiWatch and direct observation were summarized in box plots (Figure 2.4).

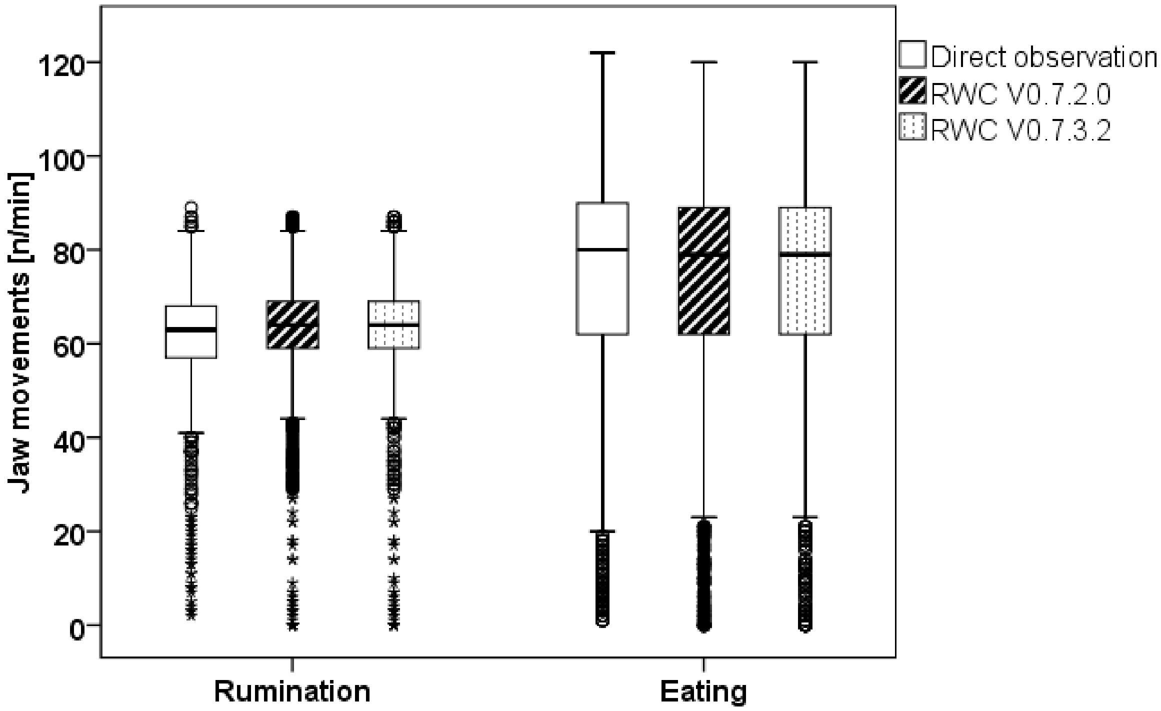

Figure 2.4. Comparison of direct observations with the RumiWatch Converters V0.7.2.0 and V0.7.3.2 for the parameters jaw movements per minute during rumination and eating. Raw data are presented as box plots showing the median as bold black line and the boxes as first and third quartiles. The whiskers indicate the 95th and 5th percentiles.

The median for ruminating jaw movements per minute was much lower, with 63-64 chews per minute, compared to the median of total eating jaw movements, with 78-79 chews per minute. The interquartile range (75th–25th percentile) followed the same pattern with 10-11 chews per minute for rumination and 27-28 chews per minute for eating. The number of chews per minute comparing rumination and eating differed significantly for all three measurement methods (Mann-Whitney U test, $p < 0.001$). The pooled sample of all observed minutes was analyzed with confusion matrices comparing the results of classification by direct observation and the respective RWC version. Confusion matrices for behavior classification of RWC V0.7.2.0 and RWC V0.7.3.2 are shown in Table 2.5 and Table 2.6, respectively.

Table 2.5. Classification results for 1-minute raw classification data for RumiWatch Converter V0.7.2.0 and direct observations.

	Direct observation [min]				
RumiWatch Converter V0.7.2.0 [min]	**Other activity time**	**Ruminating time**	**Eating time**	**Drinking time**	Total
Other activity time	**1,261**	34	96	23	1,414
Ruminating time	8	**1,095**	49	1	1,153
Eating time	56	85	**831**	7	979
Drinking time	32	1	9	**12**	54
Total	1,357	1,215	985	43	3,600

Bold values indicate the true positive classifications.

Table 2.6. Classification results for 1-minute raw classification data for RumiWatch Converter V0.7.3.2 and direct observations.

	Direct observation [min]				
RumiWatch Converter V0.7.3.2 [min]	**Other activity time**	**Ruminating time**	**Eating time**	**Drinking time**	Total
Other activity time	**1,282**	34	98	25	1,439
Ruminating time	32	**1,164**	267	5	1,468
Eating time	33	16	**616**	4	669
Drinking time	10	1	4	**9**	24
Total	1,357	1,215	985	43	3,600

Bold values indicate the true positive classifications.

The results of the statistical analysis of raw classification data (1-minute resolution) are shown in Table 2.7. Three of the parameters demonstrated a high classification performance for both RWCs. Only the parameter drinking time was found to have a low positive predictive value. However, despite a low sensitivity, specificity for raw classification of drinking time was very high. For RWC V0.7.3.2 there was an indication that sensitivity was higher for rumination time compared to RWC V0.7.2.0. For eating time, the opposite was found. In consequence, RWC V0.7.3.2 was marked by an increased probability for misclassification of other behaviors instead of identifying rumination. Both versions of the RWC showed high robustness for raw classification of other activity time.

Table 2.7. Results of the statistical analysis of RumiWatch raw classification data (1-minute resolution) compared with direct observation (pooled sample, n = 60 cows, one continuous observation hour per cow). Lower and upper 95% confidence intervals are indicated in parentheses.

Parameter	Converter version	Sensitivity	Specificity	Positive predictive value	Accuracy
Rumination time	V0.7.2.0	0.90 (0.88-0.92)	0.98 (0.97-0.98)	0.95 (0.94-0.96)	0.95 (0.94-0.96)
	V0.7.3.2	0.96 (0.95-0.97)	0.87 (0.86-0.89)	0.79 (0.78-0.81)	0.90 (0.89-0.91)
Eating time	V0.7.2.0	0.84 (0.82-0.87)	0.94 (0.93-0.95)	0.85 (0.83-0.87)	0.92 (0.91-0.93)
	V0.7.3.2	0.63 (0.59-0.66)	0.98 (0.97-0.98)	0.92 (0.90-0.94)	0.88 (0.88-0.89)
Drinking time	V0.7.2.0	0.28 (0.15-0.44)	0.99 (0.98-0.99)	0.22 (0.14-0.33)	0.98 (0.97-0.98)
	V0.7.3.2	0.21 (0.10-0.36)	1.00 (0.99-1.00)	0.38 (0.22-0.56)	0.99 (0.98-0.99)
Other activity time	V0.7.2.0	0.93 (0.91-0.94)	0.93 (0.92-0.94)	0.89 (0.88-0.91)	0.93 (0.92-0.94)
	V0.7.3.2	0.94 (0.93-0.96)	0.93 (0.92-0.94)	0.89 (0.88-0.90)	0.94 (0.93-0.94)

2.4.2 Consolidated classification (1-hour resolution)

Results of the statistical analysis of consolidated classification data (1-hour resolution) are listed in Table 2.8. Spearman nonparametric correlation coefficients (r_s) between direct observations and RumiWatch measurements were rated as very high in 10 out of 14 analyzed parameters, high in 3 parameters, and moderate in 1 parameter. Highest correlations were found when applying RWC V0.7.3.2. Lowest correlation was calculated for measurement of drinking time using RWC V0.7.2.0.

Table 2.8. Results of the statistical analysis of the RumiWatch consolidated classification (1-hour resolution) compared with direct observation (pooled sample, n = 60 cows, one continuous observation hour per cow).

Parameter	Converter version	Bland–Altman analysis				r_s	Concordance
		Mean difference	Standard deviation	Lower 95% CI	Upper 95% CI		
Rumination time	V0.7.2.0	−2.34	6.43	−15.20	10.51	0.91**	very high
[min/h]	V0.7.3.2	0.79	3.33	−5.87	7.45	0.96**	very high
Eating time	V0.7.2.0	4.56	7.21	−9.86	18.98	0.86**	high
[min/h]	V0.7.3.2	2.20	4.78	−7.35	11.76	0.96**	very high
Drinking time	V0.7.2.0	0.57	1.70	−2.82	3.97	0.42**	moderate
[min/h]	V0.7.3.2	−0.06	1.13	−2.33	2.20	0.78**	high
Other activity time	V0.7.2.0	−3.12	3.66	−10.45	4.21	0.91**	very high
[min/h]	V0.7.3.2	−3.12	3.49	−10.10	3.86	0.93**	very high
Ruminating chews	V0.7.2.0	−147.18	378.72	−904.63	610.26	0.92**	very high
[n/h]	V0.7.3.2	44.85	174.72	−304.60	394.30	0.97**	very high
Total eating jaw	V0.7.2.0	233.22	475.54	−717.86	1,184.29	0.88**	high
movements [n/h]	V0.7.3.2	58.85	321.42	−583.99	701.69	0.97**	very high
Bolus	V0.7.2.0	−2.53	7.48	−17.49	12.42	0.93**	very high
[n/h]	V0.7.3.2	0.48	4.79	−9.09	10.06	0.97**	very high

** correlation is highly significant with $p \leq 0.001$

For consolidated classification, Figure 2.5 shows the agreement of the results generated by the two converter versions in comparison with direct observations. The diagram indicates more deviation of rumination time and ruminating chews by RWC V0.7.2.0, whereas these parameters analyzed by RWC V0.7.3.2 showed higher concordance (Table 2.8). For all parameters analyzed by Bland–Altman plots (Table 2.8), the calculated mean differences were lower when using RWC V0.7.3.2, associated with narrower 95% CIs (Table 2.8; Figure 2.6), than when using RWC V0.7.2.0. This result demonstrated the effectiveness of the validity checks introduced in RWC V0.7.3.2 (cf. Table 2.1).

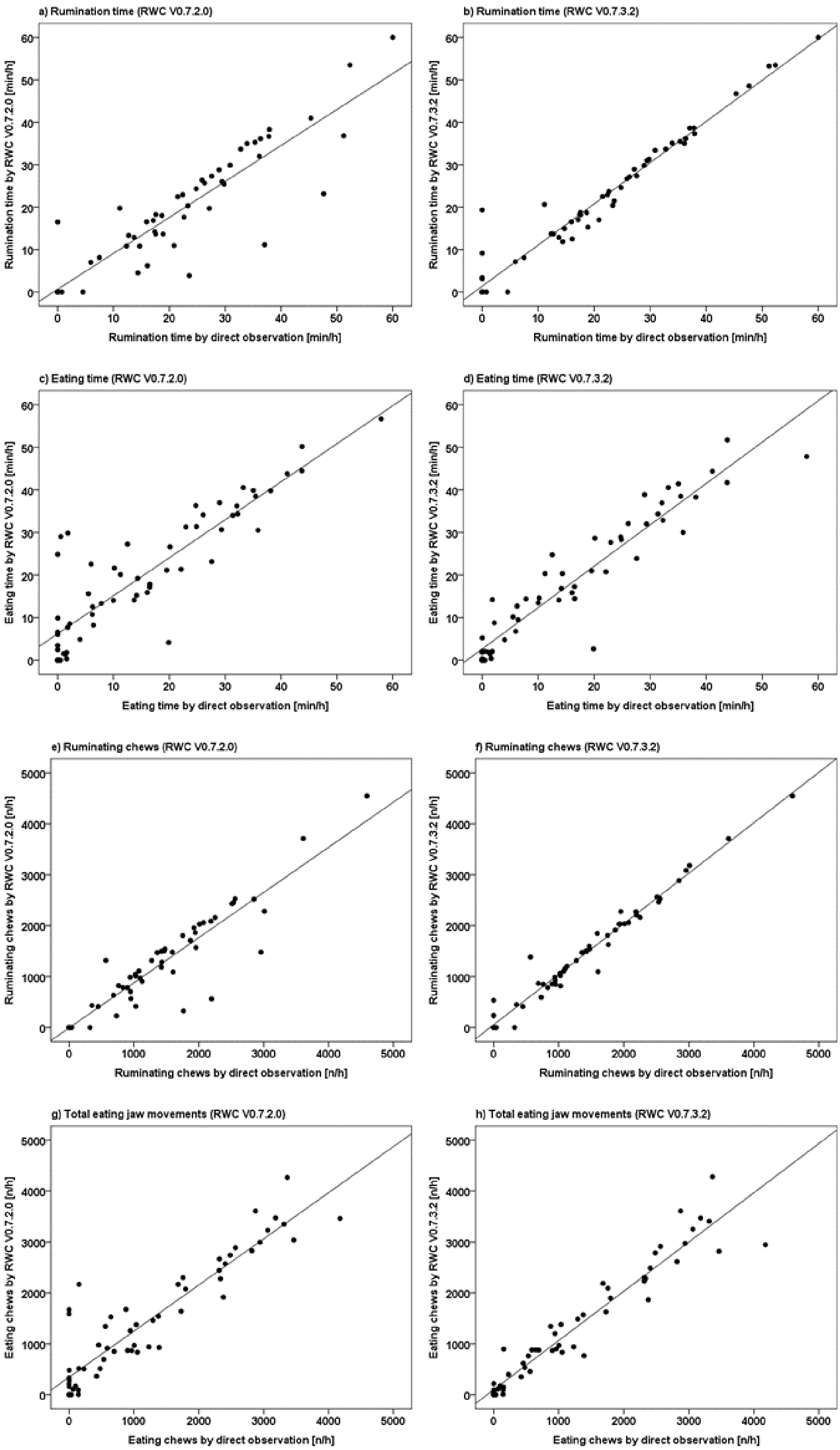

Figure 2.5. Correlations between direct observations and RumiWatch Converters V0.7.2.0 and V0.7.3.2 for rumination time (a, b), eating time (c, d), ruminating chews (e, f), and total eating jaw movements (g, h).

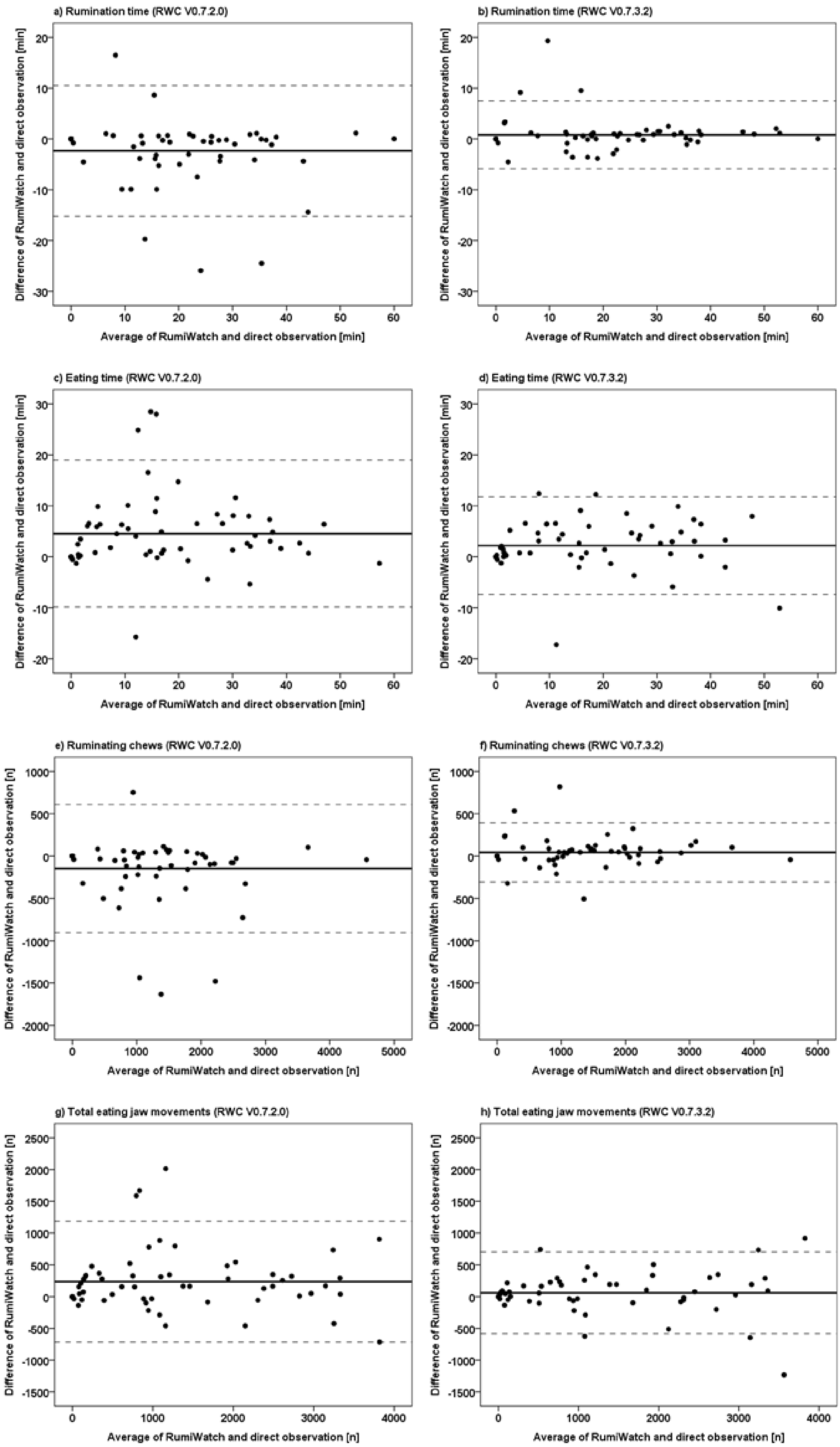

Figure 2.6. Bland–Altman plots demonstrating the agreement of direct observations with RumiWatch Converters V0.7.2.0 and V0.7.3.2, analyzed for the parameters rumination time (a, b), eating time (c, d), ruminating chews (e, f), and total eating jaw movements (g, h). Bold lines show the mean difference, dashed lines indicate the lower and upper 95% confidence interval.

2.5 Discussion

The validation showed that the development of the RumiWatch monitoring system was successful. The system was designed to meet the requirements of scientific users. Therefore, it allows recording of ingestive behavior types with full raw data accessibility and post-processing option if a different converter version shall be used at a later time. Thus, collected raw data can be repeatedly evaluated with an updated version of the analysis routines.

The obtained accuracy of measurement was high for all analyzed behavior classifications, which is indicative of relatively small systematic errors (cf. Taylor 1997). The achieved precision of measurement, as expressed by the positive predictive value was satisfactory for classification of rumination, eating, and other activity time, but not so for drinking time. Therefore, classification of drinking behavior is prone to an increased occurrence of random errors. The reinforcement of a particular behavior detection represents a tradeoff that may negatively affect the classification performance for other behavior types.

In the present study, this occurred in RWC V0.7.3.2 due to reinforced detection of ruminating behavior. Based on the analysis of raw classification data (1-minute resolution), RWC V0.7.3.2 showed a tendency for misclassification and overestimation of behaviors towards rumination, as indicated by lower specificity, positive predictive value, and accuracy for classification of rumination time as compared with RWC V0.7.2.0. The major reason for overestimation of rumination by this software version was the misclassification of eating behavior to rumination, simultaneously resulting in underestimation of eating time (Table 2.6). Sensitivity and positive predictive value for classification of drinking time was low in both RWC versions (Table 2.7). Drinking behavior was difficult to classify due to the similarities of the peak profiles of drinking, eating, or idling behavior. Additionally, short duration and low frequency of drinking bouts (drinking time 5.5–6.8 minutes per day, Huzzey et al. 2005; in 6.6–9.5 bouts, Huzzey et al. 2005, Cardot et al. 2008) represented a challenge in generating sufficient sample size for both development and validation of an analysis algorithm, particularly on individual cow level. Hence, robust detection and extensive examination of validity for measurement of drinking behavior is difficult and requires further research.

Comparison of consolidated classification data (1-hour resolution) with direct observations revealed higher correlation coefficients when using RWC V0.7.3.2 (Table 2.8). These results demonstrate the improvement of measuring performance for the consolidated classification due to the validity checks introduced in RWC V0.7.3.2 (cf. Table 2.1). Particularly for studies requiring consolidated classification of animal behavior or focusing on ruminating activity as an important health parameter, the use of this RWC version is preferable. On the other hand, if the analysis of minute-by-minute data for classification and quantification of jaw movements is of relevance for a conducted study, e.g., in feeding trials, the use of RWC V0.7.2.0 is recommended. Here, the accuracy for raw classification of rumination time and eating time was higher than in RWC V0.7.3.2. Although only to a minor degree, the suitability of a RWC version for behavior classification may vary depending on the required temporal resolution and the behavior that is of particular interest for the analysis. However, both converters provide a high standard of validity and measuring performance for eating and ruminating behavior.

As a limitation of the presented system compared with the approach described by Rutter et al. (1997) and the acoustic approach used by Ungar and Rutter (2006), it cannot discriminate between eating bites, chews, and chew-bites. Hence, the closer analysis of feed intake on pasture appears to be difficult when using the current state of the system’s analysis routines. This validation study only used continuously housed cows that were fed mixed rations with no grazing. There is a need for further validation studies where the described system is applied in grazing cows.

In a previous state of development, the noseband sensor was evaluated by Ruuska et al. (2016), but only on the basis of duration of chewing activity during eating and rumination, whereas the system's ability to detect and quantify individual chews of these behaviors was not investigated. These authors compared measurements of rumination, eating, and drinking time by the RumiWatch noseband sensor with continuous video observation (n = 6 dairy cows, total sample of 72 h) and found a very dependable relationship for rumination time (R^2 = 0.93) and eating time (R^2 = 0.94). Comparable results were obtained from the present study, shown by Spearman correlation coefficients of r_s = 0.91 (RWC V0.7.2.0) and r_s = 0.96 (RWC V0.7.3.2) for rumination time, and r_s = 0.86 (RWC V0.7.2.0) and r_s = 0.96 (RWC V0.7.3.2) for eating time. The relationship between drinking time recorded by RumiWatch and by video observation found by Ruuska et al. (2016) was poor (R^2 = 0.20). This finding was in agreement with the present study, where correlations of automatically measured drinking times were lower than those in the other ingestive parameters, with r_s = 0.42 (RWC V0.7.2.0) and r_s = 0.78 (RWC V0.7.3.2).

In a validation study of a pressure-based measuring system for chewing activity similar to the RumiWatch noseband sensor in our study, the correlation coefficients between the results from the automated system and direct observations were r = 0.99 for the duration of eating and rumination phases (Braun et al. 2013). However, the results of their study are not directly comparable with ours, as Braun et al. (2013) used scan sampling with 1-minute sampling intervals, whereas we used continuous observations for obtaining a gold standard (cf. Martin and Bateson 2007). Continuous direct observation of chewing behavior, as conducted in the current study, represents the best reference method for comparison with sensor measurement. It allows the recording of the type (specific behavior), pattern (duration and frequency of chewing activity), and intensity of chewing behavior (number of chews). The validation method used in several studies was a comparison of automated measurement with scan sampling observations (Grant et al. 1990, Maekawa et al. 2002, Couderc et al. 2006). This observational method is only a representation of activity occurring at intervals and does not trace the continuous automated measurement (Kononoff et al. 2002). Therefore, it was not a suitable method for our analysis.

2.6 Conclusions

The RumiWatch noseband sensor was successfully developed and validated as a scientific monitoring device for automated measurements of ruminating and eating activity in stable-fed dairy cows. Both system-specific software versions were suitable and showed a high performance for classification of ruminating and eating behavior but less so for the parameter drinking time. The achieved validation results indicate that the measuring performance satisfies scientific requirements. Further research is needed to allow for the differentiation of total eating jaw movements, as the described state of the analysis routines does not enable a separate classification of chews, bites, and chew-bites during eating.

2.7 Ethical statement

Ethical approval to conduct this study was obtained from the Thurgau Cantonal Veterinary Office, Switzerland (Approval No. 12.34.03.05). All experimental procedures comply with the ARRIVE guidelines.

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2.10 References

Bland, J.M., Altman, D., 1986. Statistical methods for assessing agreement between two methods of clinical measurement. Lancet, 327, 307–310.

Braun, U., Trösch, L., Nydegger, F., Hässig, M., 2013. Evaluation of eating and rumination behaviour in cows using a noseband pressure sensor. BMC Veterinary Research, 9, 164–170.

Braun, U., Tschoner, T., Hässig, M., 2014. Evaluation of eating and rumination behaviour using a noseband pressure sensor in cows during the peripartum period. BMC Veterinary Research, 10, 195–203.

Cardot, V., Le Roux, Y., Jurjanz, S., 2008. Drinking behavior of lactating dairy cows and prediction of their water intake. Journal of Dairy Science, 91, 2257–2264.

Couderc, J.J., Rearte, D.H., Schroeder, G.F., Ronchi, J.I., Santini, F.J., 2006. Silage chop length and hay supplementation on milk yield, chewing activity, and ruminal digestion by dairy cows. Journal of Dairy Science, 89, 3599–3608.

Dado, R.G., Allen, M.S., 1993. Continuous computer acquisition of feed and water intakes, chewing, reticular motility and ruminal pH of cattle. Journal of Dairy Science, 76, 1589–1600.

Goff, J.P., Horst, R.L., 1997. Physiological changes at parturition and their relationship to metabolic disorders. Journal of Dairy Science, 80, 1260–1268.

Grant, R.J., Colenbrander, V.F., Albright, J.L., 1990. Effect of particle size of forage and rumen cannulation upon chewing activity and laterality in dairy cows. Journal of Dairy Science, 73, 3158–3164.

Huzzey, J.M., von Keyserlingk, M.A.G., Weary, D.M., 2005. Changes in feeding, drinking, and standing behavior of dairy cows during the transition period. Journal of Dairy Science, 88, 2454–2461.

Kononoff, P.J., Lehman, H.A., Heinrichs, A.J., 2002. Technical note: A comparison of methods used to measure eating and ruminating activity in confined dairy cattle. Journal of Dairy Science, 85, 1801–1803.

Luginbuhl, J.-M., Pond, K.R., Russ, J.C., Burns, J.C., 1987. A simple electronic device and computer interface system for monitoring chewing behavior of stall-fed ruminant animals. Journal of Dairy Science, 70, 1307–1312.

Maekawa, M., Beauchemin, K.A., Christensen, D.A., 2002. Effect of concentrate level and feeding management on chewing activities, saliva production and ruminal pH of lactating dairy cows. Journal of Dairy Science, 85, 1165–1175.

Martin, P., Bateson, P., 2007. Measuring Behavior. An Introductory Guide, 3rd Edition. Cambridge University Press, Cambridge, pp. 48–61 and 72–85.

Matsui, K., Okubo, T., 1991. A method for quantification of jaw movements suitable for use on free-ranging cattle. Applied Animal Behaviour Science, 32, 107–116.

Nydegger, F., Bollhalder, H., 2010. Vorrichtung zum Erfassen der Kauaktivität. Swiss Patent CH 700 494 B1, filed September 24, 2009, and issued September 15, 2010.

Nydegger, F., Gygax, L., Egli, W., 2010. Automatic measurement of rumination and feeding activity using a pressure sensor. In: Conference AgEng 2010, September 6–8, Clermont-Ferrand, France. European Society of Agricultural Engineers, pp 1–8.

Nydegger, F., Münger, A., Frey, H., 2012. Research activities using the ART-MSR method of automatic recording and interpretation of rumination and feeding behavior. In: CIGR-AgEng International Conference of Agricultural Engineering 2012, July 8–12, Valencia, Spain. European Society of Agricultural Engineers, pp. 1–8.

Penning, P.D., 1983. A technique to record automatically some aspects of grazing and ruminating behavior in sheep. Grass and Forage Science, 38, 89–96.

Penning, P.D., Steel, G.L., Johnson, R.H., 1984. Further development and use of an automatic recording system in sheep grazing studies. Grass and Forage Science, 39, 345–351.

Rutten, C.J., Velthuis, A.G.J., Steeneveld, W., Hogeveen, H., 2013. Invited review: Sensors to support health management on dairy farms. Journal of Dairy Science, 96, 1928–1952.

Rutter, S.M., Champion, R.A., Penning, P.D., 1997. An automatic system to record foraging behaviour in free-ranging ruminants. Applied Animal Behaviour Science, 54, 185–195.

Rutter, S.M., 2000. Graze: A program to analyze recording of the jaw movements of ruminants. Behavior Research Methods, Instruments, & Computers, 32, 86–92.

Ruuska, S., Kajava, S., Mughal, M., Zehner, N., Mononen, J., 2016. Validation of a pressure sensor–based system for measuring eating, rumination and drinking behaviour of dairy cattle. Applied Animal Behaviour Science, 174, 19–23.

Soriani, N., Trevisi, E., Calamari, L., 2012. Relationships between rumination time, metabolic conditions, and health status in dairy cows during the transition period. Journal of Animal Science, 90, 4544–4554.

Stehman, S.V., 1997. Selecting and interpreting measures of thematic classification accuracy. Remote Sensing of Environment, 62, 77–89.

Taylor, T., 1990. Interpretation of the correlation coefficient: A basic review. Journal of Diagnostic Medical Sonography, 1, 35–39.

Taylor, J.R., 1997. An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements, 2nd Edition. University Science Books, Sausalito, California, USA.

Ungar, E.D., Rutter, S.M., 2006. Classifying cattle jaw movements: Comparing IGER Behaviour Recorder and acoustic techniques. Applied Animal Behaviour Science, 98, 11–27.

Weary, D.M., Huzzey, J.M., von Keyserlingk, M.A.G., 2009. Board-invited review: Using behavior to predict and identify ill health in animals. Journal of Animal Science, 87, 770–777.

Yang, W.Z., Beauchemin, K.A., 2007. Altering physically effective fiber intake through forage proportion and particle length: Chewing and ruminal pH. Journal of Dairy Science, 90, 2826–2838.

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3 Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows

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3.1 Abstract

Behavior is one of the most important indicators for assessing cattle health and well-being. The objective of this study was to develop and validate a novel algorithm to monitor locomotor behavior of loose-housed dairy cows based on the output of the RumiWatch pedometer (ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland). Data of locomotion were acquired by simultaneous pedometer measurements at a sampling rate of 10 Hz and video recordings for manual observation later. The study consisted of 3 independent experiments. Experiment 1 was carried out to develop and validate the algorithm for lying behavior, experiment 2 for walking and standing behavior, and experiment 3 for stride duration and stride length. The final version was validated, using the raw data, collected from cows not included in the development of the algorithm. Spearman correlation coefficients were calculated between accelerometer variables and respective data derived from the video recordings (gold standard). Dichotomous data were expressed as the proportion of correctly detected events, and the overall difference for continuous data was expressed as the relative measurement error. The proportions for correctly detected events or bouts were 1 for stand ups, lie downs, standing bouts, and lying bouts and 0.99 for walking bouts. The relative measurement error and Spearman correlation coefficient for lying time were 0.09% and 1; for standing time, 4.7% and 0.96; for walking time, 17.12% and 0.96; for number of strides, 6.23% and 0.98; for stride duration, 6.65% and 0.75; and for stride length, 11.92% and 0.81, respectively. The strong to very high correlations of the variables between visual observation and converted pedometer data indicate that the novel RumiWatch algorithm may markedly improve automated livestock management systems for efficient health monitoring of dairy cows.

Key words: accelerometer, dairy cow, behavior, locomotion, walking

3.2 Introduction

Change of animal behavior is one of the most important criteria for assessing animal welfare and health (Cook et al. 2005, Urton et al. 2005, Chapinal et al. 2011, Viazzi et al. 2013). Parameters of animal behavior can be used to build up an early disease warning system. For example, painful claw lesions cause changes in animal behavior such as lameness (Hudson et al. 2008) and are usually associated with an increased lying time (Ito et al. 2010, Alsaaod et al. 2012, Yunta et al. 2012) and a decreased overall daily activity level (O'Callaghan et al. 2003). The current gold standard for detection of lameness is manual observation by a trained professional. The degree of lameness is described, using an accepted clinical gait-scoring scheme (Sprecher et al. 1997, Flower and Weary 2006).

In general, veterinary treatments and management decisions are more effective the earlier they are initiated relative to the onset of the disease (Gonzalez et al. 2008). However, detecting behavioral changes at an early stage is difficult (Whay et al. 2003, Espejo et al. 2006). Traditionally, behavior research of loose-housed cows is based on direct observation or use of video recordings. The drawbacks of both methods are that they are time consuming and labor intensive with nocturnal observations, which limit their feasibility for long-term observations in practice (Muller and Schrader 2005).

Previous studies indicated lameness to be one of the most important health and welfare problems of modern dairy farming (Nordlund et al. 2004, Shearer et al. 2013). Practical strategies to automatically detect lameness to improve claw health have, therefore, become a major focus for the dairy industry. Consequently, real-time analysis of cattle activity could provide useful information for early detection of disease, thereby reducing its negative effect, increasing the chance of treatment success, and preventing the disease from becoming chronic. Accelerometry is a reliable and useful tool to detect standing and lying behavior (Munksgaard et al. 2006, O'Driscoll et al. 2008, Nielsen et al. 2010). So far, accelerometers, however, have not been suitable for detecting and characterizing patterns of walking behavior in cattle with a sufficient accuracy. Detailed information about the duration of walking and standing phases, number and duration of strides, and distance walked is a prerequisite for increasing the sensitivity and specificity of accelerometers to detecting lameness (Flower et al. 2005). It was already concluded by Chapinal et al. (2011) that accelerometers seem to be a promising tool for lameness detection on farm, especially when attached to a leg.

The objective of this study was to develop and validate a novel algorithm to monitor locomotor behavior based on the output of a 3-dimensional accelerometer collected from loose-housed dairy cows compared with video analysis (gold standard). It was hypothesized that a novel algorithm of the RumiWatch pedometer device (ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland, http://www.rumiwatch.ch/) can be developed that provides a moderate to high correlation of parameters of behavior of dairy cows in both upright and lying positions between the output data of the pedometers and the data derived from temporarily staggered video analysis.

3.3 Materials and Methods

3.3.1 RumiWatch Pedometer

The hardware used in this study was the RumiWatch pedometer, with the dimensions of 55 mm (width) × 100 mm (length) × 30 mm (depth) and a total weight of 126 g. It is attached to one of the hind limbs of a cow proximal to the fetlock joint by a Velcro fastener. It represents a noninvasive electronic sensor, continuously collecting data at 10 readings per second, including a 3-dimensional accelerometer. The raw data are continuously stored on the integrated micro SD Memory Card (Swissbit AG, Bronschhofen, Switzerland).

3.3.2 Concept of Algorithm Development and Validation

The basic concept of definitions underlying all stages of development of the novel algorithm (RumiWatch software, ITIN+HOCH GmbH) is depicted in Figure 3.1. The normal locomotor activity of the cow consists of either lying or being in an upright position. The latter includes either standing or walking. Walking was defined as the activity characterized by at least 3 consecutive limb movements (strides), allowing the cow to change its location in space either in forward or backward direction. Standing was defined as the activity of a cow in upright position when it did not walk.

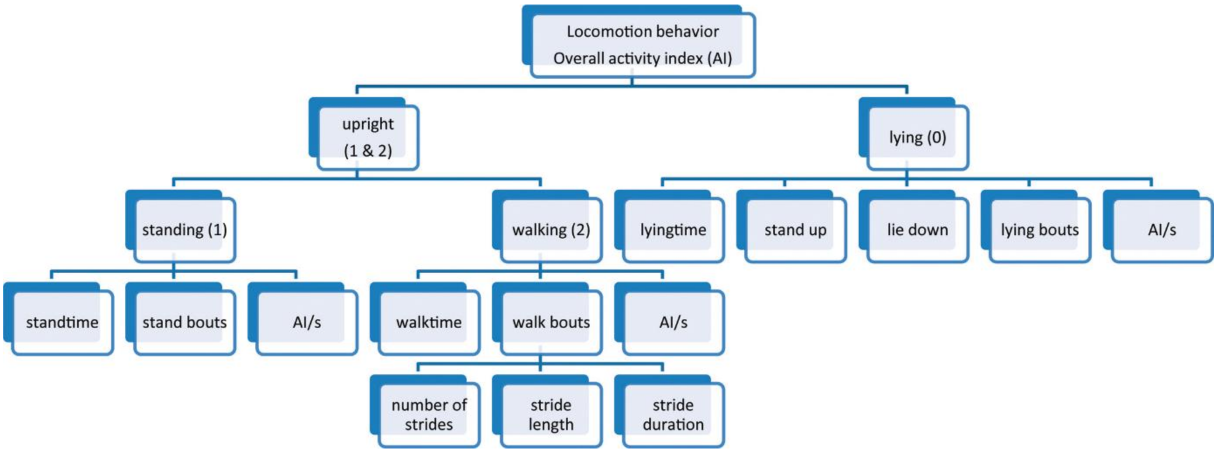

Figure 3.1. Classification tree of locomotion behavior of dairy cows used for the development of the novel RumiWatch (ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland) algorithm.

Specific definitions of locomotor activity are given in

Table 3.1. Detection of the lying and standing behavior was based on pedometer angle estimations. The walking algorithm extracted parameters from the 3-dimensional accelerometer measurements. Development of the current version (V0.7.3.6), as described and validated in this paper, followed an empiric approach of several cycles of algorithm amelioration, validation. These cycles were repeated until the accuracy of detecting position-change events and number of bouts (dichotomous data) exceeded 98% and the mean relative measurement error (RME) of continuous data describing locomotor activity was less

than 20%. The final version was validated using the 10-Hz raw data collected from cows not included in the development of the algorithm.

Table 3.1. Definitions of various variables used for quantifying locomotor activity of dairy cows.

Variable	**Definition**
Lying bout	Period with the pedometer in a position exceeding an angle of 58° toward the vertical axis lasting >50 s. Interruption of this pedometer position for less than 50 s is identified and calculated as one stand-up and one lying-down event but not as a separate standing bout. The lying bout is rated as not interrupted.
Walking bout	Period characterized by at least 3 consecutive strides in the same direction (forward or backward). The period between 2 strides must not exceed 4 s. Walking bouts are rated as separate if the time between 2 strides exceeds 10 s.
Standing bout	Periods during which the cow is in an upright position but not walking; temporary change of the pedometer angle exceeding 58° toward the vertical axis for less than 50 s is neither rated as lying-down and standing-up events nor as an additional lying bout.
Stand up	Event at which the pedometer angle changes its position from an angle >58° toward the vertical axis to an angle <58° toward the vertical axis.
Lie down	Event at which the pedometer angle changes its position from an angle <58° toward the vertical axis to an angle >58° toward the vertical axis for a duration of at least 50 s.
Stride	One forward or backward movement of the limb within a walking bout.
Lying time	Sum of the duration of all lying bouts within a given recording period.
Walking time	Sum of the duration of all walking bouts within a given recording period.
Standing time	Sum of the duration of all standing bouts within a given recording period.
Stride length	Distance between the 2 consecutive imprints of the same instrumented hind limb.
Stride duration	Time interval between 2 consecutive foot strikes of the same instrumented hind limb.
Activity index	The averaged variance of 3-dimensional acceleration in 10-s segments

3.3.3 Animals and Experimental Procedures

Development and validation of the algorithm were divided into 3 major experiments. They were carried out with the permission of the respective cantonal committee for animal experimentation.

3.3.3.1 Experiment 1

Experiment 1was performed to elaborate the parameters lying time, stand up, lie down, and number of lying bouts (

Table 3.1). The experiment was carried out at the experimental farm of Agroscope Research Station in Tänikon, Switzerland. The cows were kept in a loose housing system with straw-bedded cubicles. The walking and feeding alleys were made of plain concrete, and the outside paddock was covered with slatted concrete. The cows were milked 2 times a day and had free access to a TMR and a water trough. The cows were continuously videotaped over 24 h with 2 video recorders (Mobotix D14D-Sec and Mobotix M12D-Sec-DNight, Mobotix AG, Langmeil, Germany) mounted underneath the roof construction of the barn well above the cows. Time settings of the video recorders and pedometers were synchronized before the experiment on the computer used to initialize the devices. The cows were marked on the back and both flanks individually with colored numbers for unequivocal identification. A total of 5 different versions of the algorithm were developed, using data of 30 cows. For validation of the final version, 18 cows (11 Brown Swiss; 6 Red Holstein; 1 Swiss Fleckvieh; median age: 4.1 yr, with range of 2.0 to 8.2 yr; median milk yield of 28 kg/d) were randomly selected from a pool of cows with a lameness score (≤2) according to Sprecher et al. (1997). This revealed a pool of video data for validation of 432 h.

3.3.3.2 Experiment 2

Experiment 2 was performed to elaborate 5 parameters describing behavior during upright position: standing time, walking time, number of standing bouts, number of walking bouts, and number of strides (

Table ***3.1***). A hand-held digital video camera (Sony HDR-PJ740VE, Sony Corporation, Tokyo, Japan) was used to record the locomotion of the cows at 50 frames per second and to provide a posterior view of the hind legs while the respective cow was walking freely. The camera was initially synchronized by setting the clock of the video to match the time on the computer that was used to initialize each accelerometer. Each cow was videotaped for a period of ≥10 min. A total of 8 versions of the algorithm were developed, using data of 20 cows kept under conditions similar to experiment 1. The version V0.7.3.6 was finally used to validate the accelerometer data of 21 cows (12 Brown Swiss; 9 Red Holstein; median age: 4.0 yr, with a range of 2.0 to 8.9 yr; median milk yield of 25.45 kg/d) videotaped over ≥10 min, making up a total of 210 min of video data.

3.3.3.3 Experiment 3

Experiment 3 was performed to elaborate the parameters stride length (m) and stride duration (s;

Table ***3.1***). The cows were videotaped with a hand-held video recorder (Sony HDR-PJ740VE, Sony Corporation, Tokyo, Japan) from behind, when cows were walked by a handler for at least 5 min. The walking distance was individually measured by using a distance-measuring wheel guided by the handler that was familiar with the cows. Two versions were developed using data of 20 cows kept under conditions similar to experiment 1. The version V0.7.3.6 was finally used to validate the accelerometer data of 16 cows (16 Brown Swiss; median age of 3.1 yr, with range of 2.0 to 10.0 yr; median 305-d milk yield of 7,030.5 kg) at Hürlimann-Grimm Ernst Farm in Ettenhausen, Switzerland.

3.3.4 Data Analysis and Statistics

For dichotomous data (stand up, lie down, lying bout, standing bout, and walking bout), the number of events or bouts detected by the RumiWatch algorithm was compared with the number of events detected in the video recordings (gold standard). The proportion of detected events and the respective 95% confidence interval were calculated. For continuous data, the RME was calculated as the deviation between accelerometer algorithm value and respective video recording using this formula: percent deviation = (100/video-recording observation) × absolute value (video-recording observation − RumiWatch observation). Mean and standard deviation were calculated to describe the RME for the different variables. A RME of <1% was rated very low, 1 to 5% was rated low, and 6 to 20% was rated moderate. Agreement between continuous variables (time spent walking, standing, and lying; stride length; and stride duration) was expressed as correlation coefficients. The variables were not normally distributed; therefore, Spearman nonparametric correlation coefficient was used for the analyses. A correlation coefficient (r_s) of r_s ≥0.9 was rated as very high, r_s = 0.68 to 1.0 as strong or high, r_s = 0.36 to 0.67 as moderate, and r_s = ≤0.35 as weak correlation (Taylor, 1990). For continuous data, only one measurement for each cow was conducted; therefore, the degree of interdependence between RME and r_s was not of any relevance. Furthermore, the variability between individual cows was not considered, as the comparison between accelerometer algorithm and respective video recording was done at cow level. All statistical analyses were undertaken using NCSS[9] (NCSS LLC, Kaysville, UT).

3.4 Results

In experiment 1, all the stand up (n = 165) and lie down events (n = 165) and all lying bouts (n = 164) were correctly detected (Table 3.2). The estimate of lying time was perfect, with a mean measurement error of 0.09% and a very high correlation compared with the video recordings (r_s = 1; Table 3.3; Figure 3.2a). In experiment 2, all standing bouts were correctly detected (n = 132) and only 1 out of 127 walking bouts was not detected by the algorithm (Table 3.2). Standing time per 10 min of recording time (mean = 7.18 min; range 4.67–9.83) and walking time (mean = 2.82 min; range 0.17–5.5) were detected with a mean RME of 4.7 and 17.1%, respectively, and similarly very high correlations of r_s = 0.96 for both parameters (Table 3.2, Figure 3.2b, Figure 3.2c). The mean RME of the number of strides was 6.23%, and a very high correlation of $r_s = 0.98$ between algorithm output and video recordings was estimated, (Table 3.3, Figure 3.2d). In experiment 3, the median number of strides per 5 min of recording time was 41 strides (range 17–124 strides). The mean RME of stride duration was moderate (6.65%), with a strong correlation of $r_s = 0.75$; (Table 3.3; Figure 3.2e). The mean RME for stride length was moderate (11.92%), with a strong correlation of $r_s = 0.81$ (Table 3.3, Figure 3.2f).

Table 3.2. Number and proportion of stand ups, lie downs, lying bouts, standing bouts, and walking bouts detected by the novel RumiWatch[1] algorithm compared with the number observed by analyzing the video recordings (gold standard).

					95% CI of p	
Experiment	**Variable**	**VVR[2] (no.)**	**RumiWatch algorithm (no.)**	**Proportion detected (p)**	**Lower**	**Upper**
1	Stand up	165	165	1.000	0.978	1.000
1	Lie down	165	165	1.000	0.978	1.000
1	Lying bout	164	164	1.000	0.978	1.000
2	Standing bout	132	132	1.000	0.972	1.000
2	Walking bout	127	126	0.992	0.957	0.999

[1] ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland.
[2] VVR = visual video recording.

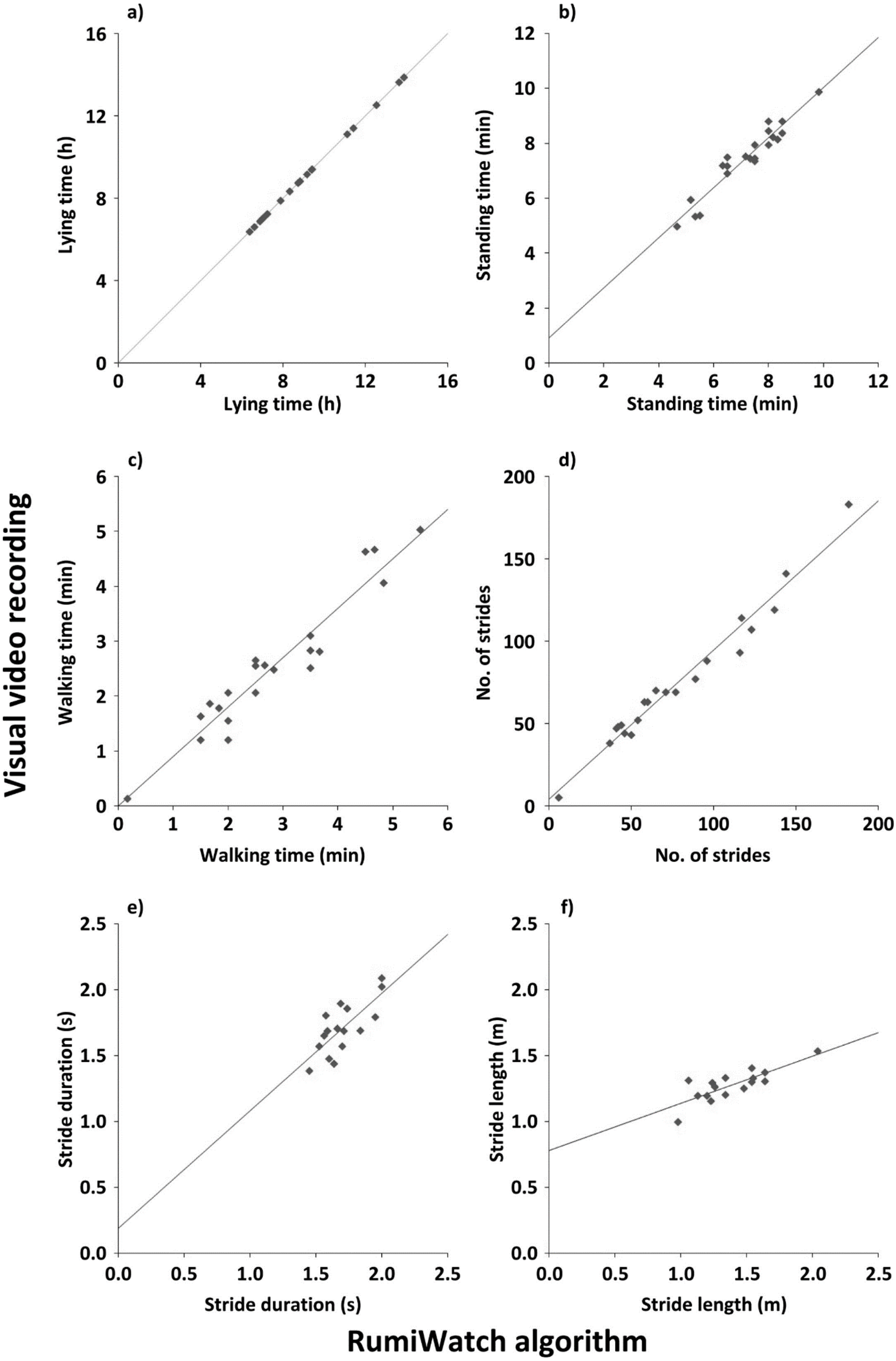

Figure 3.2. Correlations between the RumiWatch (ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland) algorithm output and the result of the manual video analysis (gold standard) of measurements of lying time (a), standing time (b), walking time (c), number of strides (d), stride duration (e), and stride length (f).

Table 3.3. Relative measurement error (RME) of the variables lying time, standing time, walking time, number of strides, stride duration, and stride length given by the novel RumiWatch[1] algorithm as compared with the result of video recording analysis (gold standard).

				Range value		95% CI of RME	
Experiment	**Variable**	**RME[2] (%)**	**SD**	**Lower**	**Upper**	**Lower**	**Upper**
1	Lying time (n = 18)	0.09	0.044	0.028	0.174	0.067	0.111
2	Standing time (n = 21)	4.7	4.32	5.62	13.21	2.73	6.67
2	Walking time (n = 21)	17.12	16.03	6.43	66.67	9.82	24.42
2	Number of strides (n = 21)	6.23	6.49	0	20.83	3.27	9.18
3	Stride duration (n = 16)	6.65	3.83	1.15	13.79	4.61	8.69
3	Stride length (n = 16)	11.92	9.95	0.2	32.93	6.61	17.22

[1] ITIN+HOCH GmbH, Fütterungstechnik, Liestal, Switzerland.
[2] RME = Mean relative measurement error between video recording and algorithm.

3.5 Discussion

To the best of the authors' knowledge, this is the first description of a pedometer software allowing the detection of a variety of characteristics of cow walking behavior, correlating at a strong to mostly very high degree with the gold standard. The differentiation between lying position and being in an upright position of loose-housed cows and calves has already been possible with a high accuracy, using data loggers available on the market (O'Driscoll et al. 2008, Trenel et al. 2009, Robert et al. 2009). With the novel algorithm, developed in this study, all lying and standing events, without exception, were correctly detected. To minimize the chance of misclassifying the grooming behavior of the hind limb with the cow standing as a lying down event, the duration at which the pedometer remains in horizontal position must exceed 50 s to detect a true lying down event with a consecutive lying bout. Similarly, to minimize the chance of misclassifying the short upright position in the course of a position change at lying as a short standing bout, the duration at which the pedometer remains in vertical position must exceed 50 s to detect a true standing bout.

As mentioned in many studies, the accuracy of correctly describing the walking behavior with the available data loggers was moderate to low (Robert et al. 2009, Trenel et al. 2009). Mattachini et al. (2013) reported that just 30% of the walking events were correctly detected. This is mainly because the transition from standing to walking and vice versa is physically less distinctive than from the lying to the upright position (Trenel et al. 2009). Furthermore, the character and extent of limb movements with the cow standing but not walking is extremely variable, reaching from a simple and very short relief of the weight bearing of the limb, over frequent weight shifting from one limb to the contralateral limb in case both limbs are affected, to an obvious flexion of the limb lasting for several seconds. Definition of a step as opposed to a stride (defined here as being a limb movement within a walking phase) is, therefore, an extremely difficult task with a low detection rate. Even classification of individual limb movements at manual observation by professionals is not conclusive (Cutler 2012). Hence, during the development of the current algorithm, it was decided to characterize the limb movements with the cow in upright position first by the walking behavior (walking phases, number of strides, stride duration, and stride length) and second by the activity index at standing and walking separately. The activity index (

Table ***3.1***) represents the averaged variance of 3-dimensional acceleration in 10-s segments. Validation of the activity index by manually comparing video sequences of the cow with the output of the pedometer is not possible.

In a recent paper, describing the development of new algorithms for detection of walking behavior, it was shown that applying the rule that a walking phase must at least last 5 s optimized the classification rate (Nielsen et al. 2010). Combining this rule with the step-count detection at walking versus standing based on a moving average of 3 s, the optimal misclassification rate was reduced to 10% (Nielsen et al. 2010). In the current study, walking phases were not defined by a minimal duration but rather by the condition that a walking phase must consist of at least 3 consecutive strides and the period between 2 strides must last less than 4 s. A walking phase was rated as separate from the previous walking phase if the interval between 2 strides exceeded 10 s. This allowed that only 1 out of 127 walking phases were not detected correctly and the correlation between automated and manual detection of the number of strides was $r_s = 0.98$. The RME of walking time was quite high (17.2%) as compared with other locomotor parameters described in this study. The reason for this high relative error might be the 10-s temporal quantization resolution of the shorter absolute walking time compared with the much longer standing or lying times.

Estimating the stride length and the stride duration represents a further important parameter of cow locomotor activity. Platz et al. (2008) showed an increase in stride length of cows kept on rubber compared with concrete floors. Flower et al. (2005) showed that lame cows have longer stride duration and shorter stride length compared with healthy cows using kinematic gait analysis. With the current algorithm, correlations of stride length and stride duration with the gold standards were both strong.

The sampling rate of the RumiWatch pedometer was set at 10 samples per second, representing a very high rate. Mattachini et al. (2013) concluded that sampling intervals ≤2 min are required to accurately measure aspects of lying behavior such as number of lying bouts per day. From the results of the current study, it remains unclear whether reduction of the sampling rate to 1 Hz might be possible without loss of important information mainly concerning the walking behavior.

3.6 Conclusions

The results of this study suggest that the newly developed algorithm of the RumiWatch pedometer allows for the detection of several characteristics of the locomotor behavior of cows with a very high (lying time, standing time, walking time, and number of strides) or strong degree of correlation (stride duration and stride length). The proportion of correctly detected events exceeded 99% for the parameters number of lying bouts, standing bouts, walking bouts, stand up events, and lie down events, and the RME was less than 10% for the parameters lying time, standing time, number of strides, and stride duration as compared with manual observation. Using the new pedometer software, further research is warranted to study in more detail the normal locomotor behavior (focusing on walking) of healthy dairy cows and to evaluate the feasibility of the newly described parameters of cow walking for early detection of lameness.

3.7 Acknowledgments

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3.8 References

Alsaaod, M., Romer, C., Kleinmanns, J., Hendriksen, K., Rose-Meierhofer, S., Plumer, L., Büscher, W., 2012. Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. Applied Animal Behaviour Science, 142, 134–141.

Chapinal, N., de Passille, A. M., Pastell, M., Hanninen, L., Munksgaard, L., Rushen, J., 2011. Measurement of acceleration while walking as an automated method for gait assessment in dairy cattle. Journal of Dairy Science, 94, 2895–2901.

Cook, N. B., Bennett, T. B. Nordlund, K. N., 2005. Monitoring indices of cow comfort in free-stall-housed dairy herds. Journal of Dairy Science, 88, 3876–3885.

Cutler, J., 2012. Welfare in dairy cattle: Epidemiologic approaches for detection and treatment of lameness. PhD Thesis in Population Medicine. University of Guelph, Ontario, Canada.

Espejo, L. A., Endres, M. I., Salfer, J. A., 2006. Prevalence of lameness in high-producing Holstein cows housed in freestall barns in Minnesota. Journal of Dairy Science 89, 3052–3058.

Flower, F. C., Sanderson, D. J., Weary, D. M., 2005. Hoof pathologies influence kinematic measures of dairy cow gait. Journal of Dairy Science, 88, 3166–3173.

Flower, F. C., Weary, D. M., 2006. Effect of hoof pathologies on subjective assessments of dairy cow gait. Journal of Dairy Science, 89, 139–146.

Gonzalez, L. A., Tolkamp, B. J., Coffey, M. P., Ferret, A., Kyriazakis, I., 2008. Changes in feeding behavior as possible indicators for the automatic monitoring of health disorders in dairy cows. Journal of Dairy Science, 91, 1017–1028.

Hudson, C., Whay, H., Huxley, J., 2008. Recognition and management of pain in cattle. In Practice, 30, 126–134.

Ito, K., von Keyserlingk, M. A. G., Leblanc, S. J., Weary, D. M., 2010. Lying behavior as an indicator of lameness in dairy cows. Journal of Dairy Science, 93, 3553–3560.

Mattachini, G., Riva, E., Bisaglia, C., Pompe, J. C. A. M., Provolo, G., 2013. Methodology for quantifying the behavioral activity of dairy cows in freestall barns. Journal of Animal Science, 91, 4899–4907.

Muller, R., Schrader, L., 2005. Individual consistency of dairy cows' activity in their home pen. Journal of Dairy Science, 88, 171–175.

Munksgaard, L., Reenen, C. G., Boyce, R., 2006. Automatic monitoring of lying, standing and walking behavior in dairy cattle. Journal of Animal Science, 84, 304.

Nielsen, L. R., Pedersen, A. R., Herskin, M. S., Munksgaard, L., 2010. Quantifying walking and standing behaviour of dairy cows using a moving average based on output from an accelerometer. Applied Animal Behaviour Science, 127, 12–19.

Nordlund, K. V., Cook, N. B., Oetzel, G. R., 2004. Investigation strategies for laminitis in problem herds. Journal of Dairy Science, 87, (E. Suppl.):E27–E35.

O'Callaghan, K. A., Cripps, P. J., Downham, D. Y., Murray, R. D., 2003. Subjective and objective assessment of pain and discomfort due to lameness in dairy cattle. Animal Welfare, 12, 605–610.

O'Driscoll, K., Boyle, L., Hanlon, A., 2008. A brief note on the validation of a system for recording lying behaviour in dairy cows. Applied Animal Behaviour Science, 111, 195–200.

Platz, S., Ahrens, F., Bendel, J., Meyer, H. H., Erhard, M. H., 2008. What happens with cow behavior when replacing concrete slatted floor by rubber coating: A case study. Journal of Dairy Science, 91, 999–1004.

Robert, B., White, B. J., Renter, D. G., Larson, R. L., 2009. Evaluation of three-dimensional accelerometers to monitor and classify behavior patterns in cattle. Computers and Electronics in Agriculture, 67, 80–84.

Shearer, J. K., Stock, M. L., Van Amstel, S. R., Coetzee, J. F., 2013. Assessment and management of pain associated with lameness in cattle. Veterinary Clinics of North America: Food Animal Practice, 29, 135–156.

Sprecher, D. J., Hostetler, D. E., Kaneene, J. B., 1997. A lameness scoring system that uses posture and gait to predict dairy cattle reproductive performance. Theriogenology, 47, 1179–1187.

Taylor, T., 1990. Interpretation of the correlation coefficient: a basic review. Journal of Diagnostic Medical Sonography, 1, 35–39.

Trenel, P., Jensen, M. B., Decker, E. L., Skjoth, F., 2009. Technical note: Quantifying and characterizing behavior in dairy calves using the IceTag automatic recording device. Journal of Dairy Science, 92, 3397–3401.

Urton, G., von Keyserlingk, M. A. G., Weary, D. M., 2005. Feeding behavior identifies dairy cows at risk for metritis. Journal of Dairy Science, 88, 2843–2849.

Viazzi, S., Bahr, C., Schlageter-Tello, A., Van Hertem, T., Romanini, C. E., Pluk, A., Halachmi, I., Lokhorst, C., Berckmans, D., 2013. Analysis of individual classification of lameness using automatic measurement of back posture in dairy cattle. Journal of Dairy Science, 96, 257–266.

Whay, H. R., Main, D. C. J., Green, L. E., Webster, A. J. F., 2003. Assessment of the welfare of dairy cattle using animal-based measurements: Direct observations and investigation of farm records. Veterinary Record, 153, 197–202.

Yunta, C., Guasch, I., Bach, A., 2012. Short communication: lying behavior of lactating dairy cows is influenced by lameness especially around feeding time. Journal of Dairy Science, 95, 6546–6549.

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4 Development and validation of a predictive model for calving time based on sensor measurements of ingestive behavior in dairy cows

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4.1 Abstract

Calving is an event with major impact on working routines in dairy farming and highly affects the physiological state of dairy cows. Hence, it is in the interest of livestock farmers to have information on approaching calving events to ensure a sound birth, health and welfare of the dairy cow and calf for profitable and sustainable milk production. Changes in the ingestive behavior of dairy cows due to the onset of calving have been revealed in several studies. Therefore, sensor data of these behaviors may be useful for automated prediction of calving time. The current study used sensor data of a novel monitoring device for ingestive behavior (RumiWatch noseband sensor, Agroscope, Ettenhausen, Switzerland and Itin+Hoch GmbH, Liestal, Switzerland) of 35 dairy cows for development and validation of a predictive model for calving time. Sensor data obtained from calving events on three farms were used as one training dataset and two independent validation datasets to evaluate the predictive performance of a Naïve Bayes classifier model for calving prediction at 1 hour before the start of calving. The model performance was evaluated on an hourly basis for 168 hours prior to the start of calving. Combined sensor variables with highest predictive performance were ruminating chews, ruminating boluses, and eating chews (sensitivity = 0.82, specificity = 0.87, positive predictive value = 0.04) in Validation Dataset 1, and ruminating chews per bolus, ruminating chews per minute, eating chews, other activity time, other chews (sensitivity = 0.69, specificity = 0.86, positive predictive value = 0.03) in Validation Dataset 2. These results indicate, that the sensitivity and specificity of the predictive model were satisfying, but the positive predictive value was low and the amount of false positive alerts was considerably high. Although the developed model is therefore not suitable for application in practice, we found that particularly variables of rumination behavior have predictive value and should be taken into consideration for future research on calving detection models. The findings of this study demonstrate that an assessment limited to the terms of sensitivity and specificity may be misleading, as these variables may achieve high values and suggest adequate performance, while the model is not appropriate in the light of its expected use.

Key words: Precision Dairy Farming, animal monitoring, transition cow, RumiWatch, Naïve Bayes classifier

4.2 Introduction

The recognition of imminent calving is highly relevant for dairy herd management. Currently, external physiological signs of approaching parturition such as pelvic ligament relaxation, udder distension, teat filling, vaginal discharge, vulva edema, and behavioral changes are widely used to predict the onset of calving in dairy cows by human observation (Berglund et al. 1987, Miedema et al. 2011a, Streyl et al. 2011). These assessments are subjective, time consuming, accompanied by wide variation of external signs among dairy cows (Ouellet et al. 2016), and require expertise and routine of the observer for adequate prediction of calving time. The importance of calving time prediction can be seen in its role to facilitate timely human intervention to assist birth and safeguard the health of calf and cow, particularly in cases of dystocia (Palombi et al. 2013). However, growing animal numbers per farm unit can impede individual and timely human observation of dairy cows in the pre-partum period. Hence, automated devices for prediction or detection of calving events based on measuring behavioral changes are considered as beneficial tools to support dairy farm management practices (Ouellet et al. 2016).

Hogeveen et al. (2010) defined three criteria that must be fulfilled for a detection model to be implemented in commercial livestock production: firstly, a high performance in terms of sensitivity and specificity, secondly, a time window corresponding to the necessary response time for the specific condition, and thirdly, a high degree of similarity between the study design and the real everyday conditions in commercial farms.

Detection models for livestock production majorly use binary target variables, i.e., either positive or negative indication of the condition to be detected, as an alert mechanism. The predictive model performance is commonly evaluated by the binary epidemiological terms of sensitivity and specificity (Dominiak and Kristensen 2017). For assessment of the suitability for practical implementation of detection models, the consideration of false positive alerts is of particular importance (de Mol and Woldt 2001). Studies on automated mastitis detection by Hogeveen et al. (2010) and Mollenhorst et al. (2012) showed a preference of farmers for alerts temporally close to an event and that false positive alerts reduced farmers' acceptance of the automated detection systems. Similarly, this perception can be assumed for automated calving detection (Rutten et al. 2017).

As a specific feature in livestock detection models, particularly those using sensor data in time series, the prevalence of the condition to be detected and, hence, the number of positive cases is low compared to all negative cases in the sample. For instance, for calving detection it must be assumed, that animal behavior is monitored over several days during the prepartum period to detect one calving event per animal. Under these circumstances, an assessment of a detection model only based on the terms of sensitivity and specificity may be misleading, as the occurring false positive alerts are not considered for the calculation of sensitivity, and specificity may be biased by a high number of true negative cases compared to the false positive cases in the sample. Hence, satisfying sensitivity and specificity values may also be achieved, although the ratio of false positive alerts is high or even prohibitive for practical implementation. An indication on the occurrence of false positive alerts is instead given by the positive predictive value that represents the ratio of true positive detections in relation to all positive detections and, therefore, gives a more suitable indication on the practical usefulness of the detection model.

Further influence on the predictive performance is the time window for classification of alerts (Dominiak and Kristensen 2017). A recent study by Rutten et al. (2017) demonstrated, that extending the time window for true positive classification of an alarm from hourly basis to broader time windows of three, six, and twelve hours significantly increased the sensitivity of prediction. The extension of time windows for classification of alerts will consequently also affect the number of false positive alerts and has to be taken into account for interpretation of the predictive performance.

Several studies have shown that sensor data of behavioral changes may be used for calving prediction (Miedema et al. 2011b, Schirmann et al. 2013, Braun et al. 2014, Büchel and Sundrum 2014, Pahl et al. 2014, Ouellet et al. 2016). However, Rutten et al. (2017) stated that an independent validation of the accuracy of such prediction has not been studied yet and developed a prediction model with a combination of expected calving date and sensor data. That model was evaluated for the last three weeks before calving, using different time windows for the generation of calving alerts in a separate dataset obtained from the same farm. The number of false positive alerts was high and using the best model, the moment at which calving started was correctly predicted for fewer than half of the calvings.

An animal monitoring device for recording behavioral changes and potentially generating calving alerts is the RumiWatch noseband sensor (Agroscope, Ettenhausen, Switzerland and Itin+Hoch GmbH, Liestal, Switzerland), that was developed and validated by Zehner et al. (2012, 2017). This system allows to monitor several variables of ingestive behavior via an animal-borne measuring device with real time on-line analysis and wireless data transmission. Measurement of ruminating and eating activity by this sensor may allow detailed analysis of pre-partum behavior and hence may be used to generate a model to predict or detect calving events. Therefore, the objectives of this study were to use automated measurements of ingestive behavior obtained from RumiWatch noseband sensors to predict the start of calving in dairy cows by (a) analyzing at which moment, prior to the start of calving, the sensor measurements have predictive value, (b) assessing the predictive value of different behavioral variables for estimation of the start of calving, and (c) developing an independently validated model that predicts the starting point of calving.

4.3 Materials and methods

4.3.1 Data collection

4.3.1.1 Experimental procedures

Data of 35 cows kept in loose housing systems with cubicles were used on three German dairy research farms, including n = 11 on Farm 1, n = 11 on Farm 2 and n = 13 on Farm 3. All farms applied comparable, standardized management procedures to maintain high-yielding dairy herds (average 305-day lactation yield: 9’897 kg on Farm 1, 9’302 kg on Farm 2, 10’134 kg on Farm 3). The measurements took place from May to December 2014. On all three farms, a total mixed ration with different proportions of forage and concentrate was provided once daily between 06:00 and 07:00 a.m. Water was available from water troughs ad libitum. Cows were continuously housed and did not have access to pasture for grazing. At least 7 days before the expected calving date, late gestation cows were moved to straw-bedded calving pens, either kept single or in groups of up to six animals. The expected calving date was calculated on the basis of insemination records at 280 days after insemination for each cow. Animals were equipped with RumiWatch noseband sensors (Agroscope, Ettenhausen, Switzerland and Itin+Hoch GmbH, Liestal, Switzerland) to record ingestive behavior at least 8 days before the expected calving date. The scheduled monitoring period for continuous noseband sensor measurements was 30 days ranging from 8 days ante partum until 21 days post-partum (Figure 4.1).

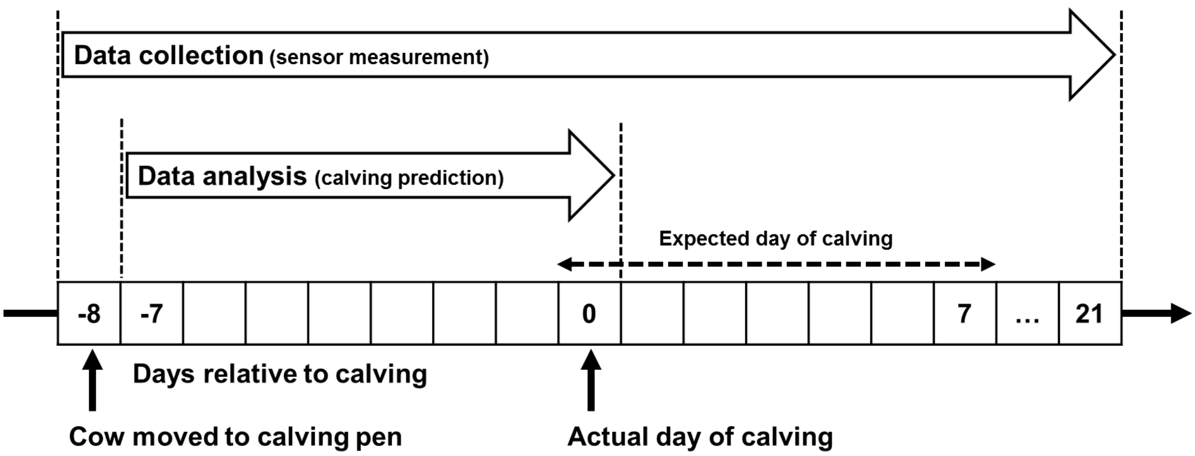

Figure 4.1. Timeframes for data collection and analysis.

Animals' reactions on device fastening and wearing were observed and documented by the observer and farm staff on duty, as well as losses and damages of the sensor devices. The 10-Hertz raw measurement data recorded on the sensor devices' built-in SD Memory Card were downloaded once after completion of the monitoring period. The behavioral variables recorded by RumiWatch noseband sensors during this study are shown in Table 4.1. These variables were considered to be potential predictors of calving for the later analysis. A definition of the noseband sensor variables was given by Beer et al. (2016) and Zehner et al. (2017).

Table 4.1. Behavioral variables recorded by RumiWatch noseband sensors.

Duration (min)	**Frequency (n)**
Rumination time	Ruminating chews
	Ruminating boluses
	Ruminating chews per bolus
	Ruminating chews per minute
Eating time	Eating chews
Other activity time, i.e., non-ingestive related behaviors	Other chews, i.e. non-ingestive related jaw movements

Calving times and course of delivery were observed and documented by the farm staff or the observer. Day, time, ease of calving, sex and weight of calves were documented according to a standard operating procedure. Newborn calves were removed from the calving pen approximately 2 to 3 hours after calving. Cows either remained in the straw-bedded calving pens or were moved to the lactating herd depending on the health state assessment by trained farm staff.

4.3.1.2 Definition of calving and timeframe for analysis

For the development of the predictive model, the start of calving was selected as the target variable, as this point in time is considered to be the most relevant for a possible intervention by the farmer in case of dystocia. The start of calving was defined for our study as the start of the second stage of parturition before complete expulsion of the calf, and referred to as Hour 0 ante partum in our analysis. At this stage, cows are most of the time in a lying position (lateral recumbency), and visible abdominal contractions indicate active labor for expulsion of the calf (Parkinson et al. 2001, Proudfoot et al. 2013). Evident signs for the start of the second stage of parturition are the appearance of the amniotic sac or the calves' feet (Schuenemann et al. 2011). For our analysis, the pre-calving hours were defined as the last 4 hours before the start of calving, as this timeframe represents the first stage of parturition (cervical dilatation). The time of parturition was defined as the completion of the fetal expulsion. The temporal offset between the start of calving and actual parturition varied. As sensors generated measurement data of behaviors for every full hour, the actual calving point was positioned non-uniformly within the 1-h sensor data period considered Hour 0 ante partum, or in the following hour. As cows are often moved to separate calving pens 7 days prior to expected calving on commercial farms, the timeframe for evaluating the predictive model was chosen to be 168 hours preceding the start of calving.

4.3.2 Data preparation and selection

4.3.2.1 Sensor data processing

Raw measurement data obtained from RumiWatch noseband sensor recording were converted into consolidated results of 1-hour classification summaries for every full hour using the device specific software RumiWatch Converter V0.7.3.2 (Itin+Hoch GmbH, Liestal, Switzerland; Zehner et al. 2017) for each animal specific data file. Within the classification summaries, measurement results represented percentages of durations and frequencies of behavioral variables per 1 hour (cf. Table 4.1). The information on datasets obtained by the RumiWatch noseband sensors were joint with the information of the respective hour relative to the start of calving. Additionally, sensor data were summed up to 24-hour summaries for the seven intervals within the analysis period before the start of calving. We calculated the sum of all variables within each 24-hour interval, except for the variables, “ruminating chews per minute”, “ruminating chews per bolus”, which were averaged within the respective interval.

4.3.2.2 Training and validation datasets

The 35 calving events and associated sensor data for further analysis were split into three farm-specific subsets to define one training dataset and two independent validation datasets. Missing sensor data was a recurrent problem in our study, as we applied prototype versions of the noseband sensors that were later described and validated by Zehner et al. (2017). For training data, the occurrence of missing sensor measurements was considered to be tolerable, as these data were only used to train the classifier and no continuous timeline for the consistent evaluation of alerts was required. For validation data, the availability of animal-specific continuous sensor data within 168 hours before the start of calving were defined to be a prerequisite for the evaluation of calving alerts generated by the predictive model. Therefore, due to partially missing sensor data within this timeframe for 6 out of 11 animals in Farm 1, this subset was chosen for training. For validation, we selected the subsets obtained from Farm 2 and 3, as here continuous sensor data within the 168 hours before the start of calving were available (Table 4.2).

Table 4.2. Datasets for training and validation of the predictive model.

	Dataset			
Sample	**Farm 1 (Training)**	**Farm 2 (Validation 1)**	**Farm 3 (Validation 2)**	**Total**
Animals:				
Cows (n)	11	11	13	35
- Multiparous (n)	7	10	7	24
- Primiparous (n)	4	1	6	11
Sensor data:				
Monitoring hours[1] (n)	9’216	9’216	9’216	27’648
- Other hours[2] (n)	7’728	7’368	7’032	22’128
- Evaluation hours[3] (n)	1’488	1’848	2’184	5’520

[1] Monitoring hours: total monitoring period
[2] Other hours = monitoring hours not covered by the evaluation hours
[3] Evaluation hours = hours -168 to -1 relative to the start of calving

4.3.3 Model development

All data processing procedures and statistical analyses for the model development and evaluation were conducted in MATLAB R2016b (The MathWorks Inc., Natick, Massachusetts, USA). Descriptive statistics were generated using IBM SPSS Statistics 24 (IBM Corporation, Armonk, New York, USA).

For the descriptive statistics, we used the non-parametric Friedman test to investigate behavioral changes in the analysis period, and to reveal at which moment, prior to the start of calving, the sensor measurements had predictive value. Firstly, differences in behavioral variables were analyzed between the seven 24-hour intervals preceding the start of calving. Secondly, behavioral variables on an hourly basis were compared within 4-hour intervals for the entire analysis period.

In a next step, a model was developed. Because of the limited number calving events, only a small training dataset was available. Therefore, a Naïve Bayes Classifier (NBC) was chosen. This method represents a comparably simple, probabilistic classification approach but has competitive performance with more complex classifiers (Domingos and Pazzani 1997, Zhang et al. 2006). It is derived from the Bayes theorem (Bayes et al. 1763) and estimates the probability of the classification given the observation and selects the class with the highest probability as classification outcome.

Applying Bayes rule (cf. Rish 2001), the conditional probability p of a given observation X classified into class *k* of a classification C is calculated as

$$\mathrm{p}(C_k \mid X) = \frac{p(C_k)\, p(X \mid C_k)}{p\,(X)} \quad \text{(Equation 1).}$$

The training dataset used to build the NBC is expressed as $\{X, C\}$ and contains observations X (measurements of behavioral variables from noseband sensor on an hourly basis) with a known binary classification C (1 = calving or 0 = non-calving) of the respective hour. The features x used to describe the observations X are denoted by $X = (x_1, x_2, \ldots, x_i, \ldots, x_n)$ and each observation is belonging to a binary classification $C \in \{0, 1\}$, where 0 denotes a non-calving classification and 1 denotes a calving classification. For an observation, the NBC generates a binary classification by calculating the posterior probability of an observation for being classified into a given class, for a calving classification according to

$$p\big(C = 1 \mid X = (x_1, x_2, \ldots, x_i, \ldots, x_n)\big) = \frac{1}{Z} p(C = 1) \prod_{i=1}^{n} p_i(x_i \mid C = 1) \quad \text{(Equation 2)},$$

and for a non-calving classification by

$$p\big(C = 0 \mid X = (x_1, x_2, \ldots, x_i, \ldots, x_n)\big) = \frac{1}{Z} p(C = 0) \prod_{i=1}^{n} p_i(x_i \mid C = 0) \quad \text{(Equation 3)},$$

with the evidence $Z = p(x)$. The two posteriors were then compared according to

$$\frac{p = \big(C=1 \mid X=(x_1, x_2, \ldots, x_i, \ldots, x_n)\big)}{p = \big(C=0 \mid X=(x_1, x_2, \ldots, x_i, \ldots, x_n)\big)} = \frac{p(C=1) \prod_{i=1}^{n} p_i(x_i \mid C=1)}{p(C=0) \prod_{i=1}^{n} p_i(x_i \mid C=0)} \quad \text{(Equation 4)}.$$

The log odds (LO) was calculated using the decadic logarithm according to

$$log_{10} \frac{p = \big(C=1 \mid X=(x_1, x_2, \ldots, x_i, \ldots, x_n)\big)}{p = \big(C=0 \mid X=(x_1, x_2, \ldots, x_i, \ldots, x_n)\big)} = log_{10} \frac{p(C=1) \prod_{i=1}^{n} p_i(x_i \mid C=1)}{p(C=0) \prod_{i=1}^{n} p_i(x_i \mid C=0)} \quad \text{(Equation 5)}.$$

The observation represented by X was classified as calving classification if

$$log_{10} \frac{p(C=1) \prod_{i=1}^{n} p_i(x_i \mid C=1)}{p(C=0) \prod_{i=1}^{n} p_i(x_i \mid C=0)} > \theta \quad \text{(Equation 6)},$$

where θ is the threshold value for calving classification. If the logarithmic probability was below this threshold, the observation X was considered as non-calving classification and classified into class 0. In the current study, the threshold θ was determined as the threshold maximizing the Youden's index (J; Youden 1950) for selecting the optimum cut-off point, and expressed by the log odds (LO) for class-conditional probability of calving (threshold for calving vs. non-calving classification).

First, n = 9 promising calving indicators recorded by RumiWatch noseband sensors were identified (cf. Table 4.1). Then the individual variables and all 2^9 possible combinations of these indicators were analyzed by multiple uses of Bayes' Theorem, resulting in a total number of 512 combinations in the analysis. For our predictive model, the NBC classifies data in two steps. Firstly, during the training of the classifier, the training dataset is used to estimate the variables of a probability distribution, assuming that the predictors are conditionally independent given the class. Secondly, for prediction in unseen validation data, the NBC computes the posterior probability of the sample belonging to each class. We assumed a Gaussian distribution for the predictors in each class. For each predictor, the NBC estimates a separate Gaussian distribution for each class by computing the mean and standard deviation of the training data in each class. Probability distributions for the continuous predictors were parameterized as probability density functions (PDF).

For the continuous attributes x (sensor data of behavioral variables) in the training dataset, the data were first segmented by the classification (calving or non-calving), then the mean and variance of x were calculated. Hence, μ_C is the mean of the values of attribute x associated with class C, and σ_C^2 is the variance of the values in x associated with class C. The probability distribution of an observational value υ given a class C, denoted by $p(x = \upsilon \mid C)$, was computed by assigning the observational values υ to a Gaussian distribution parameterized by μ_C and σ_C^2, denoted by

$$p(x = \upsilon \mid C) = \frac{1}{\sqrt{2\pi\sigma_C^2}} e^{-\frac{(\upsilon-\mu_C)^2}{2\sigma_C^2}}$$ (Equation 7).

We estimated the probability density functions for all observations i of each feature x (behavioral variable from sensor data) in each class C (calving and non-calving) per sample unit (1-hour summaries of sensor). Using this approach, we obtained the class-conditional probability density functions for the binary classification, denoted by

$$p(x \mid C_{calving}) = \prod_{i=1}^{N} p(x_i \mid C_{calving})$$ (Equation 8),

and for non-calving, denoted by

$$p(x \mid C_{non-calving}) = \prod_{i=1}^{N} p(x_i \mid C_{non-calving})$$ (Equation 9).

The PDF for the calving class was estimated based on the pre-calving hours, i.e. the last 4 hours before the start of calving, whereas the PDF for the non-calving class was estimated from all other hours contained in the training dataset. The threshold for calving detection was expressed by the log odds (LO) for class-conditional probability of calving. Hourly sensor data in the validation datasets were then compared against the calving or non-calving probability density functions in order to predict the start or the absence of a calving event.

We defined a data segmentation method that allows continuous activity recognition, i.e. detection of imminent calving events, in time series of sensor data. The sampling rate for the predictive model was chosen according to the output resolution of consolidated classification summaries of behavioral variables generated by the RumiWatch noseband sensor. Hence, we used 1-hour blocks generated every full hour for further processing in the model. For data segmentation, we used a fixed-size overlapping sliding window with a window size of 4 hours and with 3 hours (75%) overlap that was defined *a priori*. The classifier was executed over a fixed-width sliding analysis window of 4 observations, i.e., 4 consecutive hours relative to the start of calving (Figure 4.2).

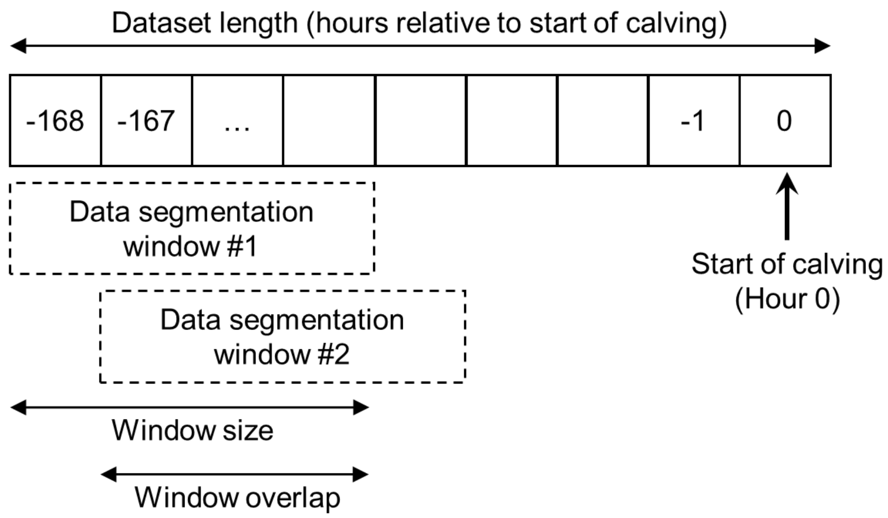

Figure 4.2. Data segmentation method for calving detection.

This method creates a moving time window for classification of the observations (probability of calving vs. non-calving), so that the latest generated behavior summary is only compared to the most recently observed behavior summaries that fall within the time window. Thereby, it is possible to provide a completed analysis window consecutively every hour that allows to generate calving alerts on an hourly basis. We implemented two selectable prediction offsets for calving detection: prediction offset -1 for detection 1 hour before the start of calving (Hour -1) and prediction offset 0 for detection of the start of calving (Hour 0).

4.3.4 Model evaluation

For evaluation of the classifier performance, the outcome for actual and predicted classification shown in Table 4.3 was defined.

Table 4.3. Definition of outcome for actual and predicted classification.

	Actual classification (human observer)	
Predicted classification (predictive model)	Calving	Non-calving
Calving	True Positive (TP)	False Positive (FP)
Non-calving	False Negative (FN)	True Negative (TN)

Based on these outcomes, the performance metrics for the prediction and detection of the start of calving as shown in Table 4.4 were calculated.

Table 4.4. Performance metrics for evaluation of the predictive model.

Parameter	**Definition**
Sensitivity	$\text{Sensitivity} = \frac{\text{True Positives}}{\text{Positives}} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Negatives})}$
Specificity	$\text{Specificity} = \frac{\text{True Negatives}}{\text{Negatives}} = \frac{\text{True Negatives}}{(\text{True Negatives} + \text{False Positives})}$
Positive predictive value	$\text{PPV} = \frac{\text{True Positives}}{(\text{True Positives} + \text{False Positives})}$
Youden's index	$\text{J} = (\text{Sensitivity} + \text{Specificity}) - 1$

To determine the performance metrics of the model prediction at a given threshold, a receiver operating characteristic (ROC) analysis was performed. The ROC curve is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied (Metz 1978, Zweig and Campbell 1993). Using the ROC curve, the true positive rate (sensitivity) is plotted as a function of the false positive rate (1-specificity) over the whole range of possible threshold values (Detilleux et al. 1999, Steensels et al. 2016). In the current study, the criterion for threshold selection was maximizing the Youden's index (J), as this parameter allows practical considerations such as choice of a false positive rate that could be suitable for farmers. ROC curves were used for the Naïve Bayes classification both for individual sensor variables and combinations of sensor variables. Derived from ROC analysis, the area under the ROC curve (AUC) was calculated to allow for comparison of the different predictors. For the predictive model, the AUC indicates the ability of the predictor to discriminate cows that will start to calve and cows that will not start to calve within the next hour. Therefore, a predictor that would be able to differentiate the two classes perfectly would have an AUC of 1, whereas a predictor that is not able to categorize the two classes at all would have an AUC of less than 0.5 (Bewick et al. 2004, Burfeind et al. 2011, Ouellet et al. 2016). According to Steensels et al. (2016), a diagnostic test is usually classified as excellent (AUC = 0.9 to 1), good (AUC = 0.8 to 0.9), fair (AUC = 0.7 to 0.8), poor (AUC = 0.6 to 7) or fail (AUC = 0.5 to 0.6). In general, a test with an AUC ≤ 0.75 is considered to be not clinically useful (Fan et al. 2006).

An evaluation scheme for classification of calving alerts was defined. The calving alerts generated by the predictive model were evaluated on an hourly basis for the 168 hours before the start of calving. The TP alarms generated by the detection model were classified by adding the information on the point in time relative to the start of calving and hereby sorting the alarms into TP and FP (Figure 4.3).

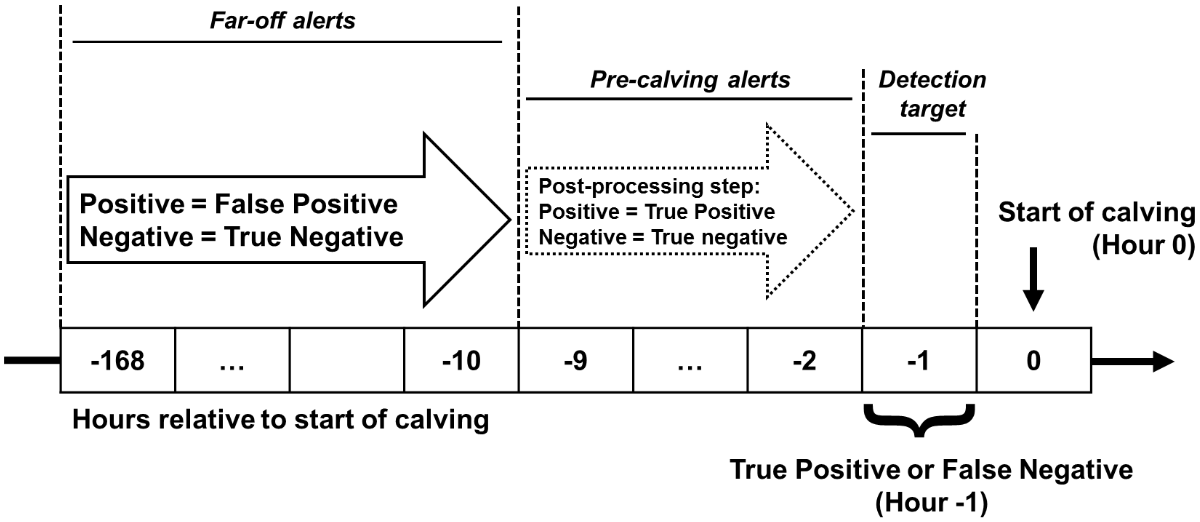

Figure 4.3. Evaluation scheme for classification of calving alerts.

This measure comprised an acceptance of the original performance level complemented by a post-processing step for classification of the alarms into TP or FP. Calving alerts generated during the hours -168 to -10 relative to the start of calving were classified to be either FP or TN. If calving alerts were generated within the hours -9 to -2 relative to the start of calving (pre-calving alerts), these were classified to be TP alerts, as they were occurring during the first stage of parturition (cervical dilatation) and, therefore, were considered useful for the identification of the onset of calving. Calving alerts in the hour before the start of calving (Hour -1) were classified to be either TP or FN.

For validation of the predictive model, a two-fold cross-validation was applied. The data were split into two complementary subsets. For the first subset, the training dataset was obtained from Farm 1 and the validation dataset was obtained from Farm 2, whereas for the second subset, the training dataset was obtained from Farm 1 and the validation dataset was obtained from Farm 3. We used a repetitive process, in which the classifier was trained with the training dataset (Farm 1) and repeatedly applied to the validation dataset (Farm 2 and Farm 3, respectively). The cross-validation was performed with 20 repetitions. During each repetition, the classifier was trained on the training dataset and the fitted model was repeatedly applied to the validation dataset to determine its predictive performance. Finally, the average of classification results generated during 20 repetitions was used to determine the classification performance.

4.4 Results

As an initial step an explorative data analysis was carried out to gain information on the behavioral changes in the pre-calving period. Graphical examination of the entire analysis period of the 168 hours before the start of calving revealed that notable behavioral changes occurred majorly during the last 24 hours before the start of calving. More detail on that can be found in the supplementary material (Supplementary Figure 1, 2, 3 and 4).

4.4.1 Predictive performance of sensor variables

The results of the predictive performance of sensor variables are shown separately for Validation Dataset 1 (Table 4.5 and Table 4.6) and Validation Dataset 2 (Table 4.7 and Table 4.8), both for the prediction (Hour -1) and detection (Hour 0) of calving events.

In Validation Dataset 1, ruminating chews had most value as an individual sensor variable for prediction of calving (AUC = 0.80, J = 0.61). The best performing combination of sensor variables for calving prediction consisted of ruminating chews, ruminating boluses, and eating chews (AUC = 0.82, J = 0.69). For detection of calving, ruminating chews had also the most predictive value out of the individual sensor variables in Validation Dataset 1 (AUC = 0.83, J = 0.63). Combined sensor variables of ruminating boluses, ruminating chews per bolus, ruminating chews per minute, and other activity time showed the best predictive performance of all analyzed combinations of variables for calving detection (AUC = 0.83, J = 0.66). On the contrary, the variables eating time and eating chews showed a low predictive performance, both for prediction and detection of calving in Validation Dataset 1.

Table 4.5. Classification results of sensor variables as predictors for prediction of calving events (Hour -1) in Validation Dataset 1 (Farm 2, n = 11 calvings) during a monitoring period of 168 hours before the start of calving. The 95% confidence intervals are indicated in parentheses. Bold values indicate predictors with an AUC ≥ 0.75. Criterion for threshold selection is maximizing the Youden's index (J).

Sensor variable	LO[1]	TP[2]	FP[3]	Sensitivity	Specificity	PPV[4]	AUC[5]	J[6]
Individual variable:								
Rumination time	**-1.7**	**8**	**243**	**0.73 (0.39-0.94)**	**0.87 (0.85-0.88)**	**0.03 (0.02-0.05)**	**0.77**	**0.60**
Ruminating chews	**-2.05**	**9**	**382**	**0.82 (0.48-0.98)**	**0.79 (0.77-0.81)**	**0.02 (0.01-0.03)**	**0.80**	**0.61**
Ruminating boluses	**-1.25**	**7**	**132**	**0.64 (0.31-0.89)**	**0.93 (0.92-0.94)**	**0.05 (0.03-0.08)**	**0.79**	**0.56**
Ruminating chews per bolus	-1.5	6	302	0.55 (0.23-0.83)	0.84 (0.82-0.85)	0.02 (0.01-0.03)	0.69	0.38
Ruminating chews per minute	**-1.6**	**8**	**293**	**0.73 (0.39-0.94)**	**0.84 (0.82-0.86)**	**0.03 (0.02-0.04)**	**0.87**	**0.57**
Eating time	-1.4	3	198	0.27 (0.06-0.61)	0.89 (0.88-0.91)	0.015 (0.006-0.039)	0.54	0.16
Eating chews	-1.4	4	200	0.36 (0.11-0.69)	0.89 (0.88-0.91)	0.02 (0.01-0.04)	0.58	0.25
Other activity time	-3.05	10	957	0.91 (0.59-1.00)	0.48 (0.46-0.51)	0.01 (0.009-0.013)	0.73	0.39
Other chews	-2.95	10	1091	0.91 (0.59-1.00)	0.41 (0.39-0.43)	0.01 (0.008-0.011)	0.67	0.32
Combination of variables:								
Ruminating chews + Ruminating boluses + Eating chews	**-2.1**	**9**	**233**	**0.82 (0.48-0.98)**	**0.87 (0.86-0.89)**	**0.04 (0.03-0.05)**	**0.82**	**0.69**

[1] Log odds for conditional probability of calving (threshold for calving vs. non-calving classification)
[2] True positive alerts
[3] False positive alerts
[4] Positive predictive value
[5] Area under the ROC curve
[6] Youden's index

Table 4.6. Classification results of sensor variables as predictors for detection of calving events (Hour 0) in Validation Dataset 1 (Farm 2, n = 11 calvings) during a monitoring period of 168 hours before the start of calving. The 95% confidence intervals are indicated in parentheses. Bold values indicate predictors with an AUC ≥ 0.75. Criterion for threshold selection is maximizing the Youden's index (J).

Sensor variable	LO[1]	TP[2]	FP[3]	Sensitivity	Specificity	PPV[4]	AUC[5]	J[6]
Individual variable:								
Rumination time	**-0.8**	**7**	**59**	**0.64 (0.31-0.89)**	**0.97 (0.96-0.97)**	**0.11 (0.07-0.17)**	**0.81**	**0.61**
Ruminating chews	**-1.55**	**8**	**175**	**0.73 (0.39-0.94)**	**0.91 (0.89-0.92)**	**0.04 (0.03-0.06)**	**0.83**	**0.63**
Ruminating boluses	**-0.8**	**7**	**67**	**0.64 (0.31-0.89)**	**0.96 (0.95-0.97)**	**0.10 (0.06-0.15)**	**0.82**	**0.60**
Ruminating chews per bolus	**-1.55**	**8**	**305**	**0.73 (0.39-0.94)**	**0.83 (0.82-0.85)**	**0.03 (0.02-0.04)**	**0.76**	**0.56**
Ruminating chews per minute	**-1.5**	**8**	**198**	**0.73 (0.39-0.94)**	**0.89 (0.88-0.91)**	**0.04 (0.03-0.06)**	**0.86**	**0.62**
Eating time	-1.35	2	149	0.18 (0.02-0.52)	0.92 (0.91-0.93)	0.013 (0.004-0.045)	0.47	0.10
Eating chews	-1.4	3	200	0.27 (0.06-0.61)	0.89 (0.88-0.91)	0.015 (0.006-0.038)	0.52	0.16
Other activity time	-0.5	4	50	0.36 (0.11-0.69)	0.97 (0.96-0.98)	0.07 (0.03-0.15)	0.63	0.34
Other chews	**-2.5**	**9**	**736**	**0.82 (0.48-0.98)**	**0.60 (0.58-0.62)**	**0.012 (0.009-0.016)**	**0.75**	**0.42**
Combination of variables:								
Ruminating boluses + Ruminating chews per bolus + Ruminating chews per minute + Other activity time	**-1.55**	**8**	**138**	**0.73 (0.39-0.94)**	**0.93 (0.91-0.94)**	**0.05 (0.04-0.08)**	**0.83**	**0.66**

[1] Log odds for conditional probability of calving (threshold for calving vs. non-calving classification)
[2] True positive alerts
[3] False positive alerts
[4] Positive predictive value
[5] Area under the ROC curve
[6] Youden's index

In Validation Dataset 2, other chews, i.e. non-ingestive related jaw movements, had most value as an individual sensor variable to predict the start of calving (AUC = 0.78, J = 0.50). The best performing combination of sensor variables for calving prediction consisted of ruminating chews per bolus, ruminating chews per minute, eating chews, other activity time, and other chews (AUC = 0.80, J = 0.55). Other chews had also the best predictive performance of individual sensor variables (AUC = 0.81, J = 0.60) for the detection of the onset of calving. However, the highest performance for calving detection was achieved by a combination of rumination time, ruminating chews, ruminating boluses, ruminating chews per bolus, ruminating chews per minute, eating chews, and other chews (AUC = 0.79, J = 0.63). For Validation Dataset 2, eating time and eating chews had more predictive value compared with Validation Dataset 1. However, predictive performance of the variables was still below those of rumination and other activity, as indicated by lower values of the Youden’s index (J).

Table 4.7. Classification results of sensor variables as predictors for prediction of calving events (Hour -1) in Validation Dataset 2 (Farm 3, n = 13 calvings) during a monitoring period of 168 hours before the start of calving. The 95% confidence intervals are indicated in parentheses. Bold values indicate predictors with an AUC ≥ 0.75. Criterion for threshold selection is maximizing the Youden's index (J).

Sensor variable	**LO[1]**	**TP[2]**	**FP[3]**	**Sensitivity**	**Specificity**	**PPV[4]**	**AUC[5]**	**J[6]**
Individual variable:								
Rumination time	-2.5	10	835	0.77 (0.46-0.95)	0.62 (0.60-0.64)	0.012 (0.009-0.016)	0.70	0.39
Ruminating chews	-2.65	10	809	0.77 (0.46-0.95)	0.63 (0.61-0.65)	0.012 (0.009-0.017)	0.70	0.40
Ruminating boluses	-2.5	10	993	0.77 (0.46-0.95)	0.55 (0.52-0.57)	0.01 (0.007-0.013)	0.64	0.31
Ruminating chews per bolus	-3.7	13	1494	1.00 (0.75-1.00)	0.32 (0.30-0.34)	0.009 (0.008-0.009)	0.70	0.32
Ruminating chews per minute	-4.3	13	1850	1.00 (0.75-1.00)	0.15 (0.14-0.17)	0.007 (0.0069-0.0071)	0.52	0.15
Eating time	-1.7	9	802	0.69 (0.39-0.91)	0.63 (0.61-0.65)	0.011 (0.008-0.016)	0.63	0.32
Eating chews	-1.8	8	762	0.62 (0.32-0.86)	0.65 (0.63-0.67)	0.01 (0.007-0.016)	0.64	0.27
Other activity time	-2.35	9	585	0.69 (0.39-0.91)	0.73 (0.71-0.75)	0.015 (0.011-0.022)	0.72	0.42
Other chews	**-1.7**	**9**	**425**	**0.69 (0.39-0.91)**	**0.81 (0.79-0.82)**	**0.02 (0.01-0.03)**	**0.78**	**0.50**
Combination of variables:								
Ruminating chews per bolus + Ruminating chews per minute + Eating chews + Other activity time + Other chews	**-2.35**	**9**	**308**	**0.69 (0.39-0.91)**	**0.86 (0.84-0.87)**	**0.03 (0.02-0.04)**	**0.80**	**0.55**

[1] Log odds for conditional probability of calving (threshold for calving vs. non-calving classification)
[2] True positive alerts
[3] False positive alerts
[4] Positive predictive value
[5] Area under the ROC curve
[6] Youden's index

Table 4.8. Classification results of sensor variables as predictors for detection of calving events (Hour 0) in Validation Dataset 2 (Farm 3, n = 13 calvings) during a monitoring period of 168 hours before the start of calving. The 95% confidence intervals are indicated in parentheses. Bold values indicate predictors with an AUC ≥ 0.75. Criterion for threshold selection is maximizing the Youden's index (J).

Sensor variable	LO[1]	TP[2]	FP[3]	Sensitivity	Specificity	PPV[4]	AUC[5]	J[6]
Individual variable:								
Rumination time	**-2.1**	**9**	**518**	**0.69 (0.39-0.91)**	**0.76 (0.74-0.78)**	**0.02 (0.01-0.03)**	**0.75**	**0.46**
Ruminating chews	**-2.2**	**9**	**526**	**0.69 (0.39-0.91)**	**0.76 (0.74-0.78)**	**0.017 (0.012-0.024)**	**0.75**	**0.45**
Ruminating boluses	-2.2	10	706	0.77 (0.46-0.95)	0.68 (0.66-0.70)	0.014 (0.010-0.019)	0.70	0.45
Ruminating chews per bolus	-2.85	11	1016	0.85 (0.55-0.98)	0.53 (0.51-0.56)	0.011 (0.009-0.014)	0.73	0.38
Ruminating chews per minute	-3.7	12	1570	0.92 (0.64-1.00)	0.28 (0.26-0.30)	0.008 (0.007-0.009)	0.53	0.20
Eating time	-1.7	10	802	0.77 (0.46-0.95)	0.63 (0.61-0.65)	0.012 (0.009-0.017)	0.67	0.40
Eating chews	-2.15	11	1089	0.85 (0.55-0.98)	0.50 (0.48-0.52)	0.01 (0.008-0.013)	0.68	0.35
Other activity time	-1.8	8	324	0.62 (0.32-0.86)	0.85 (0.84-0.87)	0.024 (0.016-0.037)	0.74	0.47
Other chews	**-1.6**	**10**	**372**	**0.77 (0.46-0.95)**	**0.83 (0.81-0.85)**	**0.03 (0.02-0.04)**	**0.81**	**0.60**
Combination of variables:								
Rumination time + Ruminating chews + Ruminating boluses + Ruminating chews per bolus + Ruminating chews per minute + Eating chews + Other chews	**-3.15**	**10**	**306**	**0.77 (0.46-0.95)**	**0.86 (0.84-0.87)**	**0.03 (0.02-0.04)**	**0.79**	**0.63**

[1] Log odds for conditional probability of calving (threshold for calving vs. non-calving classification)
[2] True positive alerts
[3] False positive alerts
[4] Positive predictive value
[5] Area under the ROC curve
[6] Youden's index

For both validation datasets and prediction offsets, the combination of sensor variables improved the predictive performance and decreased the number of false positive alerts in comparison with individual sensor variables used as calving predictors. Nonetheless, the number of false positive alerts was considerably high.

4.4.2 Effect of reducing the evaluation timeframe of calving alerts

The alterations in performance metrics in response to the timeframe for evaluation are demonstrated in Table 4.9 and Table 4.10. We compared the results for an evaluation of calving alerts for a selection of sensor variables within a timeframe for analysis within 168 hours and 24 hours before the start of calving. The positive predictive values increased for the evaluation within the 24-h timeframe, due to the higher prevalence of the condition to be detected within the sample, i.e., 1 calving per 24 hours for evaluation compared with 1 calving per 168 hours for evaluation, whereas the sensitivity and specificity values remained broadly unchanged. The number of false positive alerts remained high, leading to low positive predictive values despite the higher prevalence of calving events within the analyzed timeframe.

Table 4.9. Comparison of classification results of sensor variables for prediction of calving events (Hour -1) in Validation Dataset 1 (Farm 2, n = 11 calvings) during a monitoring period of 168 vs. 24 hours before the start of calving. The 95% confidence intervals are stated in parentheses.

Sensor variable	Timeframe	LO[1]	TP[2]	FP[3]	Sensitivity	Specificity	PPV[4]
Rumination time	168 h	-1.7	8	243	0.73 (0.39-0.94)	0.87 (0.85-0.88)	0.03 (0.02-0.05)
	24 h	-1.7	8	36	0.73 (0.39-0.94)	0.86 (0.82-0.90)	0.18 (0.12-0.26)
Eating time	168 h	-1.4	3	198	0.27 (0.06-0.61)	0.89 (0.88-0.91)	0.015 (0.006-0.039)
	24 h	-1.4	3	44	0.27 (0.06-0.61)	0.83 (0.78-0.88)	0.06 (0.02-0.16)
Other activity time	168 h	-3.05	10	957	0.91 (0.59-1.00)	0.48 (0.46-0.51)	0.01 (0.009-0.013)
	24 h	-3.05	10	146	0.91 (0.59-1.00)	0.45 (0.39-0.51)	0.06 (0.05-0.08)

[1] Log odds for conditional probability of calving (threshold for calving vs. non-calving classification)
[2] True positive alerts
[3] False positive alerts
[4] Positive predictive value

Table 4.10. Comparison of classification results of sensor variables for prediction of calving events (Hour -1) in Validation Dataset 2 (Farm 3, n = 13 calvings) during a monitoring period of 168 vs. 24 hours before the start of calving. The 95% confidence intervals are stated in parentheses.

Sensor variable	Timeframe	LO[1]	TP[2]	FP[3]	Sensitivity	Specificity	PPV[4]
Rumination time	168 h	-2.5	10	835	0.77 (0.46-0.95)	0.62 (0.60-0.64)	0.012 (0.009-0.016)
	24 h	-2.5	10	109	0.77 (0.46-0.95)	0.65 (0.59-0.70)	0.08 (0.06-0.11)
Eating time	168 h	-1.7	9	802	0.69 (0.39-0.91)	0.63 (0.61-0.65)	0.011 (0.008-0.016)
	24 h	-1.7	9	122	0.69 (0.39-0.91)	0.61 (0.55-0.66)	0.07 (0.05-0.10)
Other activity time	168 h	-2.35	9	585	0.69 (0.39-0.91)	0.73 (0.71-0.75)	0.015 (0.011-0.022)
	24 h	-2.35	9	97	0.69 (0.39-0.91)	0.69 (0.63-0.74)	0.08 (0.06-0.12)

[1] Log odds for conditional probability of calving (threshold for calving vs. non-calving classification)
[2] True positive alerts
[3] False positive alerts
[4] Positive predictive value

4.5 Discussion

We developed a detection model for calving based on sensor measurements of ingestive behavior in dairy cows. The model was evaluated under the conditions that have to be expected in farming practice. Sensitivity and specificity values were satisfying, although the amount of false positive alerts was so high that the model is not suitable for application in practice. The positive predictive values were low due to the low prevalence of the condition to be detected (1 calving per 168 evaluation hours) and the high number of false positive alerts. Positive predictive values increased when evaluating the predictive performance for a shorter timeframe due to the higher prevalence of the condition to be detected (1 calving per 24 evaluation hours), whereas the ratio of false positive alerts was similarly high. Therefore, for assessment of detection models, it is important to evaluate them under conditions that have to be expected in commercial farming, particularly concerning the treatment of data in time series and practically relevant timeframes for evaluation. For this purpose, longitudinal studies have to be preferred over cross-sectional studies. We considered this aspect by evaluating the detection model for 168 hours before the start of calving. The possibility for an independent validation of the developed model was enabled by the fact that the data collection was conducted as a multicenter study on three different farms. We suggest to assess detection models not only by using sensitivity and specificity values but also taking the positive predictive values and the quantification of false positive alerts into account.

The advantage of the chosen modelling approach was, that the Naïve Bayes classifier is also suitable for comparably small samples and training datasets (Domingos and Pazzani 1997). Further advantage of using a Naïve Bayes classifier is, that missing values in the dataset can be ignored for training the classifier (Ramoni and Sebastiani 2001). That was of high relevance for the treatment of partially missing sensor data in our study. The Naïve Bayes classifier assumes conditional independence of the treated variables, thus making estimation much less computational expensive, as interactions between variables are ignored (Silva et al. 2013). Although the assumption of independence of variables is often violated, as it is in our analysis, this classifier has been found to generate satisfactory classification results in numerous studies (Domingos and Pazzani 1997, Rish 2001). For the analyzed sensor variables as predictors the conditional independence was also not met (e.g., rumination, eating), but adverse influence on the classifier is only to be expected in cases with strong inter-correlations among predictor variables (Langley and Sage 1994). The predictive model was fitted assuming a Gaussian distribution of the data. Although this assumption was not entirely fulfilled, we considered this by application of separate fitting of the extreme values (i.e., 0 and 60 minutes) within the boundaries of a 1-hour summary of sensor data. The lower and upper extreme values per 1-hour summaries (0 and 60 min within the boundaries of a 1-hour block) were separately fitted for the model, as duration of activities can be equal to zero or exceed the duration of 60 minutes beyond the boundary of an 1-hour summary interval, whereas the non-extreme values within an 1-hour summary represent a Gaussian distribution.

Predictive performance is a trade-off between both the sensitivity and specificity. Therefore, we used the Youden's index (Youden 1950) as a single metric derived from sensitivity and specificity for comparative assessment of the different sensor variables, as it allowed incomplex identification of predictors with high values for both sensitivity and specificity. Although the calculated sensitivity and specificity of our model were satisfying, it should be pointed out that the number of false positive alerts was considerably high, as indicated by low positive predictive values.

Rutten et al. (2017) stated, that detecting the moment of actual calving, i.e. completed expulsion of the calf, is not informative for the farmer, as potential dystocia should be detected and resolved shortly after the start of calving, and therefore recommended the start of the calving process as a better moment to generate an alert for calving. In our study, we considered this by selecting the time of the start of calving, not the moment of actual calving, as target variable of the predictive model. Additionally, we implemented a second prediction offset (Hour 0) to investigate, how the model would perform for detection of the actual moment of calving.

Advantageously, two independent datasets were available to validate the selected classifier approach. These were obtained from two different farms and satisfied the requirements defined by Dominiak and Kristensen (2017), who emphasized that a detection model must be validated externally to prove its accuracy. Therefore, they suggested a validation on data, which is completely independent from the training dataset and has been obtained from another herd, as it is fulfilled in our analysis. Although it was not possible to investigate farm-specific influences on the predictive performance in detail, as the sample size per farm was small, it can by hypothesized that there are numerous animal and farm specific influences such as parity, social interactions, and group size in the calving pen that may affect the pre-calving behavior and hence a model's ability to correctly detect behavioral changes resulting in a calving event. Nonetheless, the high prevalence of false positive alerts does not provide adequate usability of the described predictive model and is prohibitive for application in commercial setups. However, our results indicate that particularly variables of rumination behavior have predictive value and should be taken into consideration for future research on calving detection models.

Based on their review on model performance and alarm reducing methods in livestock production, Dominiak and Kristensen (2017) concluded that for 20 years, no sensor-based detection model has fulfilled the performance demands needed to generate a satisfyingly low level of false positive alarms, and these demands seem close to unreachable with the few models actually obtaining high performances being associated with high error rates. Moreover, these authors stated, that instead of focusing on fulfilling unreachable demands based on binary performance parameters for more complex conditions, future research could seek alternative approaches for the output of detection models, e.g., the prior probability or the risk of a condition occurring or not.

4.6 Conclusions

The study identified different best individual predictors for the two validation datasets. Ruminating chews were identified for Validation Dataset 1 and other chews, i.e., non-ingestive related jaw movements, for Validation Dataset 2. The best combination of calving predictors consisted of ruminating chews, ruminating boluses, and eating chews for Validation Dataset 1, and ruminating chews per bolus, ruminating chews per minute, eating chews, other activity time, and other chews for Validation Dataset 2. Although the calculated sensitivity and specificity were satisfying, the number of false positive alerts was considerably high, as indicated by low positive predictive values. The high prevalence of false positive alerts is prohibitive for practical application of the described predictive model under conditions of commercial dairy farming. However, we found that particularly variables of rumination behavior have predictive value and should be taken into consideration for future research on calving detection models. Specifically for detection models in livestock production, an assessment limited to the terms of sensitivity and specificity may be misleading. These parameters may achieve high values and suggest an adequate model performance, although the model is not suitable in the light of its expected use, as it was demonstrated by the findings of our study.

4.7 Ethical statement

All described experimental procedures were executed in accordance with the German federal legislation, notably the German Federal Animal Welfare and Protection Act (TSchG). All experimental procedures comply with the ARRIVE guidelines.

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4.10 References

Bayes, T., Price, R., Canton, J., 1763. An essay towards solving a problem in the doctrine of chances (pp. 370-418). C. Davis, Printer to the Royal Society of London.

Beer, G., Alsaaod, M., Starke, A., Schuepbach-Regula, G., Müller, H., Kohler, P., Steiner, A., 2016. Use of extended characteristics of locomotion and feeding behavior for automated identification of lame dairy cows. PloS one, 11, e0155796.

Berglund, B., Philipsson, J., Danell, O., 1987. External signs of preparation of calving and course of parturition in Swedish dairy cattle breeds. Animal Reproduction Science, 15, 61–79.

Bewick, V., Cheek, L., Ball, J., 2004. Statistics review 13: receiver operating characteristic curves. Critical Care, 8, 508.

Braun, U., Tschoner, T., Hässig, M., 2014. Evaluation of eating and rumination behaviour using a noseband pressure sensor in cows during the peripartum period. BMC Veterinary Research, 10, 195–203.

Büchel, S., Sundrum, A., 2014. Short communication: Decrease in rumination time as an indicator of the onset of calving. Journal of Dairy Science, 97, 3120–3127.

Burfeind, O., Suthar, V. S., Voigtsberger, R., Bonk, S., Heuwieser, W., 2011. Validity of prepartum changes in vaginal and rectal temperature to predict calving in dairy cows. Journal of Dairy Science, 94, 5053–5061.

De Mol, R. M., Woldt, W. E., 2001. Application of fuzzy logic in automated cow status monitoring. Journal of Dairy Science, 84, 400–410.

Detilleux, J., Arendt, J., Lomba, F., Leroy, P., 1999. Methods for estimating areas under receiver-operating characteristic curves: illustration with somatic-cell scores in subclinical intramammary infections. Preventive Veterinary Medicine, 41, 75–88.

Domingos, P., Pazzani, M., 1997. On the optimality of the simple Bayesian classifier under zero-one loss. Machine Learning, 29, 103–130.

Dominiak, K. N., Kristensen, A. R., 2017. Prioritizing alarms from sensor-based detection models in livestock production – A review on model performance and alarm reducing methods. Computers and Electronics in Agriculture, 133, 46–67.

Fan, J., Upadhye, S., Worster, A., 2006. Understanding receiver operating characteristic (ROC) curves. Canadian Journal of Emergency Medicine, 8, 19–20.

Hogeveen, H., Kamphuis, C., Steeneveld, W., Mollenhorst, H., 2010. Sensors and clinical mastitis - The quest for the perfect alert. Sensors, 10, 7991–8009.

Langley, P., Sage, S., 1994. Induction of selective Bayesian classifiers. In: Proceedings of the Tenth International Conference on Uncertainty in Artificial Intelligence, 399–406. Morgan Kaufmann Publishers Inc.

Metz, C. E., 1978. Basic principles of ROC analysis. Seminars in Nuclear Medicine, 8, 283–298.

Miedema, H. M., Cockram, M. S., Dwyer, C. M., Macrae, A. I., 2011a. Behavioural predictors of the start of normal and dystocic calving in dairy cows and heifers. Applied Animal Behaviour Science, 132, 14–19.

Miedema, H. M., Cockram, M. S., Dwyer, C. M., Macrae, A. I., 2011b. Changes in the behaviour of dairy cows during the 24h before normal calving compared with behaviour during late pregnancy. Applied Animal Behaviour Science, 131, 8–14.

Mollenhorst, H., Rijkaart, L. J., Hogeveen, H., 2012. Mastitis alert preferences of farmers milking with automatic milking systems. Journal of Dairy Science, 95, 2523–2530.

Ouellet, V., Vasseur, E., Heuwieser, W., Burfeind, O., Maldague, X., Charbonneau, É., 2016. Evaluation of calving indicators measured by automated monitoring devices to predict the onset of calving in Holstein dairy cows. Journal of Dairy Science, 99, 1539–1548.

Pahl, C., Hartung, E., Grothmann, A., Mahlkow-Nerge, K., Haeussermann, A., 2014. Rumination activity of dairy cows in the 24 hours before and after calving. Journal of Dairy Science, 97, 6935–6941.

Palombi, C., Paolucci, M., Stradaioli, G., Corubolo, M., Pascolo, P. B., Monaci, M., 2013. Evaluation of remote monitoring of parturition in dairy cattle as a new tool for calving management. BMC Veterinary Research, 9, 191.

Parkinson, T. J., England, G. C. W., Arthur, G. H., 2001. Chapter 6 - Parturition and the care of parturient animals. In: David, E. (Ed.), Arthur's Veterinary Reproduction and Obstetrics, eighth ed. W.B. Saunders, Oxford, pp. 155–187.

Proudfoot, K. L., Jensen, M. B., Heegaard, P. M., von Keyserlingk, M. A. G., 2013. Effect of moving dairy cows at different stages of labor on behavior during parturition. Journal of Dairy Science, 96, 1638–1646.

Ramoni, M., Sebastiani, P., 2001. Robust Bayes classifiers. Artificial Intelligence, 125, 209–226.

Rish, I., 2001. An empirical study of the naive Bayes classifier. In: Proceedings of IJCAI-01 Workshop on Empirical Methods in Artificial Intelligence 2001, 41–46, IBM.

Rutten, C. J., Kamphuis, C., Hogeveen, H., Huijps, K., Nielen, M., Steeneveld, W., 2017. Sensor data on cow activity, rumination, and ear temperature improve prediction of the start of calving in dairy cows. Computers and Electronics in Agriculture, 132, 108–118.

Schirmann, K., Chapinal, N., Weary, D. M., Vickers, L., von Keyserlingk, M. A. G., 2013. Short communication: Rumination and feeding behavior before and after calving in dairy cows. Journal of Dairy Science, 96, 7088–7092.

Schuenemann, G. M., Nieto, I., Bas, S., Galvão, K. N., Workman, J., 2011. Assessment of calving progress and reference times for obstetric intervention during dystocia in Holstein dairy cows. Journal of Dairy Science, 94, 5494–5501.

Silva, L. O. L. A., Koga, M. L., Cugnasca, C. E., Costa, A. H. R., 2013. Comparative assessment of feature selection and classification techniques for visual inspection of pot plant seedlings. Computers and Electronics in Agriculture, 97, 47–55.

Steensels, M., Antler, A., Bahr, C., Berckmans, D., Maltz, E., Halachmi, I., 2016. A decision-tree model to detect post-calving diseases based on rumination, activity, milk yield, BW and voluntary visits to the milking robot. Animal, 10, 1493–1500.

Streyl, D., Sauter-Louis, C., Braunert, A., Lange, D., Weber, F., Zerbe, H., 2011. Establishment of a standard operating procedure for predicting the time of calving in cattle. Journal of Veterinary Science, 12, 177–185.

Youden, W. J., 1950. Index for rating diagnostic tests. Cancer, 3, 32–35.

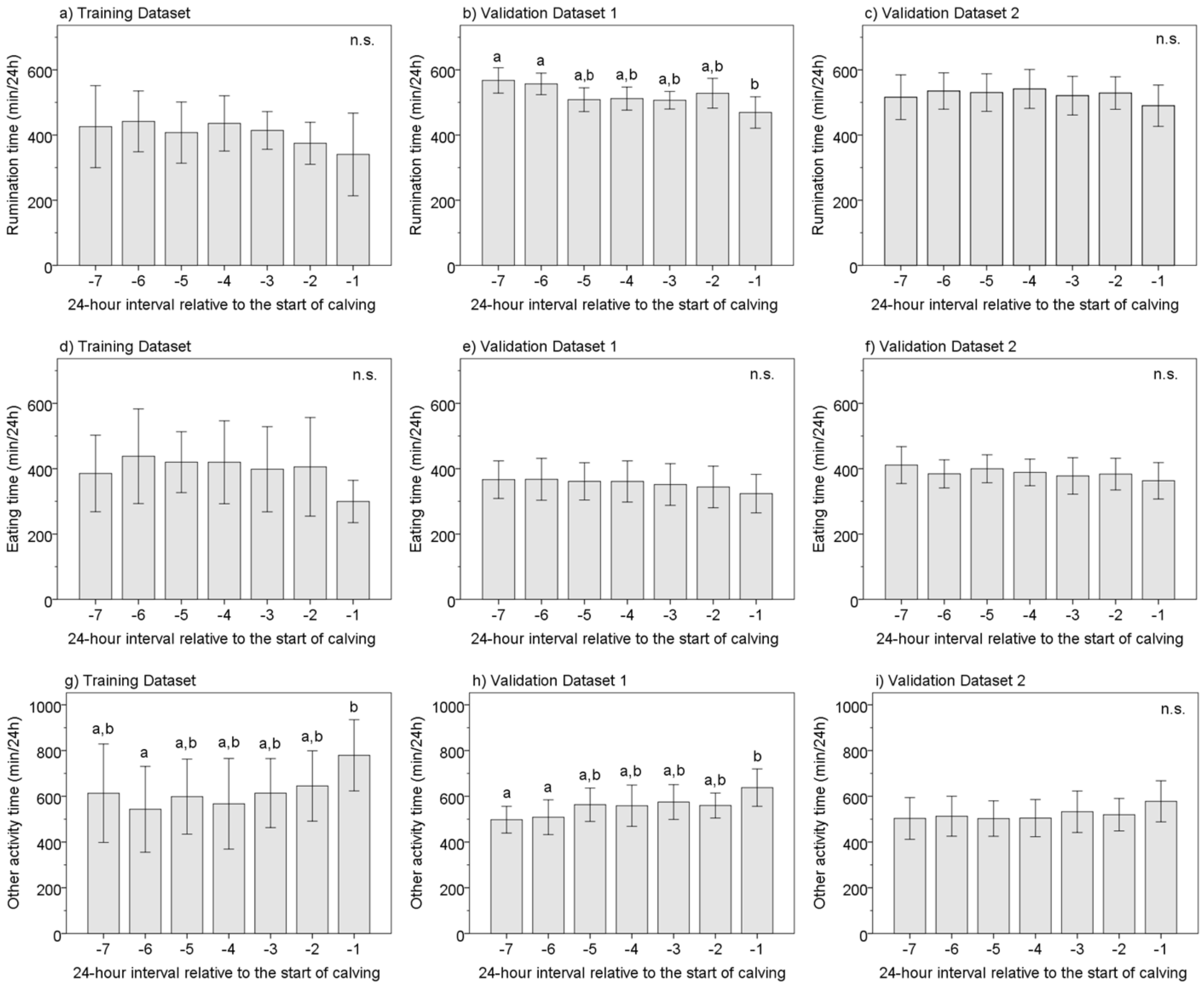
Zehner, N., Niederhauser, J. J., Nydegger, F., Grothmann, A., Keller, M., Hoch, M., Schick, M., 2012. Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows. In: Proceedings of International Conference of Agricultural Engineering CIGR-Ageng 2012, C0438.

Zehner, N., Umstätter, C., Niederhauser, J. J., Schick, M., 2017. System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows. Computers and Electronics in Agriculture, 136, 31–41.

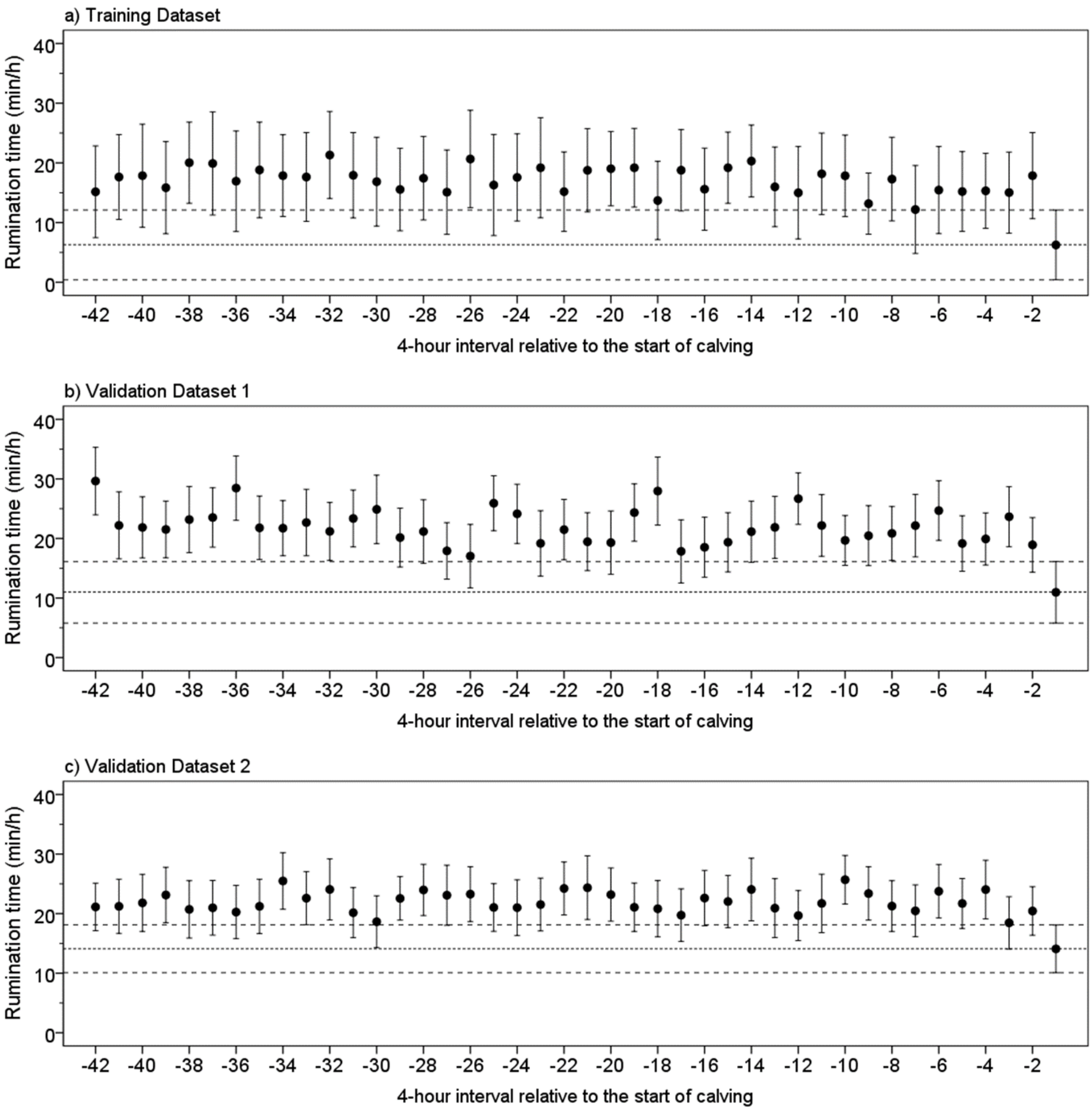
Zhang, J., Kang, D. K., Silvescu, A., Honavar, V., 2006. Learning accurate and concise naïve Bayes classifiers from attribute value taxonomies and data. Knowledge and Information Systems, 9, 157–179.

Zweig, M. H., Campbell, G., 1993. Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine. Clinical Chemistry, 39, 561–577.

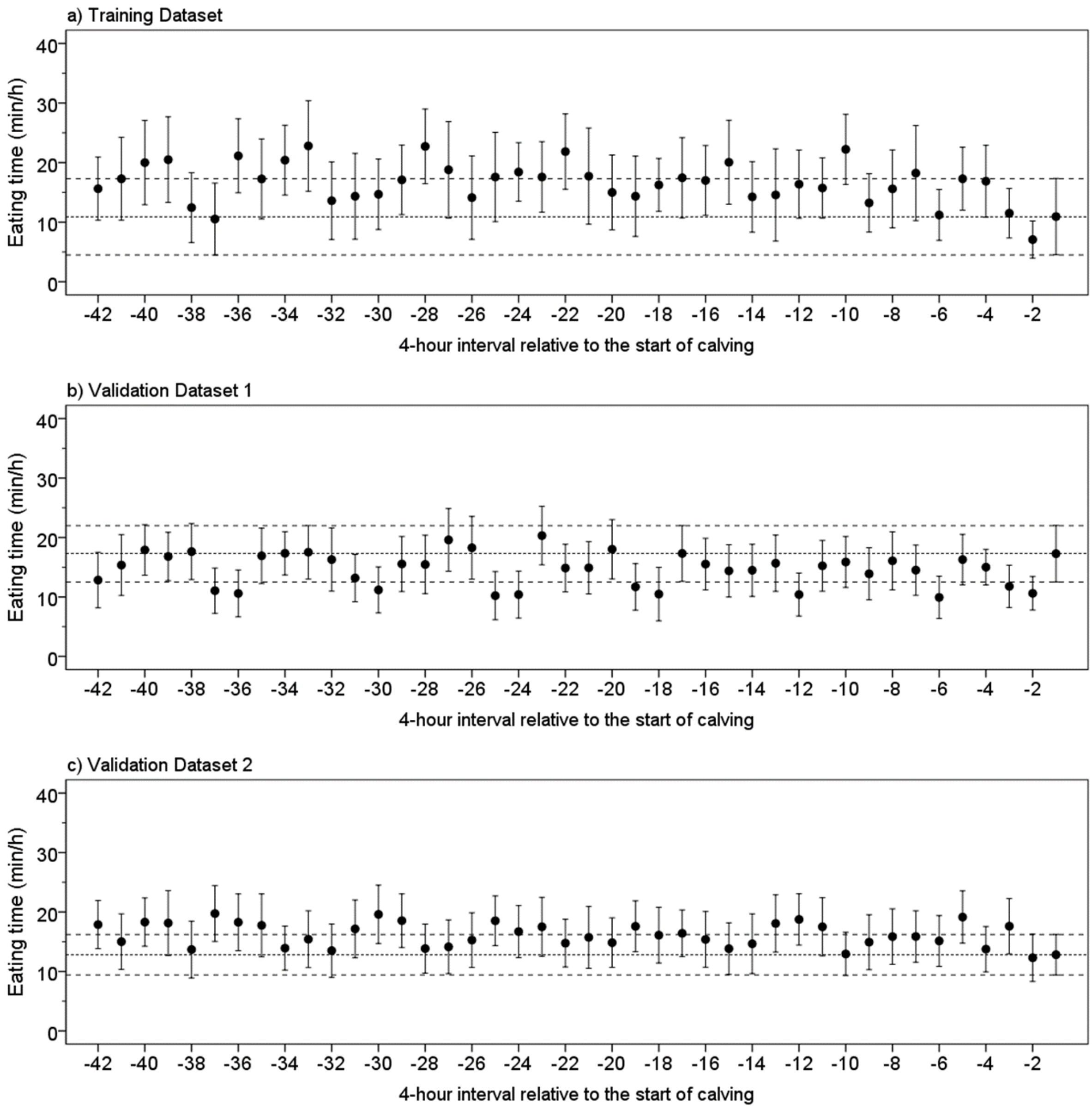
4.11 Supplementary material



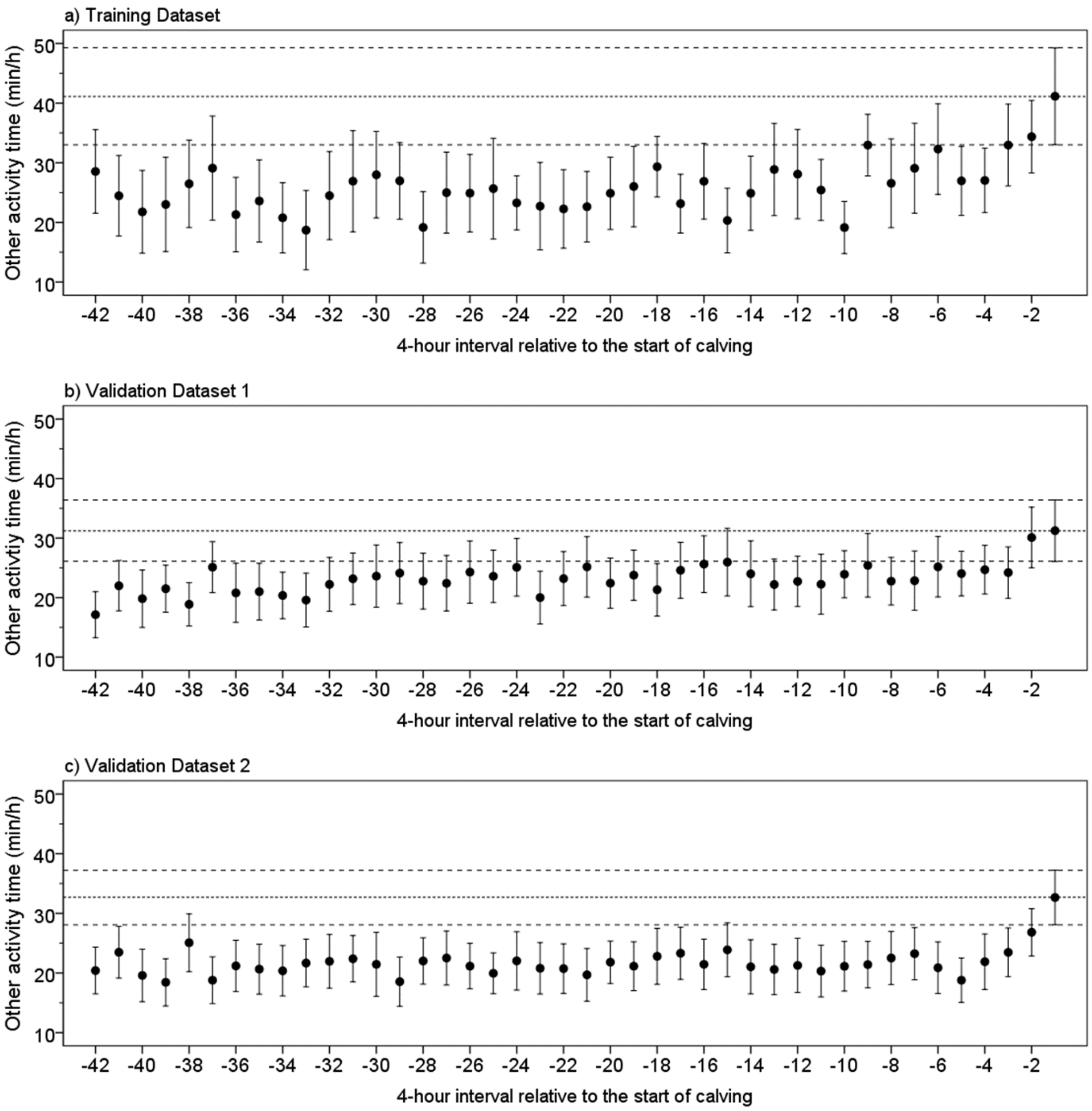
Supplementary Figure 1. Comparison of mean values per 24h-intervals preceding the start of calving for rumination time (a–c), eating time (d–f), and other activity time (g–i) in all three datasets. Intervals with different superscripts within a row differ significantly according to Friedman test ($p < 0.05$; n.s. = not significant). Error bars indicate the 95% confidence intervals of the mean.



Supplementary Figure 2. Average rumination times per hour within 4-hour intervals in the analysis period of 168 hours before the start of calving for all three datasets. Error bars indicate the 95% confidence intervals of the mean. Dotted lines show the mean and dashed lines indicate the lower and upper 95% confidence interval for the last 4-hour interval before the start of calving.



Supplementary Figure 3. Average eating times per hour within 4-hour intervals in the analysis period of 168 hours before the start of calving for all three datasets. Error bars indicate the 95% confidence intervals of the mean. Dotted lines show the mean and dashed lines indicate the lower and upper 95% confidence interval for the last 4-hour interval before the start of calving.



Supplementary Figure 4. Average other activity times per hour within 4-hour intervals in the analysis period of 168 hours before the start of calving for all three datasets. Error bars indicate the 95% confidence intervals of the mean. Dotted lines show the mean and dashed lines indicate the lower and upper 95% confidence interval for the last 4-hour interval before the start of calving.

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5 Validation of a sensor-based automatic measurement system for monitoring chewing activity in horses

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5.1 Abstract

The aim of this study was to determine the feasibility of using a jaw movement measuring system developed for cattle, the “RumiWatchSystem”, on horses. The system records the chewing activity and consists of a noseband pressure sensor, integrated into a halter, and a software package. In order to investigate the accuracy of the system, 10 horses (5 mares, 5 stallions) were equipped with the device. Additionally, they were observed visually as a reference method, while feeding three different feeds (hay, haylage and concentrate). To ensure similar conditions, the horses were stabled individually and fed twice daily with roughage and twice or three times with concentrate. The results of the visual observation were compared to the automatic measurement as an evaluation of the accuracy of the automatic measurement system. The overall agreement of the observed and automatically measured data within all feedstuffs was 93%. The agreement of feeding roughage was even higher with 95%. However, for concentrate the visual observations and automatic measurements agreed only in 91.4%. The decreased agreement compared to the roughage is due to the high sensitivity of the automated system. Horses tend to display a high amount of lip movements towards the end of the concentrate intake. This is different compared to cattle behaviour and their feeding regime. However, the system was not specifically adapted to horses so far and can be optimized in order to improve accuracy. Consequently, the system has a high potential to become a reliable tool for research and practical use.

Key words: Animal welfare, Feeding behaviour, Feeding management, RumiWatch, EquiWatch, Stereotypies

5.2 Introduction

The chewing activity of horses can be a suitable parameter for health and welfare assessment as the prevalent housing and feeding conditions often leave horses unsatisfied. Evolutionary, horses adapted over a long period of time to their ecological niche (Janis 1976). They used to live as grazers in steps with poor vegetation. Therefore, they are adjusted to a low energy and high fibre diet. The feed intake behaviour is defined by a long intake time of 12–16 h (Zeitler-Feicht 2008, McGreevy 2004) and travelling long distances of up to 28 km a day (Hampson et al. 2010). Because of the natural food resource, the gastric system is well adapted to small feeding bouts and a consistent filling of the stomach. With the help of microbial fermentation in the large caecum, it is possible to split high fibre feed (Frape 2010). In modern housing systems, compared to the natural behaviour, horses are often fed roughage restrictive (twice daily) with an additional feeding of grains. This leads to a high amount of starch over a small period of time and can cause illness of the gastro-intestinal system like gastric ulcerations (Hymøller et al. 2012). Even in pleasure horses the prevalence of gastric ulcer is 40–60% (Niedźwiedź et al. 2013). Additionally, horses are mostly individually stabled and there is often little or no possibility of social contact to other horses. In Northern Germany, 10% of stabled horses do not even have the possibility to observe their environment (Petersen et al. 2005). This deviation of natural behaviour may lead to abnormalities or stereotypies (Cooper and Albentosa 2005) and even to serious health problems. To evaluate and monitor the feed intake behaviour of a horse, it would be very valuable to measure the chewing activity automatically. The “RumiWatchSystem” could provide us with an assessment tool for different feeding regimes and husbandry systems.

There are still a number of unanswered questions, e.g. why such a high number of stomach ulcers occur in horses. Analyzing the chewing behaviour linked to different feeding regimes would provide us with valuable information and might lead us to the solution how to reduce stomach ulcers. Another possibility to use the system is to apply it in horse dentistry.

The jaw movements are an empiric and valid parameter to determine the chewing behaviour and was already subject of investigations (Bonin et al. 2007, Vervuert et al. 2013). However, there was no appropriate system to measure the chewing activity automatically until 2012, when the “RumiWatchSystem” became commercially available for cattle. Therefore, our aim was to test the equipment on horses in order to find out, if this would be an appropriate tool to improve horse management.

5.3 Material and methods

5.3.1 The automatic measurement system

The “RumiWatchSystem” (Itin+Hoch GmbH, Liestal, Switzerland) consists of a noseband pressure sensor with acceleration sensor, data logger with on-board analysis, and a software package including the “RumiWatch Converter Version 0.7.2.0” and the “RumiWatch Manager Version 0.9.6”. The sensor system was integrated into a commercially available horse halter as already described in Nydegger et al. (2010), (Figure 2.1). An oil-filled silicon tube with integrated pressure sensor in the noseband transmitted a signal to the data logger with a 10 Hz frequency, which was mounted in a plastic box at one end of the noseband. The signal was formed by a pressure difference inside the silicon tube due to jaw movements of a horse. These raw data were saved as binary data on an SD memory card, which was also located in the plastic box. Additionally, raw data were saved as a csv-file, labelled according to the four categories: eating, ruminating, drinking or other activities. This classification was done by an algorithm, originally developed for cattle.

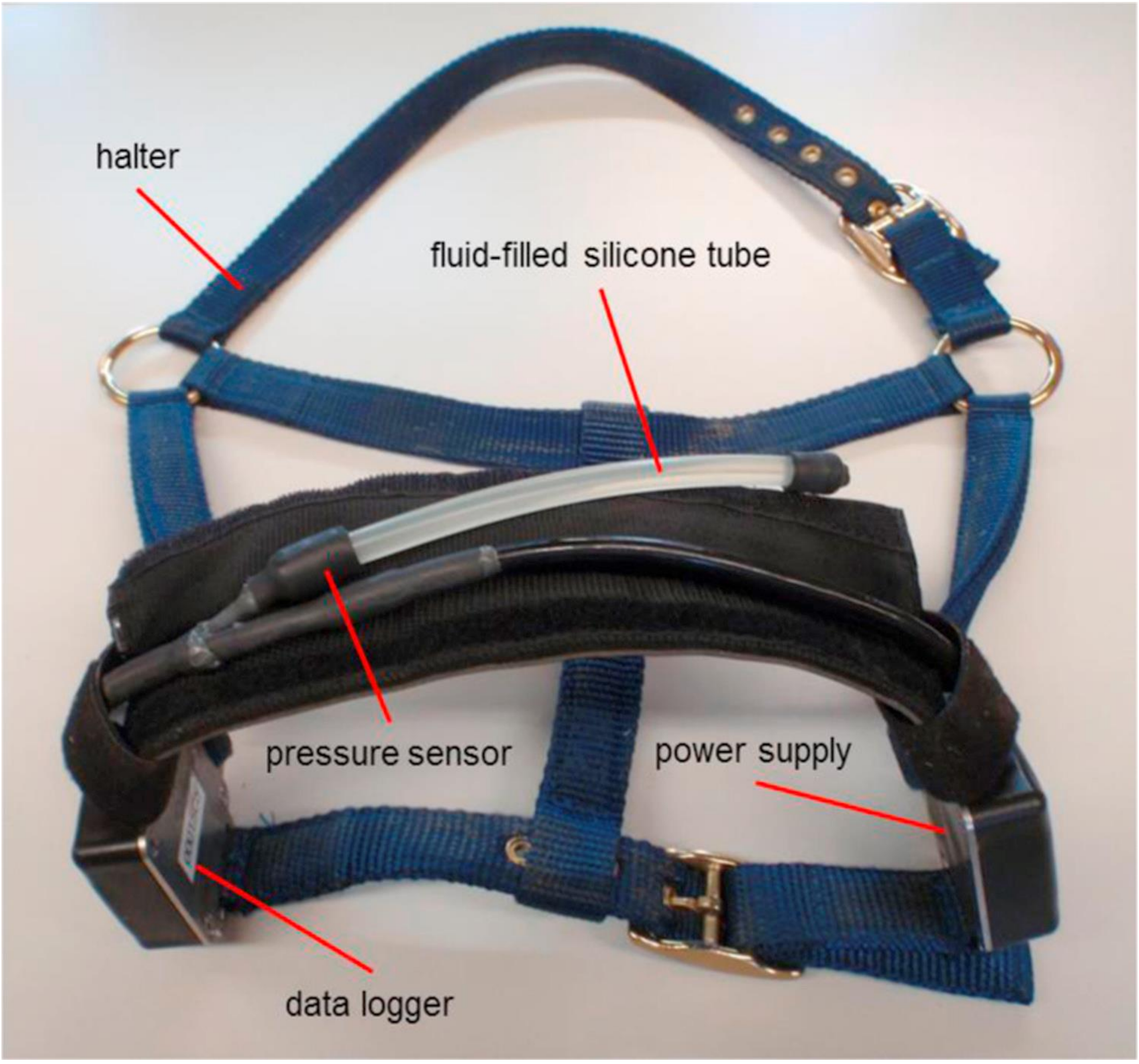

Figure 5.1. Specifics of the automated measurement system ("RumiWatch"), integrated in a commercially available horse halter

The power supply was provided by a 3.6 V battery, which lasts for 3 years under laboratory conditions due to a low energy operating system. It was mounted in a second plastic box on the other side of the noseband. The raw data transfer was made via a USB plug-in connection. Additionally, 24 h-summaries divided in 1 h-summaries were transmitted wireless via an ANT-standard-antenna to the "RumiWatch Manager" software.

The automatic quantification of the chewing activity was determined by pressure peaks. Every peak above the threshold of 28 mbar was counted as a chew. The absolute values could not be taken into account because the pressure inside the silicon tube was not standardized. That means precisely, that not the height of a peak determined the chewing activity but the frequency of peaks. In this study, there was no differentiation between chews and bites. Additional information about the system can be found in Nydegger et al. (2011), Zehner (2012) and Zehner et al. (2012).

5.3.2 Animals, housing, feeding management

In this study, ten horses (5 stallions, 5 mares) were used. Two breeds were included in the trials, eight "Freiberger" and two "Swiss Warmblood". They aged 8 to 17 years and weighed on average 601±38 kg. All horses were stabled individually and were bedded on straw with daily access to paddocks. Mares were not used for exercise, but stallions were schooled under saddle or driven 2-4 days a week. Before the study commenced, all horses were checked by veterinarians of the "Institut suisse de médecine equine" (ISME-Swiss Institute of Equine Medicine, Avenches, Switzerland) regarding their body condition and dental health. There were no specific findings, which would differ from a normal health status.

The feeding management was adjusted to the experimental design. All horses were fed twice daily with roughage (hay or haylage). Concentrate was fed twice a day to mares and three times a day to stallions. The sensory analysis of feed revealed a good quality for both groups, stallions and mares. However, the hay of the stallion group appeared to have a lower amount of structure than the hay of the mares group. The haylage for both groups was of equal quality and appearance. The concentrate was a mixture of pellets, bruised barley, corn flakes, sunflower seeds and linseeds.

5.3.3 Experimental design

The horses were observed visually – as a reference method – while feeding three different types of feed (hay, haylage and concentrate). Therefore, all five horses of each group (mares/stallions) were equipped with a noseband pressure sensor, integrated in a leather halter. The visual observations were recorded with a tablet device. A modified Microsoft

Excel sheet with a user interface enabled the observer to record each jaw movement with a time stamp and behavioural category (Zehner 2012). These categories needed to be determined manually in advance. In our case we chose the categories “feed intake roughage”, “feed intake concentrate”, “drinking” and “other activities”.

The study was divided into four trial periods (Table 5.1); mares hay, mares haylage, stallions hay, stallions haylage. Within each trial period, the horses were observed visually for 10 min in the morning and 10 min in the evening while feeding either hay or haylage over duration of three days. There was an adaptation period with no observation of at least three days in between the different trial periods. Additionally, all horses were observed while eating concentrate for 5 min, except of the mares in Trial period 2. As Trial period 1 showed that the concentrate intake of the mares lasted often less long than the observation period, it was decided to adapt the observation period to the actual intake time (3–9 min) in Trial period 2.

Table 5.1. Experimental design. Horses were equipped with the RumiWatch system continuously and were observed additionally for determined periods. There was an adaptation period of three days between the different trial periods.

Trial period	Feed	Horses	Observation period (per horse/day)	No. of days
1	hay + concentrate	5 mares	hay: 2x10 min, concentrate: 2x5 min+1x5 min	3 days
2	haylage + concentrate	5 mares	haylage: 2x10 min, concentrate: 2x3–9 min+ 1x3–9 min	3 days
3	hay + concentrate	5 stallions	hay: 2x10 min, concentrate: 2x5 min+1x5 min	3 days
4	haylage + concentrate	5 stallions	haylage: 2x10 min, concentrate: 2x5 min+1x5 min	3 days

5.3.4 Data evaluation

The comparison of both systems (observational and automated) was based on the amount of chews per minute. The evaluation software “RumiWatch Converter” was used for the analysis of the automatically recorded data. The converter was able to summarize the recorded data minute by minute regarding the amount of chews. The observational measurements were analyzed by manually counting the detected chews.

5.3.5 Statistical analysis

Preliminary data analysis and handling of statistical information was done using Microsoft Excel Version 2010 (Microsoft Corporation, Redmond, USA). The major statistical analysis was carried out using the statistics program SPSS Version 22 (IBM Corporation, Armonk USA).

At first, the mean “amount of chews” measured automatically and visually within the observational periods was compared. Due to a not normally distributed sample of chews per minute for each feed, a non-parametric statistical test was used. As halters were allocated to individual horses throughout the experimental period, we used the Wilcoxon-signed-rank-test for analyzing the paired samples. The significance level was set at $p=0.05$.

Afterwards, the agreement of both measurement methods was analyzed by the following formula: Agreement in percentage = (Chews(aut) / Chews(vis))*100.

Chews vis = amount of chews measured visually in an observation period.

Chews aut = amount of chews measured automatically in an observation period.

A graphical analysis was made by using the Bland–Altman-Plot (Bland and Altman 1986, Grouven et al. 2007). This plot demonstrates the agreement between both measurement methods. The middle line indicates the mean difference between the paired automated and visual observations (chews visual-chews automated) plotted against the mean of the automated and visual paired values ((chews visual+chews automated)/2). The lines above and below indicate the confidence interval of 95%.

5.4 Results

5.4.1 Pressure signatures

The software package “RumiWatch Converter” enabled a visualization of the data. Figure 5.2 shows the pressure signatures, generated by the noseband pressure sensor, while three different types of feed were fed.

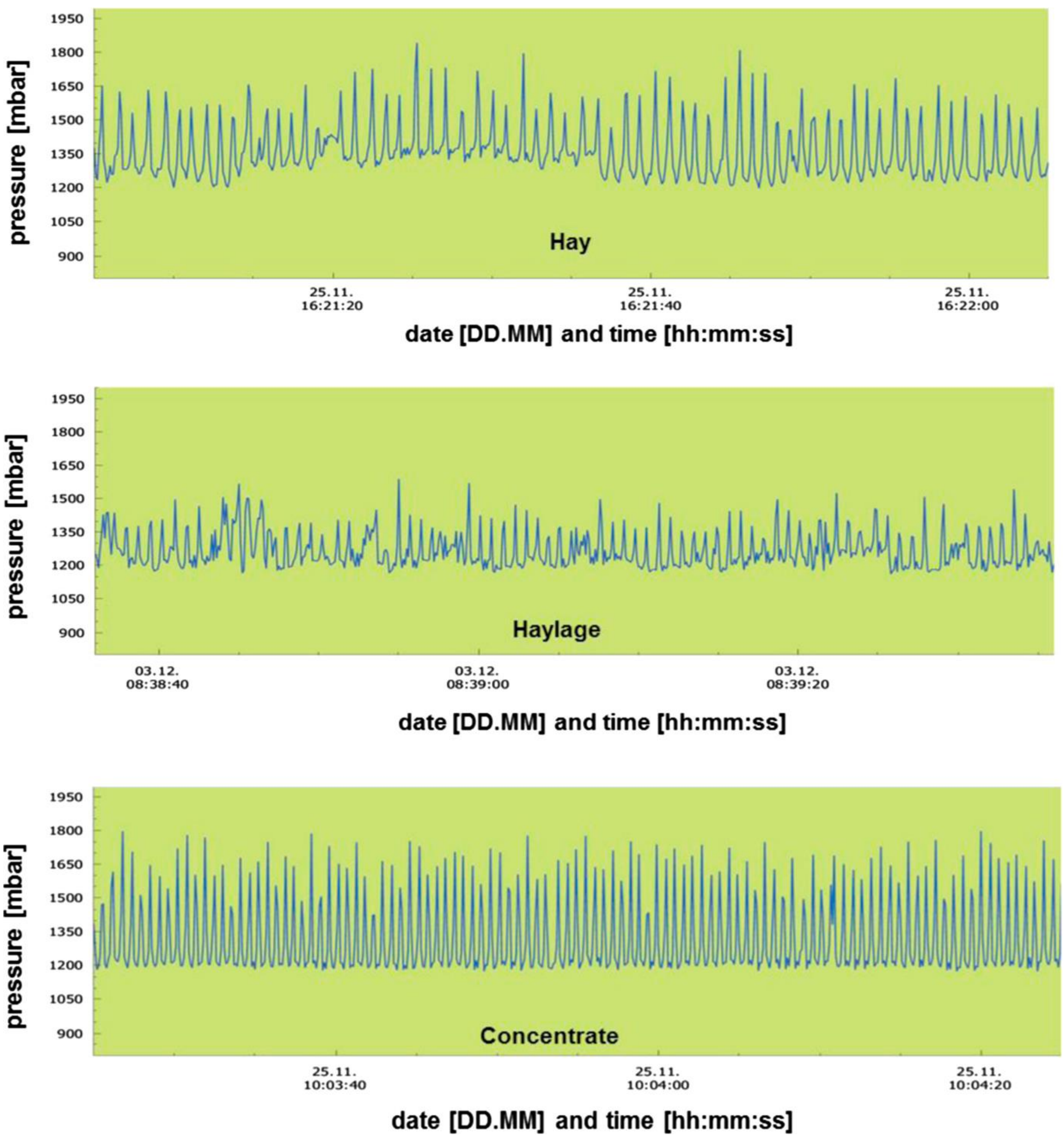

Figure 5.2. Pressure signatures of the same noseband pressure sensor for different feed types.

Each feed type was fed to each horse. Comparing the three different varying profiles, the difference between hay and haylage in the horses' chewing activity is apparent. However, even more distinct is the difference of chewing activity during concentrate intake. The frequency of chews increased from feeding hay to haylage to concentrate. That means chews per minute are highest in feeding concentrate.

5.4.2 Mean of chews per minute

The results of chews per minute measured visually and automatically by feeding three different feeds were summarized in a Box–Whisker-Plot (Figure 5.3). It can be found that the whisker down to the minimum is always longer than the whisker up to the maximum value for all combinations (feed types and measurement methods). That means, the deviation of the amount of chews in the smaller values is larger than in the range above the median. There is also a larger span in visual observations in the area of upper and lower quartiles, compared to the automatically measured values in all feedstuffs, especially in feeding hay. In feeding haylage the box of 75% of all data is smallest in both measurement methods, whereas the feeding of concentrate causes a wider range of amount of chews per minute, recorded by both systems.

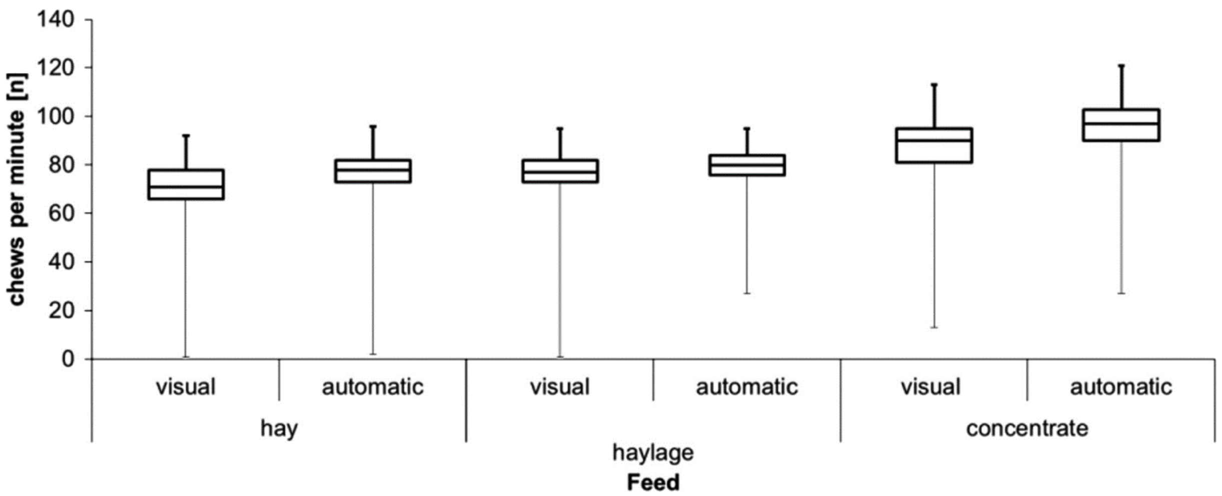

Figure 5.3. Box–Whisker-Plots detailing the amount of chews per minute for both measurement methods (visual vs. automatic) and three different feed types (hay, haylage, concentrate).

The mean of all measurements while feeding hay was 70±13 chews per minute observed visually and 76±11 chews per minute measured automatically. That led to a difference of 6 chews per minute in favour of the automatic measurement system. Due to a not normally distributed sample, the Wilcoxon-signed-rank-test as a non-parametric test was carried out to analyze the differences between means. In case of feeding hay, the mean for “amount of chews” of both measurement methods was different ($p<0.001$).

The second feed, which was tested, was haylage. The mean amount of chews were 76±9 chews per minute by visual observation and 79±7 chews per minute by automatic measurement. This resulted in a higher amount of chews for the automatic recording of 3 chews per minute. The statistical analysis revealed a difference between both measurement methods while feeding haylage ($p<0.001$).

In addition to the two roughages, the horses were observed over a period of 5, respectively 3–9 min while eating concentrates. The mean amount of chews, measured visually were 86±15 chews per minute. In comparison, the automatic measurement system recorded 95±11 chews per minute. That implies, that the value of the automatic measurement is 9 chews per minute higher than the visual observation. The difference between the measurement methods is verified by statistical analysis ($p<0.001$).

Summarizing all measured minutes across the three different feeds, the amount of chews per minute observed visually (78±15) was always lower than the value of the automatic measurement system (85±13).

5.4.3 Agreement between measurement methods

The agreement between the automatic measurement and the visual observation as a reference method was determined by the comparison of amount of chews per minute (Table 5.2). A highly encouraging overall agreement of 93.3% between both measurement methods was found. Looking at the results of the different feed types, the agreement between the automated system and visual observations was greatest when feeding haylage (96.8%). Overall, the agreement of roughage (94.7%) was higher than the agreement while feeding concentrate (91.4%).

Table 5.2. Agreement between measurement methods. Mean of agreement and standard deviation between the visual reference method and the automatic measurement system in percent.

	Mean of agreement[a] [%]	**Standard deviation [%]**
Total	93.3	18.1
Hay	92.4	13.9
Haylage	96.8	14.0
Concentrate	91.4	22.5

Chews aut = amount of chews per minute measured automatically in an observation period.
Chews vis = amount of chews per minute measured visually in an observation period.
[a] Mean of agreement [%]= (chews(aut)/(chews(vis)*100.

The agreement between both measurement methods is presented graphically in a Bland–Altman-Plot (Figure 5.4). The figure shows, that if the amount of chews per minute increased, then the difference between the measurement methods decreased. The greatest variation between the systems was identified in ranges of lower than 70–75 chews per minute.

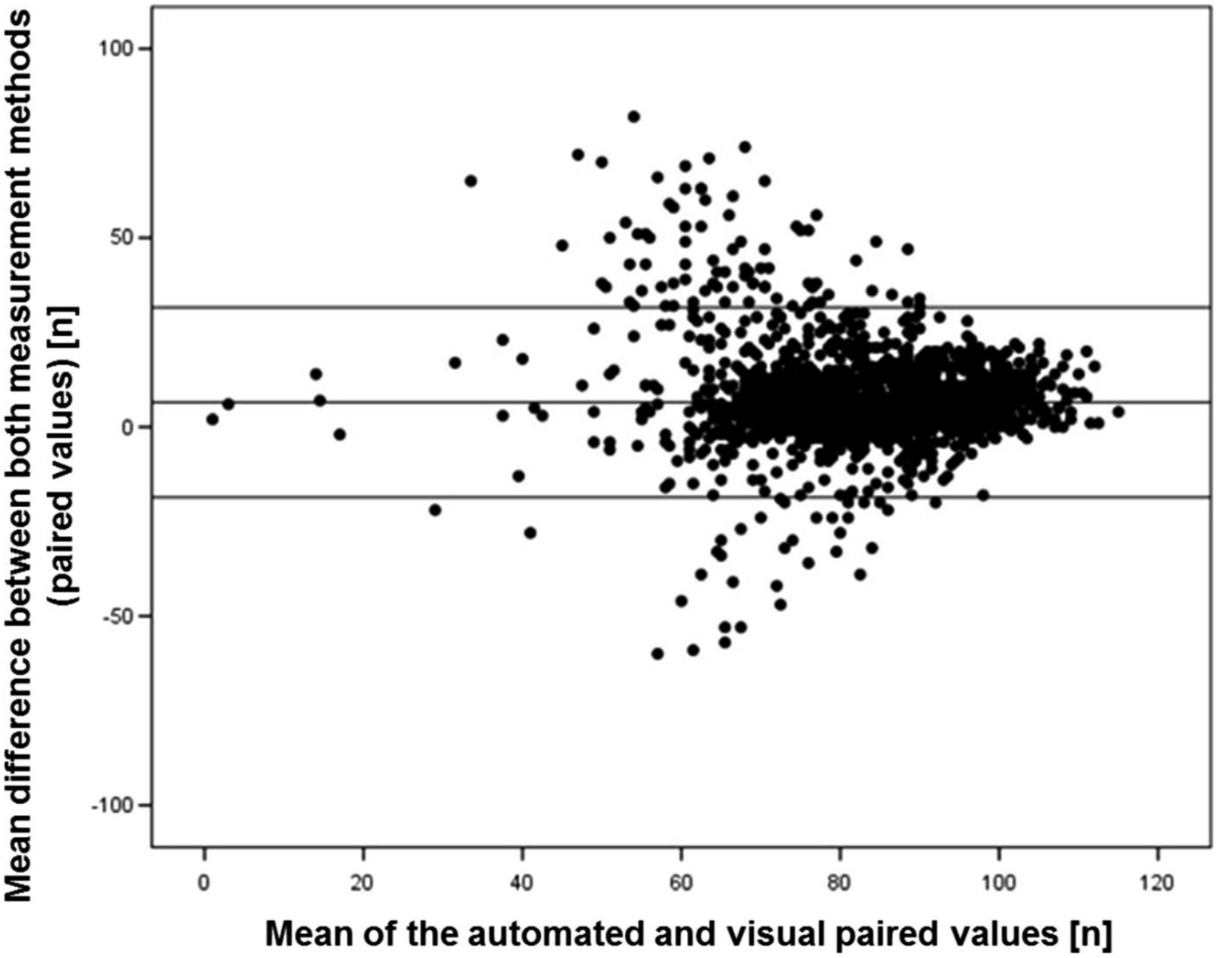

Figure 5.4. The Bland–Altman-Plot demonstrates the difference between both measurement methods. The middle line indicates the mean difference between the paired automated and visual observations (chews vis-chews aut) plotted against the mean of the automated and visual paired values ((chews vis+chews aut/2)). The lines above and below indicate the confidence interval of 95% (Mean=6.25; limit lines=+32 and −19).

By looking at the individually measured minutes, it was found, that the difference between both measurement methods changed with increasing minute number (Figure 5.5), particularly for feeding concentrate. However, it should be pointed out that the sample size for Minutes 6–9 of concentrate feeding decreased considerably. Therefore, the data interpretation needs to be done carefully.

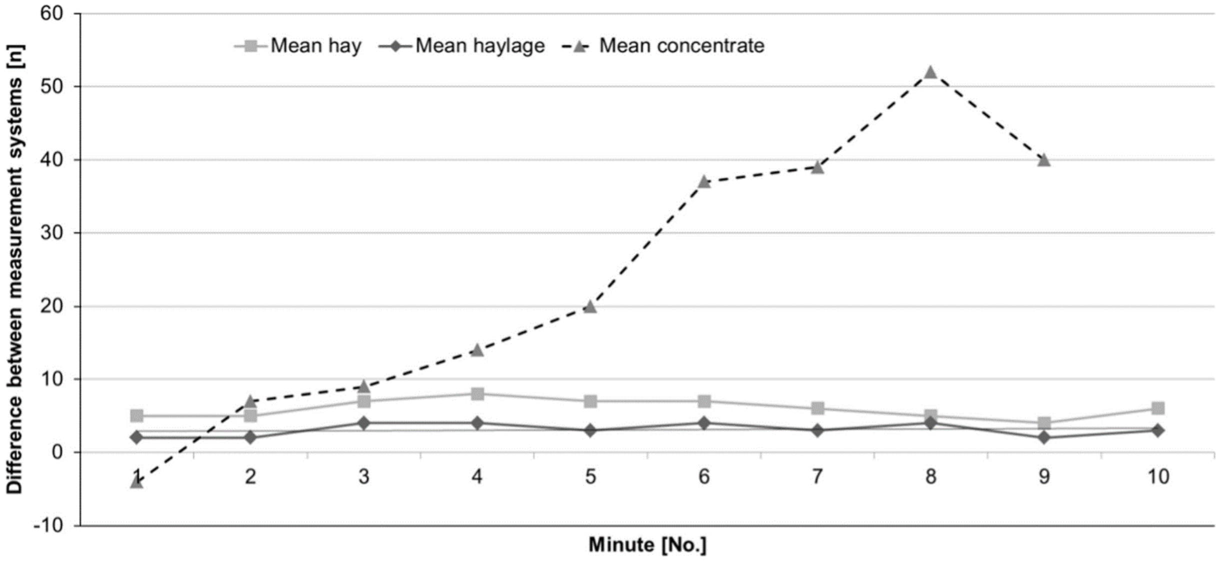

Figure 5.5. Mean of differences between visual observations and automatic measurement of amount of chews per minute while feeding different feeds. Positive values are caused by a higher amount of chews measured automatically. The sample size of Minutes 6–9 is much smaller for feeding concentrate (n<18) compared to Minutes 1–5 and give, therefore, only an indication of the trend.

5.5 Discussion

The results of the study showed successfully that it is feasible to use the “RumiWatchSystem” on horses. The overall agreement of 93% between visual and automatic measurements demonstrated the good accuracy, even though the system was developed for cattle.

The agreement of feeding haylage (97%) was higher compared to feeding hay (92%). One reason might be, that the chewing activity was more rhythmical than feeding hay. Another reason for falsely identified chews could have been the interruptions by drinking behaviour while feeding hay, as the moisture content in hay is much lower than in haylage. The automatic system might have identified the lip movements while drinking as chewing, whereas the observer did not count them as chews.

The amount of chews per minute while feeding three different feeds is noteworthy. It increased from hay to haylage to concentrate. Unlike our results, Vervuert et al. (2013) found a lower amount of chews (66±12 chews per minute) for feeding haylage than feeding hay (70±15 chews per minute). This might have been caused by the ad libitum feeding in their study, whereas in our study a restricted feeding regime was carried out. Another possible reason for influencing the results might have been the quality of the feed stuff as horses tend to prefer good quality hay to good quality haylage (Müller and Udén 2007).

The amount of chews while feeding concentrate (95±11 chews/min automatically vs. 86±15 chews/min visually) correspond with results of a study done by Meyer et al. (1975), 70–93 chews per minute.

The results in Figure 5.5 show, that the sensor system detected more chews than the observer after the fourth minute. This was caused by the fact, that the horses used their lips to search the last feed crumbs. These movements were detected as chews whereas the observer did not count them as chews. This resulted in the large differences between both measurement methods occurring after the fourth minute. It should be kept in mind, that the algorithm to detect chews was developed for cattle. In their specific chewing behaviour, cattle use their tongue to rip the grass. Therefore, they show less lip movements than horses. The system overestimates horses' chewing activity because of the adaption to the specific chewing behaviour of cattle.

The automatic measurement system is very easy to use, as the device is similar to a standard horse halter. This improved the acceptance of wearing the system by the horse, as all horses were halter trained. Additionally, the three buckled straps of the halter enabled us to fit the halters individually. The storage and analysis of raw data was user-friendly and easy to carry out with the help of the software package. One critical issue might be the danger of injuries as a horse could get stuck, caused by the halter. Integrating a predetermined breaking point or an elastic connecting piece might be a suitable fix to avoid accidents. The wearing over a period of 6 days was causing small skin irritations in two horses. This might be fixed by changing the halter material or adding appropriate padding. In this study, heavy leather halters were used, with the seams being inside, close to the horses' skin, rubbing on the cheek bones. Another critical location for small skin irritations was at the moving jaw bone. However in comparison to some invasive systems, which were used by Vervuert et al. (2013), the noseband sensor is more justifiable under animal welfare criterias.

The benefit of an automatic measurement system of chewing behaviour could be manifold. In Precision Livestock Farming (PLF) automated animal monitoring is often used to develop early warning systems for health and welfare issues. Although the aims and circumstances in horse husbandry often differ from other livestock production branches, the principals of PLF can also be advantageous in the equine sector. As Berckmans (2006) pointed out, observations done by humans are a limiting factor compared to an automatic monitoring system. The “RumiWatchSystem” could be employed e.g. as an early warning system for the beginning of parturition. Furthermore, it could be used as an assessment tool for husbandry systems or feeding regimes or even providing additional information on the development of stereotypies.

5.6 Conclusions

The study successfully demonstrated that it is feasible to use the “RumiWatchSystem” to horses. Although it was developed for cattle, the overall agreement of 93% was highly encouraging. The analysis indicated that the differentiation between chews and other muzzle and lip movements could improve the overall performance of the system. Therefore, to optimize the recording of the chewing activity, the analysis algorithm developed for cattle, could be adapted to the monogastric species ‘horse’. However, the system could be, after minor refinements, a valuable and easy-to-use tool for equine research and management.

5.7 Acknowledgements

The study was carried out in collaboration with the Swiss National Stud Farm in Avenches. Special thanks is owed to the facility staff and the people, who helped with the organization and realization of this study.

5.8 References

Bland, J.M., Altman, D., 1986. Statistical methods for assessing agreement between two methods of clinical measurement. The Lancet, 327, 307–310.

Berckmans, D., 2006. Automatic on-line monitoring of animals by precision livestock farming, in: Geers, R., Madec, F. (Eds.), Livestock production and society. Wageningen Academic Publishers, The Netherlands, pp. 287–294.

Bonin, S.J., Clayton, H.M., Lanovaz, J.L., Johnston, T., 2007. Comparison of mandibular motion in horses chewing hay and pellets. Equine Veterinary Journal, 39, 258–262.

Cooper, J.J., Albentosa, M.J., 2005. Behavioural adaptation in the domestic horse: potential role of apparently abnormal responses including stereotypic behaviour. Livestock Production Science, 92, 177–182.

Frape, D., 2010. Equine nutrition and feeding. Fourth edition, John Wiley & Sons, Hoboken, United Kingdom.

Grouven, U., Bender, R., Ziegler, A., Lange, S., 2007. Vergleich von Messmethoden [German]. Deutsche Medizinische Wochenschrift, 132, e69-e73.

Hampson, B.A., De Laat, M.A., Mills, P.C., Pollitt, C.C., 2010. Distances travelled by feral horses in 'outback' Australia. Equine Veterinary Journal, 42(s38), 582–586.

Hymøller, L., Dickow, M.S., Brøkner, C., Austbø, D., Jensen, S. K., 2012. Cereal starch, protein, and fatty acid pre-caecal disappearance is affected by both feed technological treatment and efficiency of the chewing action in horses. Livestock Science, 150, 159–169.

Janis, C., 1976. The evolutionary strategy of the Equidae and the origins of rumen and cecal digestion. Evolution, 30, 757–774.

McGreevy, P., 2004. Equine behavior: a guide for veterinarians and equine scientists. Saunders, Philadelphia, USA.

Meyer, H., Ahlswede, L., Reinhardt, H.J., 1975. Untersuchungen über Fressdauer, Kaufrequenz und Futterzerkleinerung beim Pferd [German]. Deutsche Tierärztliche Wochenschrift, 82, 54–58.

Müller, C.E., Udén, P., 2007. Preference of horses for grass conserved as hay, haylage or silage. Animal Feed Science and Technology, 132, 66–78.

Niedźwiedź, A., Kubiak, K., Nicpoń, J., 2013. Endoscopic findings of the stomach in pleasure horses in Poland. Acta Veterinaria Scandinavica, 55, 45.

Nydegger, F., Gygax, L., Egli, W., 2010. Automatic measurement of rumination and feeding activity using a pressure sensor. In: International Conference on Agricultural Engineering-AgEng 2010: towards environmental technologies, Clermont-Ferrand, France, 6-8 September 2010. Cemagref.

Nydegger, F., Gygax, L., Wendelin, E., 2011. Automatic measurement of jaw movements in ruminants by means of a pressure sensor. Agrarforschung Schweiz, 2, 60–65.

Petersen, S., Tölle, K.H., Blobel K., Grabner A., Krieter J., 2005. Erhebungen zur Pferdehaltung in Pensionsbetrieben Schleswig-Holsteins [German]. Züchtungskunde 78, 207–217.

Vervuert, I., Brüssow, N., Bochnia, M., Cuddeford, D., Coenen, M., 2013. Electromyographic evaluation of masseter muscle activity in horses fed (i) different types of roughage and (ii) maize after different hay allocations. Journal of Animal Physiology and Animal Nutrition 97, 515–521.

Zehner, N., 2012. Validation of a new method (RumiWatch) for combined automatic measurement of rumination, feed intake and locomotion in dairy cows. Master thesis, University of Kiel, Faculty of Agricultural and Nutritional Science.

Zehner, N., Niederhauser, J.J., Nydegger, F., Grothmann, A., Keller, M., Hoch, M., Schick, M., 2012. Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows. In: Proceedings of International Conference of Agricultural Engineering CIGR-Ageng 2012, C0438.

Zeitler-Feicht, M.H., 2008. Handbuch Pferdeverhalten - Ursachen, Therapie und Prophylaxe von Problemverhalten [German]. Second edition. Eugen Ulmer-Verlag, Stuttgart, Germany.

6 General Discussion

6.1 Further development and prospects

6.1.1 Analysis routines

The RumiWatch (RW) System, comprising a noseband sensor integrated into a halter and a pedometer, were successfully developed and validated for an indoor environment. The next development step will be the adaptation for a grazing environment. This further development is already on the way for the RW noseband sensor (Rombach et al. 2015a, Werner et al. 2017a). The broadening of its usage, by including the grazing environment, is a valuable step for supporting the advisory services and dairy farming. It is estimated that 9 billion people will be starving in 2050 and it is envisaged that a big part of the solution will be the usage of the world's grasslands (O'Mara 2012). In this light, intake estimation on pasture will play an important role in optimizing pasture management. The RW device can be utilized to develop algorithms for intake estimation on pasture as well as to determine bite to chew ratios for a qualitative assessment of herbage. Rombach et al. (2015b, 2016, 2017) focused on the estimation of herbage intake based on measurements of grazing behavior using the RW noseband sensor and calculated it including the parameters herbage dry matter per hectare, daily milk yield, milk protein and lactose content. A potential user interface for such easy-to-use software for intake estimation is depicted in Figure 6.1. Further research by Werner et al. (2017b) has given an indication of importance of some of the RW parameters to evaluate pasture allocation for dairy cows. In their study, grazing behavior in terms of bite frequency was significantly increased for a treatment (60% herbage allowance) over a control (100% herbage allowance) group, whereas rumination behavior in terms of rumination time per day and chews per bolus were significantly decreased for the treatment group. These results showed that particularly rumination behavior may be a suitable indicator of appropriate grass allocation per cow. Hence, automated monitoring of these parameters in dairy cows may be indicative of insufficient grass allocation and may allow decision support for improved management of pasture based dairy systems.

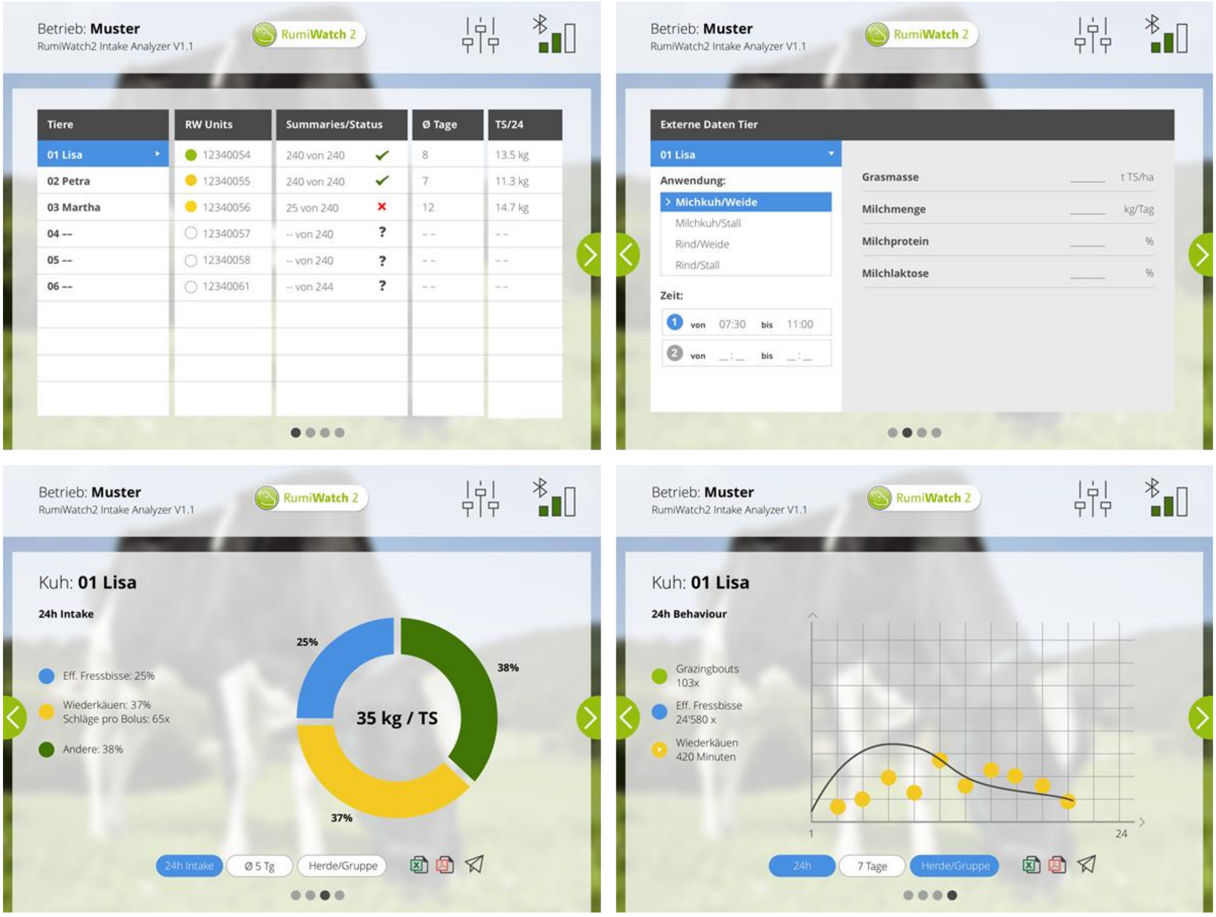

Figure 6.1. RumiWatch 2 – user interface for a software tool for intake estimation on pasture based on measurements of the RW noseband sensor, containing an animal list (upper left), herbage and milk yield data (upper right), intake calculation (lower left), and visualization of chewing activities (lower right).

Further enhancement of the RW System is projected by integrating standardized chronobiological analysis routines based on the work of Berger et al. (1999, 2002) and Scheibe et al. (1999). Berger et al. (2003) identified the degree of a harmonic behavioral rhythmicity as a key welfare indicator. The intention for the RW development is now to apply a mathematical approach to feeding and activity data in order to identify disturbances in behavioral patterns, and therefore, reveal social, feeding, and husbandry deficits or human interventions affecting animal welfare and health. Such a tool could be important for advisors and researchers alike to improve animal husbandry. In addition, a smart phone application for visualization of RW measurement data with connection to a cloud storage is conceivable, particularly in terms of enhancing user-friendliness and practicability of the system for farming practice.

6.1.2 Noseband sensor

In its current state, the RW noseband sensor is suitable for scientific application and for advisory purposes in agronomics and veterinary medicine. Potential research and application areas are feed evaluation for dairy cattle, assessment of housing systems and animal welfare, and ethological studies on ruminants. The RW noseband sensor may particularly assist for detection of metabolic health disorders and feeding deficiencies, and for post-surgery recovery monitoring in dairy cows. After further development and extension of the analysis routines, e.g. by implementation of automated detection of calving, heat, and health disorders, a potential field of application also has to be seen in intensive dairy farming systems with high numbers of individuals, high level of productivity and high management expenditure. Here, the intended use of the system may be to serve as a decision-support-tool for nutrition management and as a health and welfare sensor to enable reactions to critical conditions by dairy farmers and veterinarians at an early stage. Also a transformation of the system's hardware and analysis routines for application in other species, e.g. small ruminants, have been projected (Figure 6.2).

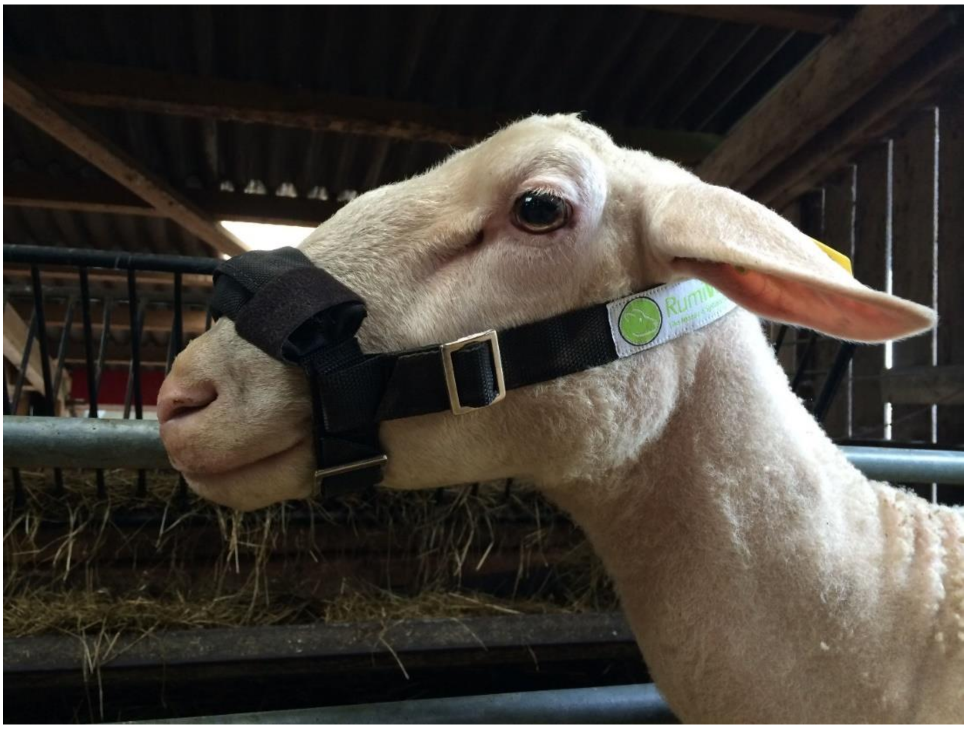

Figure 6.2. Modification of the RW noseband sensor for application in sheep.

Application potentials of the noseband sensor technology in horses can be seen both in scientific studies and for easy-to-use equine feeding and husbandry assessment. For this purpose, it is conceivable to merge the ruminating and eating recordings obtained from application of noseband sensors in horses into only one class “ingestive behavior”. Nonetheless, it may be useful to maintain a separate classification of “rumination” (slow, regular jaw movements) and “eating” (accelerated, irregular jaw movements) in order to enable a differentiation of chewing rhythmicity that might be valuable, i.e., for assessment of feedstuffs or feeding technology. The usefulness of analysis routines that were originally developed for cattle but applied in other species was demonstrated in a study by Dittmann et al. (2017) that compared mastication behavior using RW noseband sensors in domestic horses, cattle, and Bactrian camels.

6.1.3 Pedometer

In its current state of development, the RW pedometer is a measuring device dedicated to scientific use. The abundance of analysis parameters of movement behaviors allows application in several fields of agronomic and veterinary research, e.g. for assessment of housing systems or detailed investigation of lameness. Werner et al. (2017a) validated the RW pedometer in a pasture-based dairy system and found similar accurate results for standing and lying time as shown in Chapter 3. The measuring performance in detecting walking was slightly weaker than in detecting standing and lying, but still considered appropriate for a measurement system in a grazing environment. Going to further stages of development, particularly concerning extended ranges for wireless data transmission and connectivity to commercially available herd management software, the RW pedometer may also represent a valuable device for application in farming practice.

6.1.4 Economic viability

Current structural change in dairy farming is characterized by increased livestock numbers per farm unit, concomitant lower personnel capacities for individual animal monitoring, and occurrence of production stress in dairy cows. Despite this development, the economic viability of automated decision support tools is often under question. In order to enhance the chances for establishing the use of such supporting tools in herd management and for the justification of automated health monitoring systems, separate studies on economic effectiveness and user acceptance are desirable. Thereby, the aim may be to determine the potential for reduction of costs and production losses related to health disorders, and to identify additional features of health monitoring systems requested by users in farming practice.

6.2 Extended application potentials

The following section provides an outlook on extended application areas of the developed RW monitoring system by discussion of the findings and methodology of studies described in scientific literature.

6.2.1 Intake estimation

Leiber et al. (2016) applied the RW noseband sensor in stable-fed cows and concluded, that the random factor model developed in their study allowed estimation of individual changes in feed intake within animal but not across animals. Chewing behavior measurements proved to have a potential for the detection of relative intake alterations with roughage-based TMR diets but data were not sufficient for quantitative estimations. This may also be due to the use of the RW Converter V0.7.3.2 for analysis, as this version only classifies total eating jaw movements and does not allow to discriminate between eating bites, chews, and chew-bites (cf. Chapter 2). Using such differentiation of eating jaw movements might increase the possibility for quantitative intake estimations. Meanwhile, the values obtained from the acceleration sensor are included in the analysis routines as an additional criterion for behavior classification, in order to further improve the measuring performance and enable the differentiation of prehension and mastication bites during grazing (RumiWatch Converter V0.7.4.5, Itin+Hoch GmbH, Liestal, Switzerland). This might reveal the possibility for intake estimation on pasture based on the measurements of the noseband sensor (Rombach et al. 2016).

6.2.2 Heat detection

Automated heat detection is gaining interest in dairy farming, particularly as fertility problems have high prevalence in intensive livestock systems. Therefore, Zehner et al. (2014) conducted a pilot study to determine the feasibility of automatic heat detection in dairy cows using the RW noseband sensor described in this thesis. The aim of the study was to assess the suitability of the device for automated detection of heat and to investigate changes in behavioral parameters between peri-estrus vs. estrus days. In total, 10 estrus events were monitored at Agroscope Tänikon research stable (Ettenhausen, Switzerland). Experimental animals were equipped with noseband sensors two weeks before the calculated estrus day. Estrus events were verified by several reference methods (visual observation, pedometers, color markers). Behavioral changes in ruminating, eating, and motion activity during estrus cycles were analyzed and compared for all monitored estrus cycles (n = 10). Three reference days before and after the day of estrus, and the day of estrus itself were compared in the evaluation. Overall results were generated by calculating the average change in activity parameters for all experimental animals (n = 7). Results indicated that estrus significantly influences ruminating and eating activity in dairy cows. Motion activity of the head clearly increased by 34.5% compared to non-estrus days. On average, decrease in number of ruminating chews was -18.3% and -23.7% in number of eating chews when comparing the day of estrus versus the reference (peri-estrus) period. The number of ruminating boluses decreased by -16.0% on the day of estrus. Based on the findings of this study, several parameters of ruminating, eating, and motion behavior were identified as potentially significant indicators for automatic heat detection in dairy cows. The RW noseband sensor used for this study may have the potential to become a suitable tool for heat detection, as it constantly measures relevant behavioral parameters for reliable estrus detection, e.g. ruminating activity (cf. Reith and Hoy 2012). Further research and development works are needed for implementation and validation of a function for automated heat detection as part of the RW monitoring system. Particularly in a systematic approach when used in combination with a pedometer, very high heat detection rates may be achievable.

6.2.3 Health disorder detection

During the data collection of the study described in Chapter 4, several disease cases were monitored. However, there was no generalizable intra-individual or inter-individual course of behavioral changes before and after the diagnosis of a disease. The feasibility of early detection of health disorders using the RW monitoring system will have to be subject to further research. Probably, extended data evaluation processes will be required, as the early detection of diseases using established statistical methods for two-dimensional analysis of behavioral changes over the course of time has proven to be difficult in the current thesis and remains without unequivocal results (unpublished data). Beer et al. (2016) developed logistic regression models for lameness detection based on the output of the RW noseband sensor and pedometer. A model considering the number of standing bouts and walking speed was the best predictor of cows being lame with a sensitivity of 90.2% and specificity of 91.7%. Sensitivity and specificity of the lameness detection model were considered to be very high, even without the use of the noseband sensor data. They concluded that under the conditions of the study farm, pedometer data were suitable for accurately distinguishing between lame and non-lame dairy cows, even in cases of slight lameness with a gait score of 2.5.

6.2.4 Chronobiological analysis

For the development of animal monitoring systems, a fundamental intent was to provide a technology for early detection of health and welfare impairments. However, despite the growing amount of data, solutions for data evaluation that are of enormous relevance for this intent, were often not found to be practicable and reliable. In a pioneering approach, Berger et al. (2003) developed a chronobiological procedure to evaluate living conditions, behavior and the internal state of free-ranging animals. These authors found high Degrees of Functional Coupling (DFCs) in healthy animals and after a disturbance in behavior patterns the DFCs dropped. Umstätter et al. (2016) used this method combined with RW sensor and software technology to measure activity and ingestive behavior in housed cattle to investigate biological rhythms and its use for farming systems. The DFCs were used to measure the correlation between internal rhythms of the animal and the external 24-h period given by the environment. DFCs state the percentage of the circadian component and harmonic ultradian components in relation to all rhythmic components of a spectrum. In addition, the harmonic parts (HPs) were calculated as the equivalent to the total intensity of all harmonic rhythmic components of activity behavior. Different parameters were tested for analysis on cattle, from activity behavior, feeding time to rumination time. Interestingly, the DFCs and HPs calculated by Umstätter et al. (2016) for domestic cattle did not reach comparable high levels that were described for free-ranging ruminants by Berger et al. (2003). For this reason, chronobiological analyses may be used to identify impairments of animal welfare and health under human directed conditions, i.e., in livestock farming and zoo animal husbandry.

6.3 Customer benefits

Meanwhile, the RW System is an internationally acknowledged and established research tool for behavior monitoring in ruminants. It has been applied in validation studies (Kröger et al. 2016, Ruuska et al. 2016, Werner et al. 2017a), for veterinary research (Beer et al. 2016, Kohler et al. 2016, Nechanitzky et al. 2016, Aditya et al. 2017, Giovannini et al. 2017), and for investigation of nutritional aspects (Felber et al. 2015, Dittmann et al. 2016, Ertl et al. 2016, Leiber et al. 2016, Dittmann et al. 2017, Kleefisch et al. 2017, Werner et al. 2017b).

The presented animal monitoring system is manufactured and commercially distributed by the industry partner Itin+Hoch GmbH Feeding Technology (Liestal, Switzerland). Introductory courses for application of the RW system and customer advice are offered for scientific users. Operating procedures for application of the system-specific hardware and software have been published as technical documentations in German and English language (Zehner et al. 2015a, 2015b, 2015c, 2015d). In the described state of development, the RW System is dedicated to scientific application. Further development works aim to generate extended usability for advisory purposes and commercial farming.

6.4 Connected agriculture – future evolution

Due to rapid technological progress in sensor and computer technology in the last decade, animal monitoring systems are able to generate and store considerable amount of data. However, these data can only provide impact to farmers if clear and concise information can be extracted. Therefore, the core challenge for future research and development work will be to create efficient data management and information processing structures that can operate in real-time. For farming practice, the massive amount of data that can be generated by Precision Farming solutions needs to be connected between the devices of different manufacturers and processed into a practically relevant decision basis or unequivocal recommendation for action. Further interest of farmers for such connected solutions may be the generation of end-to-end data for dairy production, enabling the traceability of forage throughout the entire crop cycle and including the consumption by the animal. The RW noseband sensor and pedometer act as a system and have the potential to render a contribution to the vision of connected agriculture. The data formats and transmission standards of RW are potentially suitable for data exchange between systems from different manufacturers and have been projected for integration into a farm information system which combines data from different sources to a central database in real-time (Nikander et al. 2015). Further application potential would be to connect the RW System via a standardized interface to veterinarians and herd books for systematic health and fertility management. Integrated and validated analysis routines for the detection of health disorders and estrus would be a prerequisite to attain adequate usability for such application and remain subject of future research.

6.5 References

Aditya, S., Humer, E., Pourazad, P., Khiaosa-Ard, R., Huber, J., Zebeli, Q., 2017. Intramammary infusion of Escherichia coli lipopolysaccharide negatively affects feed intake, chewing, and clinical variables, but some effects are stronger in cows experiencing subacute rumen acidosis. Journal of Dairy Science, 100, 1363–1377.

Beer, G., Alsaaod, M., Starke, A., Schuepbach-Regula, G., Müller, H., Kohler, P., Steiner, A., 2016. Use of extended characteristics of locomotion and feeding behavior for automated identification of lame dairy cows. PloS one, 11, e0155796.

Berger, A., Scheibe, K. M., Eichhorn, K., Scheibe, A., Streich, J., 1999. Diurnal and ultradian rhythms of behaviour in a mare group of Przewalski horse (Equus ferus przewalskii), measured through one year under semi-reserve conditions. Applied Animal Behaviour Science, 64, 1–17.

Berger, A., Scheibe, K. M., Brelurut, A., Schober, F., Streich, W. J., 2002. Seasonal variation of diurnal and ultradian rhythms in red deer. Biological Rhythm Research, 33, 237–253.

Berger, A., Scheibe, K. M., Michaelis, S., Streich, W. J., 2003. Evaluation of living conditions of free-ranging animals by automated chronobiological analysis of behavior. Behavior Research Methods, Instruments, & Computers, 35, 458–466.

Dittmann, M. T., Hammond, K. J., Kirton, P., Humphries, D. J., Crompton, L. A., Ortmann, S., Misselbrook, T. H., Südekum, K.-H., Schwarm, A., Kreuzer, M., Reynolds, C. K., Clauss, M., 2016. Influence of ruminal methane on digesta retention and digestive physiology in non-lactating dairy cattle. British Journal of Nutrition, 116, 763–773.

Dittmann, M. T., Kreuzer, M., Runge, U., Clauss, M., 2017. Ingestive mastication in horses resembles rumination but not ingestive mastication in cattle and camels. Journal of Experimental Zoology Part A: Ecological and Integrative Physiology.

Ertl, P., Zebeli, Q., Zollitsch, W., Knaus, W., 2016. Feeding of wheat bran and sugar beet pulp as sole supplements in high-forage diets emphasizes the potential of dairy cattle for human food supply. Journal of Dairy Science, 99, 1228–1236.

Felber, R., Münger, A., Neftel, A., Ammann, C., 2015. Eddy covariance methane flux measurements over a grazed pasture: effect of cows as moving point sources. Biogeosciences, 12, 3925–3940.

Giovannini, A. E. J., Borne, B. H. P., Wall, S. K., Wellnitz, O., Bruckmaier, R. M., Spadavecchia, C., 2017. Experimentally induced subclinical mastitis: are lipopolysaccharide and lipoteichoic acid eliciting similar pain responses? Acta Veterinaria Scandinavica, 59, 40.

Kleefisch, M. T., Zebeli, Q., Humer, E., Kröger, I., Ertl, P., Klevenhusen, F., 2017. Effects of the replacement of concentrate and fibre-rich hay by high-quality hay on chewing, rumination and nutrient digestibility in non-lactating Holstein cows. Archives of Animal Nutrition, 71, 21–36.

Kohler, P., Alsaaod, M., Dolf, G., O'Brien, R., Beer, G., Steiner, A., 2016. A single prolonged milking interval of 24h compromises the well-being and health of dairy Holstein cows. Journal of Dairy Science, 99, 9080–9093.

Kröger, I., Humer, E., Neubauer, V., Kraft, N., Ertl, P., Zebeli, Q., 2016. Validation of a noseband sensor system for monitoring ruminating activity in cows under different feeding regimens. Livestock Science, 193, 118–122.

Leiber, F., Holinger, M., Zehner, N., Dorn, K., Probst, J. K., Neff, A. S., 2016. Intake estimation in dairy cows fed roughage-based diets: An approach based on chewing behaviour measurements. Applied Animal Behaviour Science, 185, 9–14.

Nechanitzky, K., Starke, A., Vidondo, B., Müller, H., Reckardt, M., Friedli, K., Steiner, A., 2016. Analysis of behavioral changes in dairy cows associated with claw horn lesions. Journal of Dairy Science, 99, 2904–2914.

Nikander, J., Laajalahti, M., Kajava, S., Sairanen, A., Järvinen, M., Pastell, M., 2015. Development of a general cowshed information management system from proprietary subsystems. In: Proceedings of the 7th European Conference on Precision Livestock Farming, 15-18 September 2015, Milano, Italy.

O'Mara, F. P., 2012. The role of grasslands in food security and climate change. Annals of Botany, 110, 1263–1270.

Reith, S., Hoy, S., 2012. Relationship between daily rumination time and estrus of dairy cows. Journal of Dairy Science, 95, 6416–6420.

Rombach, M., Münger, A., Südekum, K-H., Schori F., 2015a. Validation of a new monitoring system (RumiWatch) for recording the grazing and rumination behaviour of dairy cows. In: Proceedings of the Second DairyCare Conference 2015. 3-4 March 2015, Cordoba, Spain, 31.

Rombach, M., Münger, A., Südekum, K-H., Schori, F., 2015b. Estimation of individual intake of grazing dairy cows with RumiWatch. In: Proceedings of the Third DairyCare Conference 2015. 5-6 October 2015, Zadar, Croatia, 3.

Rombach, M., Münger, A., Südekum, K.-H., Schori, F., 2016. Schätzung der Grünfutteraufnahme von weidenden Milchkühen anhand verschiedener Ansätze basierend auf Verhaltensmerkmalen. ETH-Schriftenreihe zur Tierernährung, 39, 88–94.

Rombach, M., Südekum, K.-H., Schori, F., 2017. Einfluss der Grasmasse bei gleicher Grasmenge je Tier auf die Bissgrösse, das Fressverhalten, die Futteraufnahme und die Leistung von Milchkühen. ETH-Schriftenreihe zur Tierernährung, 40, 124–128.

Ruuska, S., Kajava, S., Mughal, M., Zehner, N., Mononen, J., 2016. Validation of a pressure sensor-based system for measuring eating, rumination and drinking behaviour of dairy cattle. Applied Animal Behaviour Science, 174, 19–23.

Scheibe, K.-M., Berger, A., Langbein, J., Streich, W. J., Eichhorn, K., 1999. Comparative analysis of ultradian and circadian behavioural rhythms for diagnosis of biorhythmic state of animals. Biological Rhythm Research, 30, 1–18.

Umstätter, C., Marsiglio-Sarout, B., Duthie, C.-A., Zehner, N., Haskell, M. J., Waterhouse, T., Berger, A., 2016. Using animal mounted sensors to characterise behavioural rhythms in cattle and sheep. In: Proceedings of DairyCare Working Group 2 Focused Meeting. Activity measurement in ruminant research and beyond. June 20–21, 2016, Leeuwarden, The Netherlands, p. 12.

Werner, J., Leso, L., Umstatter, C., Niederhauser, J., Kennedy, E., Geoghegan, A., Shalloo, L., Schick, M., O'Brien, B., 2017a. Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. Journal of Neuroscience Methods, Available online 24 August 2017.

Werner, J., Leso, L., Umstätter, C., Kennedy, E., O'Leary, N., Schick, M., O'Brien, B., 2017b. Effect of restricted feeding conditions on cow's feeding behaviour and activity on pasture-based milk production systems. In: Proceedings of Precision Livestock Farming '17, 8th European Conference on Precision Livestock Farming, Nantes, France, 12-14 September 2017, 443–450.

Zehner, N., Hürlimann, M., Nydegger, F., Schick, M., Bolt, R., Hoch, M., 2014. Application of a chewing sensor (RumiWatch) for automatic heat detection in dairy cows: a pilot study. In: Proceedings of EurAgEng International Conference of Agricultural Engineering 2014, July 6–10, 2014, Zurich, Switzerland. C0687.

Zehner, N., Hürlimann, M., Hoch, M., 2015a. User Guide RumiWatch - RumiWatch Noseband Sensor FW-Version 1.16, RumiWatch Pedometer FW-Version 1.16, RumiWatch Manager Version 1.0.0.1 and higher. Itin+Hoch GmbH Feeding Technology , Liestal, Switzerland (Eds.).

Zehner, N., Hürlimann, M., Hoch, M., 2015b. Bedienungsanleitung RumiWatch - RumiWatch Nasenbandsensor ab FW-Version 1.16, RumiWatch Pedometer ab FW-Version 1.16, RumiWatch Manager ab Version 1.0.0.1. Itin+Hoch GmbH Fütterungstechnik, Liestal, Schweiz (Hrsg.).

Zehner, N., Hürlimann, M., Hoch, M., 2015c. User Guide RumiWatch Converter Version 0.7.3.2 and higher. Itin+Hoch GmbH Feeding Technology, Liestal, Switzerland (Eds.).

Zehner, N., Hürlimann, M., Hoch, M., 2015d. Bedienungsanleitung RumiWatch Converter ab Version 0.7.3.2. Itin+Hoch GmbH Fütterungstechnik, Liestal, Switzerland (Hrsg.).

7 General Conclusions

The RumiWatch noseband sensor and pedometer were successfully developed and validated as scientific monitoring devices for automated measurements of ingestive and movement behavior in dairy cows. The achieved validation results indicate that the measuring performance satisfies scientific requirements. The development and validation of a predictive model for calving time based on measurements of the RumiWatch noseband sensor revealed that the achieved sensitivity and specificity were satisfactory, but the number of false positive alerts was too high for practical application of the developed model under conditions of commercial dairy farming. However, we found that particularly parameters of rumination behavior have predictive value and should be taken into consideration for future research on calving detection models. We successfully demonstrated that it is feasible to apply the RumiWatch noseband sensor to horses. The analysis indicated that the differentiation between chews and other muzzle and lip movements could improve the overall performance of the system. However, the system will be, after minor refinements, a valuable and easy-to-use tool for equine research and management.

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List of Abbreviations

bit	Binary digit
cf.	confer (compare with)
CSV	Comma-Separated Values
e.g.	exempli gratia (for example)
et al.	et alii (and others)
Eq.	Equation
Fig.	Figure
g	grams
GB	Gigabit
GmbH	Gemeinschaft mit beschränkter Haftung (≈ Ltd.)
h	Hour
Hz	Hertz = 1/s
i.e.	id est (that is)
cap.	Chapter
kg	Kilogram
m	Meter
mbar	Millibar
min	Minute
mm	Millimeter
ms	Millisecond = 10^{-3} seconds
n	total number
no.	Number
p	Probability
PC	Personal Computer
r	Pearson correlation coefficient
R^2	Coefficient of determination

RME	Relative measurement error
r_s	Spearman correlation coefficient
RWC	RumiWatch Converter
RW	RumiWatch
s	Second
SD	Standard deviation
SD Memory Card	Secure Digital Memory Card
TMR	Total mixed ration
USB	Universal Serial Bus
V	Volt
VVR	Visual video recording
%	Percent

List of Publications

Articles in international scientific journals with referee practice:

Alsaaod, M., Niederhauser, J. J., Beer, G., Zehner, N., Schuepbach-Regula, G., Steiner, A., 2015. Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows. Journal of Dairy Science, 98, 6236–6242.

Leiber, F., Holinger, M., Zehner, N., Dorn, K., Probst, J. K., Neff, A. S., 2016. Intake estimation in dairy cows fed roughage-based diets: An approach based on chewing behaviour measurements. Applied Animal Behaviour Science, 185, 9–14.

Ruuska, S., Kajava, S., Mughal, M., Zehner, N., Mononen, J., 2016. Validation of a pressure sensor–based system for measuring eating, rumination and drinking behaviour of dairy cattle. Applied Animal Behaviour Science, 174, 19–23.

Werner, J., Umstätter, C., Zehner, N., Niederhauser, J. J., Schick, M., 2016. Validation of a sensor-based automatic measurement system for monitoring chewing activity in horses. Livestock Science, 186, 53–58.

Zehner, N., Umstätter, C., Niederhauser, J. J., Schick, M., 2017. System specification and validation of a noseband pressure sensor for measurement of ruminating and eating behavior in stable-fed cows. Computers and Electronics in Agriculture, 136, 31–41.

Zehner, N., Niederhauser, J. J., Schick, M., Umstätter, C., 2018. Development and validation of a predictive model for calving time based on sensor measurements of ingestive behavior in dairy cows. Computers and Electronics in Agriculture, https://doi.org/10.1016/j.compag.2018.08.037

Monographs:

Zehner, N., 2010. Labour time requirement for milking goats. Bachelor thesis, University of Hohenheim, Faculty of Agricultural Sciences.

Zehner, N., 2012. Validation of a new method (RumiWatch) for combined automatic measurement of rumination, feed intake and locomotion in dairy cows. Master thesis, University of Kiel, Faculty of Agricultural and Nutritional Sciences.

Publications in conference proceedings:

Zehner, N., Niederhauser, J. J., Nydegger, F., Grothmann, A., Keller, M., Hoch, M., Haeussermann, A., Schick, M., 2012. Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows. Proceedings of International Conference of Agricultural Engineering CIGR-AgEng2012, July 8–12, 2012, Valencia, Spain.

Nydegger, F., Zehner, N., Niederhauser, J. J. , Schick, M., 2012. Optimale Fütterungstechnik durch Monitoring der Tieraktivität. In: Tagungsband der Fachtagung „Feed for Health", 03.05.2012, ETH Zürich. ETH-Schriftenreihe zur Tierernährung 35, 78–87.

Zehner, N., Nydegger, F., Keller, M., Schick, M., 2013. Validierung einer neuen Methode (RumiWatch) zur automatischen Erfassung des Wiederkau- und Futteraufnahmeverhaltens von Milchkühen. In: 4. Tänikoner Melktechniktagung: Automatisierung rund ums Melken. Hrsg. Agroscope, 20. –21.03.2013, Ettenhausen, 37–41.

Zehner, N., Hürlimann, M., Nydegger, F., Schick, M., Bolt, R., Hoch, M., 2014. Application of a chewing sensor (RumiWatch) for automatic heat detection in dairy cows: a pilot study. In: Proceedings of EurAgEng International Conference of Agricultural Engineering 2014, July 6–10, 2014, Zurich, Switzerland. C0687.

Werner, J., Zehner, N., Umstätter, C., Nydegger, F., Schick, M., Wyss, C., Hoch, M., 2014. Application of a noseband pressure sensor for automatic measurement of horses' chewing activity: a pilot study. In: Proceedings of EurAgEng International Conference of Agricultural Engineering 2014, July 6–10, 2014, Zurich, Switzerland. C0686.

Kajava, S., Mughal, M., Frondelius, L., Ruuska, S., Zehner, N., Mononen, J., 2014. Validation of RumiWatch pedometers measuring lying, standing and walking of cattle. In: Proceedings of EurAgEng International Conference of Agricultural Engineering 2014, July 6–10, 2014, Zurich, Switzerland. C0683.

Werner, J., Zehner, N., Umstätter, C., Nydegger, F., Hoch, M., Wyss, C., Schick, M., 2014. Development of a sensor-based automated measurement system for monitoring chewing and animal activity in horses. In: Proceedings of 7th Conference of the European Workshop on Equine Nutrition. September 29 – October 2, 2014, Leipzig, Germany, 1-2.

Abstracts in conference proceedings:

Zehner, N., Umstätter, C., Schick, M., 2015. Smart farming in dairy cattle: application of RumiWatch noseband sensors for monitoring of calving events in dairy cows. In: Proceedings of the Third DairyCare Conference 2015, October 5–6, 2015, Zadar, Croatia, p. 36.

Zehner, N., Umstätter, C., Schick, M., 2016. Validation of RumiWatch noseband sensors: a comparison of algorithms for classification of ingestion behaviour. In: Proceedings of DairyCare Working Group 2 Focused Meeting. Activity measurement in ruminant research and beyond. June 20–21, 2016, Leeuwarden, The Netherlands, p. 20.

Umstätter, C., Marsiglio-Sarout, B., Duthie, C.-A., Zehner, N., Haskell, M. J., Waterhouse, T., Berger, A., 2016. Using animal mounted sensors to characterise behavioural rhythms in cattle and sheep. In: Proceedings of DairyCare Working Group 2 Focused Meeting. Activity measurement in ruminant research and beyond. June 20–21, 2016, Leeuwarden, The Netherlands, p. 12.

Publications in non-refereed agricultural journals and series:

Zehner, N., Werner, J., Nydegger, F., Umstätter, C., Wyss, C., Hoch, M., Schick, M., 2014. EquiWatch – Eine neue Methode zur Erfassung der Kauaktivität bei Pferden. Agroscope Science 3 (2014), 52–53.

Leiber, F., Probst, J. K., Zehner, N., Spengler Neff, A., 2015. Feeding and rumination behaviour of dairy cows fed by varied feeding regimes. Agrarforschung Schweiz 6(10), 462–469.

Werner, J., Umstätter, C., Zehner, N., Wyss, C., Schick, M., 2015. Einsatz eines automatischen Messsystems zur Erfassung des Kauverhaltens bei Pferden. Agroscope Science 19 (2015), 38–39.

Technical reports:

Zehner, N., Hürlimann, M., Hoch, M., 2015. User Guide RumiWatch - RumiWatch Noseband Sensor FW-Version 1.16, RumiWatch Pedometer FW-Version 1.16, RumiWatch Manager Version 1.0.0.1 and higher. Itin+Hoch GmbH Feeding Technology , Liestal, Switzerland (Eds.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. Bedienungsanleitung RumiWatch - RumiWatch Nasenbandsensor ab FW-Version 1.16, RumiWatch Pedometer ab FW-Version 1.16, RumiWatch Manager ab Version 1.0.0.1. Itin+Hoch GmbH Fütterungstechnik, Liestal, Schweiz (Hrsg.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. User Guide RumiWatch Converter Version 0.7.3.2 and higher. Itin+Hoch GmbH Feeding Technology, Liestal, Switzerland (Eds.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. Bedienungsanleitung RumiWatch Converter ab Version 0.7.3.2. Itin+Hoch GmbH Fütterungstechnik, Liestal, Switzerland (Hrsg.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. FAQ RumiWatch - Frequently Asked Questions. Itin+Hoch GmbH Feeding Technology, Liestal, Switzerland (Eds.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. FAQ RumiWatch - Häufig gestellte Fragen. Itin+Hoch GmbH Fütterungstechnik, Liestal, Switzerland (Hrsg.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. Summaries and Raw Data RumiWatch - Basic Information. Itin+Hoch GmbH Feeding Technology, Liestal, Switzerland (Eds.).

Zehner, N., Hürlimann, M., Hoch, M., 2015. Summaries und Rohdaten RumiWatch - Hinweise für Anwender. Itin+Hoch GmbH Fütterungstechnik, Liestal, Switzerland (Hrsg.).

Print media:

Zehner, N., Hoch, M., 2012. RumiWatchSystem. Measurement system for automatic health monitoring in ruminants. Brochure. Itin+Hoch GmbH Feeding Technology, Liestal, Switzerland (Eds.).

Zehner, N., Hoch, M., 2012. RumiWatchSystem. Ein Messinstrument zur Gesundheitsüberwachung von Wiederkäuern. Broschüre. Itin+Hoch GmbH Fütterungstechnik, Liestal, Switzerland (Hrsg.).

Social media:

Zehner, N., Möri, S., 2017. RumiWatch on Facebook – Animal monitoring for scientists. https://www.facebook.com/RumiWatch-1845302459085007 (accessed 12/21/2018).

Möri, S., Hoch, M., Zehner, N., 2017. RumiWatch – The Grazing Movie. simisFarm Productions. https://www.youtube.com/watch?v=TTG9GEu5u9k (accessed 12/21/2018).

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