DISSERTATION

INVESTIGATION OF AN EMBEDDED-OPTICAL-BASE SYSTEM'S FUNCTIONALITY IN DETECTING SIGNAL EVENTS FOR GAIT MEASUREMENTS

Submitted by

Colton A. Atkins

Department of Animal Sciences

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2018

Doctoral Committee:

Advisor: Kevin R. Pond

Valerie J. Moorman
Temple Grandin
I. Noa Roman-Muniz
Shawn L. Archibeque

Copyright by Colton A. Atkins 2018

All Rights Reserved

ABSTRACT

INVESTIGATION OF AN EMBEDDED-OPTICAL-BASE SYSTEM'S FUNCTIONALITY IN DETECTING SIGNAL EVENTS FOR GAIT MEASUREMENTS

Optical sensors have the potential to provide automated gait analysis and lameness detection in livestock. Measuring animals in motion while under field conditions is difficult for current gait analysis tools, such as plate and mat methods. This has caused a lack in commercially available systems. Additionally, a deficit of these systems and others is too much noise in their signal. Current sensor systems for static or in-motion measurements rely significantly on managing this noise as a source of error. From these problems, the primary objective of this body of work was to assess the use of an embedded-optical-base system (EOBS) and its ability to obtain real-time gait measurements from livestock. The research was composed of 3 field studies and 1 controlled study. Gait data was obtained using a commercial platform (2.4 m x 0.9 m; length x width) containing 1 EOBS. A signal-base-unit (SBU) and computer were setup near the EOBS platform by integrated cabling to collect real-time signal data. Signal fluctuation measurements (i.e., signal amplitude from hoof contact; 0 to 1 arbitrary units (au)) and kinematics (e.g., estimated speed, velocity and time duration) were recorded. The sensor detected hoof contact as signal amplitudes that could be examined in real time. Visual observations and video analyses were used for validating and classifying signal readings.

The initial pilot study (field test) included 8 fistulated, crossbred steers (n = 8) tested over 1 d with 2 passes per animal over the EOBS platform. Pilot study data were used to evaluate

initial signal fluctuations from animal contact. A second field study included 50 crossbred and purebred (n = 20, Angus; n = 10, Hereford; n = 20, Angus x Hereford) steers and heifers (n = 50; average BW = 292.5 kg) tested on 2 d over a 1-wk period with a total of 6 passes over the EOBS platform per animal. Steer and heifer normal walks, runs, and abnormal passes over the EOBS platform were analyzed. A third controlled study consisted of 3 mixed breed horses (n = 3) that had bilateral forelimb injections. Horses had both deep digital flexor muscles injected (1 with Botox and 1 with saline) with right and left forelimbs randomized. Horses were observed on 3 d over a 124-d period consisting of pre-treatment (baseline), post-treatment, and recovery test days with 10 passes over the EOBS platform per horse per day. Primary fluctuations, true (anomaly free) signal readings, from animal contact with the EOBS platform were analyzed. True signal readings were determined based on no influence observed from other limbs. A fourth field study consisted of 8 commercial bulls (n = 8) tested on 1 d with 3 passes over the EOBS platform per bull. Bulls were classified as either normal or abnormal in musculoskeletal structure and compared to one another to observe differences in signal fluctuation patterns. During the cattle studies, animals were not controlled and allowed to walk over the EOBS platform at their own pace. These studies formed the groundwork to determine the EOBS's functionality when animals passed over the platform.

Signalment (i.e., breed, sex and age) and physiological characterizations were recorded. Temperature was also recorded for cattle field tests (e.g., min -6°C to max 4°C, respectively). For all 4 studies individual animal signal measurements were analyzed for each pass over the EOBS platform, compared to video data and classified for analysis. Results from all 4 studies showed intra- and inter-animal repeatability (qualitative observation) of observed signal readings. Though a variety of hoof contact signatures were obtained, repeating patterns were evident for both groups and individual animals. The embedded-optical-base system's (EOBS) functionality proved to be robust and operable under field trial conditions. Additionally, the signal showed extremely minimal noise. Lastly, the EOBS showed a stable baseline with clear deviations from it that could be correlated to hoof contact through video validation. Though the EOBS detected animal contact per pass, future work will investigate the system's operating readiness in accurately assessing variable gait measurements for lameness detection. Overall, data provides evidence that the embedded-optical-base system (EOBS) can detect hoof contact and differentiation between types of gait based on signal events.

ACKNOWLEDGEMENTS

I would like to take this opportunity to acknowledge those who helped throughout this research. First, I would like to say thank you to my family for supporting me. Without the constant love I probably wouldn't have succeeded. Second, thank you to Dr. Christi Madsen for guiding, teaching and helping me through this research. Third, thank you to Dr. Sam Cunningham and Dr. David Schafer for being two great individuals who held me up. Fourth, thank you to my friends (Catie McVey, Ashley Budde, Ty Sexton, Kaysie Jennings, Helen Brown, Matt Seigler and Thomas Tran) for being supportive and helpful from beginning to end. I would also like to express my gratitude to Mrs. Laura Bonner, Dr. Brett Kirch, Dr. Terry Engle, Ms. Melissa Harmon and the staff/faculty at CSU, ARDEC and the EORC for their assistance throughout my studies. While this list is short, there are so many more people who have come and gone during my time at CSU and I am appreciative for every person's influence in my life.

As for the technical parts of my research, I would like to say thank you to Ag Tech Optics, LLC (ATO; Bryan, Texas); Mr. Luke and Kenneth Kleckley of Brazos Industries (Bryan, Texas); Mr. John Wilson and Family of Wilson Machining (Fort Collins, Colorado); Mr. John Ragsdale of Texas A&M University's Texas Transportation Institute (TTI; College Station, Texas); Mr. Sammy Piraino of Piraino Services (Bryan, Texas); Dr. Christi K. Madsen of Texas A&M University (College Station, Texas); and my committee members, Dr. Valerie Moorman, Dr. Temple Grandin, Dr. Shawn Archibeque and Dr. Noa Roman-Muniz. Thank you to all for providing the knowledge, support and tools to help make this research a success. Lastly, I want to say thank you to Dr. Kevin Pond who gave me this opportunity and provided me with priceless wisdom - Without you seeing my potential I wouldn't have achieved my dreams.

DEDICATION

I dedicate this paper to my family, mentors and friends.

Thank you for believing in me through this emotional ride.

As a wise man once told me: You can’t make this stuff up!

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter One

Investigation of a novel in-motion optical sensor and

its functionality in obtaining gait measurements

INTRODUCTION

The emergence of sensor technology in the agriculture industry has moved to the growing field of understanding animal behavior, optimizing performance and well-being. Engineering and biomaterial advancements coupled with decreasing costs of electronics has resulted in emerging sensing solutions and smart computing including internet and cloud-based connectivity for integrated and networked physical devices for data collection and analysis (Neethirajan et al., 2017). From these solutions, collection of real-time objectively-quantifiable livestock variables and/or parameters has become an essential automated practice for efficient livestock production. Poor to limited acquisition of data can lead to inaccuracies in decision-making and management. From this, indirect issues such as declining animal health and well-being can occur while causing a poor return on investment.

One major issue that can negatively impact a range of welfare and financial investment factors on a farm or ranch is lameness. Lameness is defined as any deviation in an animal's normal gait due to pain. Lameness implies pain; however, animals can exhibit asymmetric gait without pain. If untimely diagnostics and treatments are implemented, lame animals may develop chronic detrimental conditions requiring significant costly care or result in culling from the herd, farm or ranch. Lameness can be detected/assessed using subjective, visual scoring methods (Barker et al., 2018). Recently, efforts have focused on providing supplemental diagnostic tools for gait analysis to improve detection of lame or abnormal animals. These gait analysis tools/systems can aid in early diagnosis where subjective systems may lack due to greater variability in scoring. However, these solutions for detecting lameness have relied heavily on identification of abnormal gait using load cells, pressure-sensitive mats, image recognition, accelerometers, and pedometers (Van Nuffel et al., 2015; Barker et al., 2018). Though proven and each beneficial, there is a need for methods that can be easily used on operations and are robust enough to be implemented in said environment. One way to improve current methods is to use optical sensors for animal gait analysis. This novel approach differs from previous solutions due to the robust durability and efficient implementation style of optical sensors. Thus, optical sensors may provide a robust new technology option in monitoring animal gait.

Study Objective

The primary objective of this research is to investigate the functionality and operability of an embedded-optical-base system's (EOBS) distinguishable sensing features (signal fluctuations or deviations) by testing agreement, repeatability, and differentiations of aggregated in-motion livestock measurements with visual gait analysis. The most current methods used are lameness scoring tools. Lameness scoring (Likert scales with gait characterizations) is subjective gait analysis that can provide particular indicators of an animal's health at specific time intervals intermittently throughout an animal's lifespan. Gait analysis, whether quantitively or qualitatively observed, is a unique measurement tool to address musculoskeletal and locomotion problems for health assessment. Nevertheless, objective analysis should be incorporated more thoroughly on livestock operations due to its ability to reduce subjective error during visual lameness scoring.

Purpose of Study

The purpose of this research was to determine if the embedded-optical-base system (EOBS) platform was appropriate for concise detection and evaluation of gait measurements through the collection of hoof contacts, with a long-term goal of utilizing the system in a commercial, animal production environment. While optical systems have been used in measuring the weight of vehicles driving over state and national highways and for assessing fat thickness on cuts of meats, they have not been previously used for gait analysis.

Early detection and identification of lameness before it progresses into an irreversible problem is critical for both production and animal welfare. As a multifaceted problem, diagnosis requires development of methods that are feasible, durable and have a low-learning curve. Optical sensing exhibits promise in trucking, telecommunication and meat processing leading to its evaluation of functionality, efficacy and operability within livestock production.

As such, research provided data from four studies that investigated the functionality and operability of optical sensing for potential detection of gait features based on signal fluctuations in both controlled and field studies. Signal fluctuations and baseline deviations from animal contact with the EOBS platform were examined to correlate to primary and secondary dynamic features that represented livestock gait measurements. By determining the EOBS's functionality and operability under livestock conditions, its production-value could be assessed along with providing directions for future implementation.

Specific Aims and Hypotheses

SA1: Investigate and validate that the EOBS can detect fore- and hind limb contact.

H1: Signal fluctuations and baseline deviations result from animal contact with the EOBS.

H1a: Animal contact with EOBS results in time-series markers.

H1b: Signal amplitude is not influenced by time-series.

H1c: Animals exhibit repeatable time groupings for unique contacts with EOBS.

SA2: Investigate and validate that EOBS aggregated animal contact measurements can be used for initial gait assessment.

H2: Signal fluctuations are related to hoof contacts and break-overs; not noise (i.e., error).

H2a: Animal first hoof contact is detectable from first forelimb impacting the EOBS.

H2b: Animal last break-over is detectable from last hind limb lifting off the EOBS.

H2c: Significant difference in hoof contacts and break-overs can be measured.

SA3: Identify appropriate EOBS detection threshold of animal contact.

H3: Signal amplitude per fluctuation from animal contact is strongly correlated with platform grid row and column.

SA4: Identify uniform and non-uniform contact patterns from fore- and hind limbs at various gaits.

H4: A uniform pattern of signal fluctuations from animal contact can be detected for walking gait of a structurally sound animal during a set time interval.

H5: A non-uniform pattern of signal fluctuations from animal contact can be detected for walking gait of a structurally abnormal animal during a set time interval.

Delimitations, Limitations and Assumptions

One limitation was in using a convenience sample of animals that were available through both the Agricultural Research, Development and Education Center (ARDEC) and the Equine Orthopaedic Research Center (EORC). Limited sampling size can reduce the ability to draw conclusive statistical inferences from data collected. Cattle for first and second field studies were assumed to be structurally sound prior to data collection. Additionally, control cattle for the fourth field study were assumed to be structurally sound. Visual observations in assessing structural soundness were based on spine arching, shortened strides, limb favoring and visible reluctance to move.

References

1. Barker, Z. E., J. A. Vásquez Diosdado, E. A. Codling, N. J. Bell, H. R. Hodges, D. P. Croft, and J. R. Amory. 2018. Use of novel sensors combining local positioning and acceleration to measure feeding behavior differences associated with lameness in dairy cattle. J. Dairy Sci. 101:1-2. doi: 10.3168/jds.2016-12172.

2. Neethirajan, S., S. K. Tuteja, and D. Kelton. 2017. Recent advancement in biosensors technology for animal and livestock health and management. Biosens. Bioelect. 98:398-407. doi: 10.1016/j.bios.2017.07.015.

3. Van Nuffel, A., I. Zwertvaegher, S. Van Weyenberg, M. Pastell, V. M. Thorup, C. Bahr, B. Sonck, and W. Saeys. 2015. Lameness detection in dairy cows: Part 2. Use of sensors to automatically register changes in locomotion or behavior. Anim. 5:861-885. doi: 10.3390/ani5030388.

Chapter Two

Review of scientific literature on the general use of technology to detect biometrics in livestock

Precision Livestock Management

By 2050, the human population is projected to rise to approximately 9 billion individuals (UNPD, 2017). Rising urbanization, ever-changing demographics, and growing incomes in developing countries, cause increasing pressures for livestock producers to meet growing consumer demands for animal-based proteins. Along with this projection, the Food and Agriculture Organization of the United Nations estimates that the annual consumption of animal-based proteins will increase by 50% (Thornton, 2010; Fournel et al., 2017). To amplify the problem, the number of livestock producers (operations) have decreased over the years putting pressure on the livestock industry to manage the greater demand with limited resources. As a result, producers have opted to use larger-intensified operation models to handle large animal populations (Pedersen, 2005; Berckmans, 2017). Consumer awareness of animals raised in this manner has created greater demands on improving animal well-being through humane management practices. Additionally, the livestock sector has been under scrutiny by being associated with 15% of global greenhouse gas emissions, 70% of available agriculture land usage and approximately 8% of global water consumption adding to surmounting barriers for producers from regulations (Scholten et al., 2013). From these growing constraints and pressures innovative facilities, equipment, and practices are needed to address the growing list of issues for livestock production while meeting population demands.

Precision livestock management: A general overview

Precision livestock management (PLM) is defined as the management of livestock production utilizing the principles and technologies of engineering (Wathes et al., 2008). It is based around automatic monitoring of livestock, whether physiological, behavioral or production indicators along with the environment in which they are raised in, through a set of interlinked processes that act together in a complex network of communicative, information-driven technologies (Wathes et al., 2008; Borchers and Bewley, 2015). Precision livestock management (PLM) is not only useful but imperative to handle the complexities of livestock production Since animals create physiological and behavioral measurands, PLM relies on accurate data collection and meaningful interpretation. When discussing physiological, behavioral, and production indicators of livestock, one must understand that each is multi-factorial. Each of these indicators cannot be evaluated independently as areas overlap or exhibit a co-dependence when examining causation. It is then pertinent to not only discuss the technologies used to detect, sense and measure, but also how these technologies work as a whole. Various technologies can be applied to collect, predict and analyze these measures; however, the costs and functionality associated with implementing these technologies can raise concerns about wide-scale commercial adoption. Low-cost, non-invasive and simplistic design of technology built with an understanding of livestock and the livestock industry is necessary for successful commercial implementation. To understand the landscape of PLM more effectively, this literature review will provide a brief analysis of current trends in the use of technology to advance monitoring, analyzing, and managing physiological, behavioral and production characteristics in livestock.

This chapter will focus on sensing and detecting technologies as a brief introductory review into technology for livestock production. Overview of these technologies will be based on the applications used to determine, detect, and predict physiological and anatomical, behavioral and production indicators with attentiveness to their production uses. Brief discussion of the analysis and management (e.g. control) areas are touched on to provide a better idea of how operations and researchers utilize data once it is collected. However, expansion of these areas is needed in future writings to understand the true extent and capabilities of PLM. Additionally, this chapter hopes to set the groundwork for introducing both producers and academics to the changing market of PLM technologies.

Adoption of new technologies is dependent on a variety of factors related to management, ease-of-use, perceived benefit-to-cost ratio and production facilities to name a few (Borchers and Bewley, 2015). Implementation requires understanding of which tool to use to measure the parameter of interest as technologies can measure a variety of categories ranging from nutrition, production, health and fertility to the environment (Borchers and Bewley, 2015). Understanding the concepts behind PLM technologies is important when making decisions on which tools are the most appropriate to implement. The following sections will provide insight from scientific literature to examine technologies and associated biometrics for two main areas: environmental and animal factors.

Smart Sensing for Environmental Inputs and Animal Factors

Continuous, real-time monitoring and control is needed to accomplish dynamic, large-scale production that is socially and humanely appropriate while being economically efficient. Smart sensing is the act of implementing sensors to collect data from surroundings. It allows numerous factors such as growth, feed intake, protein, endemic disease, behavior and environment conditions to be observed from both individual animals and groups (Wathes et al., 2008). Thus, smart sensing is the best starting point for understanding PLM as sensors provide continuous opportunities in obtaining specific targets and trajectories (i.e. emission reduction, carcass weight, disease reduction, etc.) within dynamic, large-scale production.

Sensors, transducers and actuators

To adequately approach smart sensing (i.e. data acquisition and transmission over a network), a basic understanding of the components should be discussed. Sensors are real-world, sampling devices that detect events, stimulations or changes in their environment which are then conveyed in analog and digital forms to be used for various data-oriented tasks. When multiple sensors are combined and work in tandem to collect an entire image on an operation they form a PLM ecosystem (PLM-E). Contained within a sensor is a transducer which transduces (i.e. transforms) the measured activity into a different energy form, such as an electrical signal. An example of a sensor transducer heavily-utilized in both livestock production and research are accelerometers for monitoring gait analysis. Transducers can function as unidirectional for simple receiving of a physical stimulus or as bidirectional in which both signal reception and creation is achieved. In addition, actuators are a type of transducer that take pneumatic, hydraulic, electric or mechanical energy inputs and convert them into kinetic energy such as motion, movement or action. A general example of an actuator used in livestock production is the rotary milking parlor and its mechanical rotation of dairy cattle. Though actuators are part of the PLM-E's sensor aspect, this chapter does not discuss them in detail. Actuators are more commonly applied to automation and robotics. However, from this general overview, it can be determined that sensors, transducers and actuators are the base tools at the physical-digital junction of a PLM-E.

As sensors and transducers sample properties in the physical plane, signals are generated for data acquisition. Signals are representations of information; physical signals are realized when voltage, current or electromagnetic waves are modulated (Azadeh, 2009). In optics, modulation occurs when a physical impression is converted to a representation of an optical signal that is then transmitted across a physical media or link (Azadeh, 2009).

From obtained signals, sensor and transducer performance are measured then evaluated based on precision, accuracy, sensitivity, offset, linearity and dynamic linearity, resolution, hysteresis, response time and range. Actuator performance is measured based on force, speed and durability. Once a signal is converted from its physical stimulus into an electrical signal, the signal conditioning process can then proceed, which can include filtering, amplifying, excitation, isolation and linearization. Lastly, the conditioned electrical signal is converted into digital values that computing systems process and store as data for analysis.

Within livestock production, sensors can be found on (ear, leg, neck, rump, rumen or vagina) or around (bulk tank, barn, in-line, milking-unit, lots, alleyways or parlor) the animal in various locations forming a PLM-E. Sensors are important for livestock operations because they collect data from environmental inputs, animal characteristics, and animal outputs used for ongoing management. The following sections discusses how sensors are used to collect various inputs, characteristics, and outputs.

Environmental Inputs

Environmental inputs are the outside variables that an animal interacts with or has placed on it. Variables can include temperature, humidity, barometric pressure and ventilation. These environmental inputs are monitored to ensure a proper control system is in place.

For instance, season, weather and climate conditions can influence an animal's immune response along with its reproductive cycle and behavior. To maintain some form of control, sensors can be used to provide unique methods for detecting the external factors that are placed on livestock. A variety of sensors are enlisted to monitor these inputs and the fluctuations that occur within them. Many studies have demonstrated the value of using sensors and sensing systems to monitor environmental factors, particularly in crop production (Pedersen and Lind, 2017). The sensors can be integrated in the livestock industry when discussing environmental factors such as ambient temperature, humidity (i.e. moisture) and emissions/air quality. The following section provides an overview of sensors utilized to measure, monitor and collect environmental data.

Ambient temperature is one environmental factor that may impact an animal's productive life-cycle (Schwartzkopf-Genswein et al., 2012). The most common sensor(s) used to measure ambient temperature on livestock operations are thermocouples/thermistors due to their above average tolerance to large temperature differences and sensitivity (Frost et al., 1997; CIGR, 1999; Eigenberg et al., 2009; Fournel et al., 2017). These instruments measure a variety of temperature related inputs including constant pressure, electrical resistance, thermal voltage and visible color (Doebelin, 1990; ASHRAE, 2013; OMEGA, 2016; Fournel et al., 2017). Measuring ambient temperature is important because it can play a major effect on activity, feed intake, and production of cattle (West et al., 2003). Ambient temperatures above or below recommended thresholds have been shown to cause cattle to exhibit behavior correlated to heat and cold stress (Berman et al., 1985). Humidity on a livestock operation can also influence temperature and cause pathogens to flourish in the environment. Relative and absolute humidity in the form of water vapor content can be collected by thermometric, chemical, electrical, radiometric, and hygroscopic methods (Fournel et al., 2017). Hygrometers are commonly used for measuring water vapor and amount of humidity. Quantifying humidity is based on ratio-specific humidity, saturation water vapor pressure, dew-point temperature, dry- and wet-bulb temperatures, percent saturation and water activity (Fournel et al., 2017). However, humidity sensors require proper protection to provide accurate readings in harsh environments. Lastly, though not as prevalent in some operations that are based on pasture, air quality and emissions can play an important part in the overall health of an animal. A variety of sensors exist for measuring concentration, particulate matter and emission such as chemiluminescence, ultraviolet fluorescence and infrared gas analyzers along with a variety of electrochemical sensors. Poor air quality can cause risks for animals through airborne dust particles combined with humidity and temperature factors (Van der Fels-Klerx et al., 2000; Snowder et al., 2006; Fraser et al., 2013). However, these issues are more present in only some types of operations due to the inclusion of animal housing facilities. If ventilation and air flow are not provided, atmospheric ammonia, fecal hydrogen sulphide, methane, nitrous oxide, carbon dioxide and various debris/dust particles can prove damaging or fatal (Al-Mashhadani and Beck, 1985; Donham et al., 1988; Wu et al., 2012; Fraser et al., 2013). Thus, lacking proper monitoring of environmental factors may greatly affect animal health.

Overall, though this section review was nowhere near exhaustive, it shows that sensing of environmental variables is of importance in terms of detecting influencing factors on an animal's productive life-cycle. As such, utilizing sensors as automated tools to measure humidity, temperature and air quality is a useful piece in making a comprehensive PLM-E. At this point, there are many more environmental variables to analyze but understanding the animal characteristics which sensors can measure is necessary when discussing a broad picture of precision livestock management (PLM).

Animal Factors

Animal characteristics are the biological aspects or processes based on collected data related to factors such as genetics, progeny, physical attributes, health and behavior. Data collected from animal characteristics can be used in prediction models to determine indicators such as growth trajectories, variations in biological patterns and health statuses for management and/or prevention of risks. Animal outputs are the measurable responses derived from animal characteristics. Responses can be described by: behavioral, anatomical and physiological characteristics. Sensors can then monitor these variables based on an operation's daily management routine which can be used in the analysis process. These sensors can be external from the animal to collect indirect variables, directly attached to the animal for direct variable measurement, or intrusively in the animal to obtain internal variables. In turn, the sensors collect near- to real-time data on a continuous time scale for producers to analyze and make informed decisions. The following section provides a review of how sensors are used to detect and measure behavioral, anatomical and physiological characteristics from animals.

Behavior: Overview

Sensors, when combined, form a modern sensing system (i.e. PLM-E) that is used to monitor standard behavioral patterns from individual animals or groups. Behavior is measured by a variety of sensors such as optical cameras, accelerometers, pedometers, gyroscopes, magnetometers and pressure/force sensors. Since behavior is a multifaceted topic, the following sections will cover the use of sensors used to collect behavioral inputs related to feeding, health and welfare, and reproduction.

Behavior: Feeding

Feeding behavior over a given timeframe can be an indirect measurement of an animal's daily nutritional intake. Producers need to understand feeding patterns for daily intake as they have vast implications on future growth and production (Grant and Albright, 2000). Several sensor-based systems exist today with a variety of functions that yield different results. For instance, microphones sense sound which can provide an acoustic signal for monitoring chewing that is then correlated to feeding behavior. The most commonly researched and utilized sensor-based system for feeding observations is the electronic feed bunk such as the GrowSafe system. GrowSafe Systems Ltd. (USA) [1] uses an electronic monitoring system that measures bunk attendance patterns through radio frequency tagging (Schwartzkopf-Genswein, 1999). Despite the availability of this technology, the methods used to measure bunk attendance patterns are subject to external challenges. Specifically, true accuracy in reflecting bunk use in large groups of cattle is questionable as observed external interferences from gates and fencing, climate conditions and non-feeding-based behavior from animals have skewed results providing erroneous data (DeVries et al., 2003). As found in validation studies, the GrowSafe System requires time-lapse video recordings to appropriately reduce errors in obtaining reasonable conclusion about an animal's feeding pattern (DeVries et al., 2003). However, the GrowSafe System serves as a general example of how sensors can be used for analysis of feeding. Additionally, accelerometers, microphones, switches and electrical resistant sensors all have been utilized with variable results in determining patterns for feeding behavior. However, the possibilities for sensor- based monitoring of feeding behavior are evolving in the industry.

---

[1] GrowSafe Systems Ltd. 2018. GrowSafe Global Headquarters, #300-151 Canada Olympic Road SW, Calgary Alberta Canada, T3B 6B7. URL www.growsafe.com.

Behavior: Health and welfare

Sensors can be used to measure livestock health and welfare by determining behavior associated with locomotion, motion and related factors. For example, lying times, lying bouts and variable durations of these phases can be associated with lameness (Ito et al., 2010). Decreased feedings and visitations to feeders have been shown to be costly expenditures resulting in diminished locomotion ability (Flower and Weary, 2009; Bach et al., 2007; Borderas et al., 2008; De Mol et al., 2013). Locomotion ability with lying phases can be assessed from a single sensor or combination of sensors. The general concepts to understand locomotion and lying phases are based on kinematics and kinetics. Kinematics quantifies gait features as time-related, linear (i.e. distance-related) and angular measurements describing movements of the body segments and joint angles (Clayton and Schamhardt, 2001; Nalon et al., 2013). Reflective markers, accelerometers, pedometers, gyroscopes and magnetometers have all been utilized to determine kinematic movements. Reflective markers are fixed devices at determined locations on an animal's body that track critical points with 3-dimensional (3D) video-graphic or optoelectronic systems and cameras (Chateau et al., 2001; Nalon et al., 2013). In addition, these cameras and their low-cost counterparts can quantify behavior along with animal size, shape and weight when machine learning software is used concurrently (Schofield, 1990; Whittemore and Schofield, 2000; De Wet et al., 2003; Chedad et al., 2003; Leroy et al., 2004; White et al., 2004; Wathes et al., 2008). Variables often recorded for kinematics are stride length, walking speed, swing and stance time, hoof height, and joint angles for determining patterns that may represent structural problems or abnormalities (Von Wachenfelt et al., 2008). Furthermore, accelerometers combined with gyroscopes and magnetometers have been utilized for collection of non-camera-oriented kinematics.

As such, accelerometers are devices used to measure acceleration, vibration and shock felt by an object. Accelerometers can be built on piezoelectrics, integrated electronics and charge mode (Wilson, 2005). These sensors can be bi-axial and tri-axial in use of understanding dynamic characteristics which govern an object's behavior (Wilson, 2005). Commonly, piezoelectric accelerometers are used in a wide range of measurements. Piezoelectric accelerometers are composed of materials that generate electrical signals (proportional to applied stress) and an incorporated signal processor for wireless transmission (Wilson, 2005). When gyroscopes and magnetometers are combined with an accelerometer they form an inertial measurement unit (IMU) used as an animal activity monitor. Gyroscopes are inertial sensors that determine orientations while magnetometers have been implemented as a directional compass. These sensors have been used in a variety of activity research studies to determine unique gait cycle variables such as swing and stance phase durations, along with hoof-load and toe-off peaks to determine differences across lame and sound cows (Alsaaod et al., 2017). Commercially available activity monitors such as Ice Tags (IceRobotics Ltd.) [2], are attached to an animal's leg above the fetlock. Other monitors are attached as either ear tags or neck collars (Chapinal et al., 2011). Studies have reported that hoof contact frequency from these monitors can correlate to gait score but exhibit extremely large variability between animals (Ito et al., 2009; Chapinal et al., 2010). In addition, these instruments are tied with radio frequency identification to provide animal tracking/traceability and can be attached to the head for monitoring sounds, rumination, drinking and eating (Stobbs and Cowper, 1972; Rutter et al., 1997; Schirmann et al., 2009; Ueda et al., 2011; Nielsen, 2013; Braun et al., 2013; Delagarde and Lamberton, 2015; Ambriz-Vilchis et al., 2015; Ruuska et al., 2016). However, kinematics only provides one part of behavioral

---

[2] IceRobotics Ltd. 2018. 5th Floor, 125 Princess Street, Edinburgh, EH2 4AD, United Kingdom. URL www.icerobotics.com.

analysis for health and welfare assessment. When combined with kinetics, a whole picture of an animal can be obtained for improved management.

Kinetics is the study of body movement including force, pressure, load and weight. To collect this data, a variety of pressure, load, force and weight sensors can be used. These sensors can be found on kinetic-based instruments that provide vertical, cranial-caudal and medial-lateral orthogonal directions. An example of how kinetic instruments and their sensors are used in industry is through gait analysis. Common commercial items for gait analysis include the GaitRite, GaitFOUR, and GAITWise systems (CIR Systems Inc.) [3]. The GaitRite System is comprised of electrical sensing elements formed into a pressure sensitive mat that can determine spatial and force measurements during gait cycles (Maertens et al., 2011). Several studies have analyzed its uses on dairy farms to assess and validate cattle gait scores. From these studies, measurements were obscured due to cow traffic and behavior while designs of the actual mats lacked spatial-temporal variability and reduction in costs (Middleton et al., 2005; Maertens et al., 2011). Force plates and pressure mats are other instruments used to capture kinetic measures. Currently, they lack commercial accessibility due to complex installation and hefty costs. A standard instrument of kinetics is the use of livestock scales. Several companies sell commercial scales that provide reliable accuracy and speed in determining animal weights (Tru-Test Inc.) [4]. In addition, kinetic sensor-based systems have been developed to measure head and jaw movements for feeding behavior. These sensors, such as the RumiWatch pressure noseband (Itin + Hoch Gmbh) [5], can measure rumination, drinking and eating behavior (Zehner et al., 2012; Ruuska et al., 2016). The noseband is placed over the cow’s nose as a halter attached directly

---

[3] CIR Systems Inc. 2018. 12 Cork Hill Rd, BLDG 2, Franklin, NJ, 07416. URL https://www.gaitrite.com.
[4] Tru-Test Inc. 2018. 528 Grant Road, Mineral Wells, TX, 76067. URL https://www.tru-testgroup.com.
[5] Itin + Hoch Gmbh. 2018. Liestal, Switzerland. URL https://www.rumiwatch.ch.

to the head, allowing it to be a smaller, low-cost means of measurement versus a stationary feed intake unit (Ruuska et al., 2016). Overall, kinetic and kinematic sensors provide dynamic measures of locomotion, motion and related factors that influence movement and forces for determining animal health and welfare.

Behavior: Reproduction

Aside from health and welfare, sensors can also be used to determine the reproductive status of livestock through behavioral measurements. For example, estrus and its detection are a prominent variable in reproduction with a wide variety of techniques and devices developed that have vast or little market presence (Mottram, 2015). Accelerometers, pedometers, inclinometers, and mount detectors have all been utilized to determine reproductive status and parturition in livestock. Tri-axial accelerometers combined with signal processors have been utilized in animal collars to detect and differentiate between feeding and estrus-induced motion (Voronin et al., 2011, Mottram, 2015). Pedometers are sensors similar in use for motion detection that utilize electrical switches for movement counts. Pedometers have been used as fitted leg sensors to count the number of steps an animal takes that is then compared to a predefined threshold. In turn, exceeding a defined threshold relates to ovulation or estrus. Previous researchers found positive predictive values in determining estrus with pedometer activity (Peter and Bosu, 1986; Koelsch et al., 1994; Van Vliet and Van Eerdenburg, 1996; Kamphuis et al., 2012). Mount detectors are additional tools that have been utilized to determine estrus though they are based on pressure or force, not mobility. Mount sensing units are kinetic devices that require activation from weight of a mounting animal on the unit (Stevenson et al., 1996; Mottram, 2015). The number of mounts on the unit correlate to whether an animal is in standing heat (estrus). This is similar in functionality to dye patches used for estrus detection. However, conventional visual observations have shown greater success rates indicating that commercial viability of mount units may not be realistic (Hempstalk et al., 2013). Lastly, parturition or calving is also tied to reproduction and behavioral signs and indicators have been evaluated through sensor devices such as inclinometers. Inclinometers, such as Moocall (Moocall Ltd.) [6], have been utilized to detect the raising of a heifer's tail as a predictor of approaching calving (Saint-Dizier and Chastant-Maillard, 2015). As such, sensors to determine reproductive status are important tools in helping producers monitor animals to improve pregnancy rate, calving ease and reach maximum offspring potential during an animal's productive life-cycle.

Overall, sensors have been used in the livestock industry for various functions on operations. This section provided a review of different sensors and their applications to evaluate behavioral-based factors as key characteristics to determine animal health and well-being. Deviations from normal animal patterns can indicate if an animal is declining in health or is already suffering from a chronic problem. As such, sensing animal behavior is a multifaceted section in precision livestock management (PLM).

Anatomy and physiology: Overview

Sensors have been used to evaluate anatomical and physiological aspects of various livestock species. By using sensors to determine biometric patterns, internal indicators including temperature, digestion and various functions can be measured externally and internally. Like behavior, they can be measured by utilizing sensors that sense pressure, temperature, light and mechanical signals. These sensors are either surgically stitched inside an animal, attached to the posterior of an animal or placed in the environment to observe an animal. The following sections provide an overview of indicators and technology used in determining an animal's

[6] Moocall Ltd. 2018. Carraig House, Brookfield Terrace, Blackrock, Co. Dublin, Ireland, 01-9696038. URL https://www.moocall.com.

anatomy and physiology. These sections will discuss peripheral and internal body temperature and the use of biosensors to capture physiological metrics.

Anatomy and physiology: Peripheral and internal body temperature

Temperature sensors can be found directly attached to an animal internally or indirectly by monitoring an animal peripherally. Normally, temperature sensors are used to determine increases or decreases in animal body temperature but have been used for sensing expulsion of allantochorion (extraembryonic membrane; Saint-Dizier and Chastant-Maillard, 2015). Peripheral and internal body temperature sensors can vary in function depending on the manner of implementation.

The most current peripheral sensor is infrared (IR) thermography. IR thermography uses cameras and optics to perform visual analyses to detect radiant animal temperatures. This approach is non-invasive in measuring body surface temperature as an indicator of core body temperature. By measuring heat radiation from an object or animal, a point-specific surface temperature can be used to predict local and systemic body temperatures, along with stress and estrus in cattle (Stewart et al., 2007; Rainwater-Lovett et al., 2009; Johnson et al., 2011; Kammersgaard et al., 2013; George et al., 2014; Talukder et al., 2014; Hoffman et al., 2015). Other approaches for detecting surface and internal temperatures exist and are more widely discussed in various literature. For example, subcutaneously implanted integrated transponders and remote skin-surface radio transmitters have been implemented with variable limitations (Sellier et al., 2014; Hoffman et al., 2015; McCafferty et al., 2015). When these peripheral sensors are exposed to the environment, they are subject to external factors that affect the ability to accurately measure body temperature.

Internal body temperature sensors provide a closer measure of an animal's true core temperature. The most common method used to measure internal temperature is rectal analysis, which can be time consuming and invasive as direct contact is required (Hoffman et al., 2015). Other methods for obtaining internal temperature are rumen/reticulum boluses, intra-vaginal or tympanic (i.e. ear) thermocouple/thermistor probes and intra-peritoneal or abdominal implant loggers and radio transmitters (Eigenberg et al., 2009; Sellier et al., 2014; McCafferty et al., 2015). These methods may require surgical implanting, ingestion or short-term contact to work. For example, ingestion of rumen/reticulum boluses have been extensively researched as to their capabilities in collecting data for monitoring the ruminant digestive system. Research has found that internal methods, such as boluses, for sensing temperature lack in overall efficiency for detecting sickness in cattle (Yazdanbakhsh et al., 2017). Some of these limitations include lacking battery power, challenges with data logging and small operating times with limited sampling rates which affect sensor effectiveness and accuracy in measuring body temperature.

Anatomy and physiology: Biosensors

Many biosensing applications and devices exist to measure numerous physiological biometrics. Biosensing refers to any biological measure in an animal. Biosensors can detect basic components such as olfactory and auditory signals to determine physical and behavioral characteristics. Olfactory signals can be detected electronically and chemically with research having been done on vaginal swabs using tin oxide sensors for estrus detection (Llobet et al., 1999; Mottram et al., 2000). Olfactory sensors do not technically smell but simulate the smelling and sensing of chemical signals. Another basic signal that can be detected are auditory signals. Auditory sensors, such as microphones, detect sound signals (i.e. vocalization frequency patterns) to monitor and determine sickness in cattle (Van Hirtum and Berckmans, 2004).

Aside from olfactory and auditory measures, additional biometrics can also be collected to provide a complete understanding of an animal. Biosensors have also been used to detect cardiac and respiratory rates. A few examples of these biosensors include ambulatory electrocardiography devices (e.g. halter recorder) and electrode belts (e.g. polar recorder) that have been used to analyze beat intervals of an animal's heart without being surgically implemented unlike intracardiac bipolar electrodes (von Borrell et al., 2007; Kovács et al., 2014). Respiration rate has been observed using film transducers, lasers and microphones to determine both acoustic and physical properties of breathing (Eigenberg et al., 2000; Eigenberg et al., 2002; Pastell et al., 2007). However, these few examples of biosensors have only been primarily used in research and have yet to transition to commercial viability. With advancements, the field of biosensors is growing and expected to expand to include new applications for industry use.

Since the progressive development of automated machinery and robotics, biosensors have evolved from not only detecting physiological characteristics of animals to sensing the biological and chemical agents found in animal milk, meat, and blood (i.e. byproducts). Applications in microfluidics, fluorescence resonance energy transfer, quantum dots and surface plasmon resonance technology have all been adapted to detect microbial and chemical changes to determine pathogens [7], stress, estrus and various agent activities in cattle (Neethirajan, 2017). Many of these methods require direct contact with an animal or its byproducts (e.g. milk) to obtain data. This can be seen in the dairy industry with the advent of automated milking machines and the sensors embedded in them. Milk temperature, yield, somatic cell counts, protein percentage, lactose percentage, electrical conductivity and progesterone levels are measured to determine an animal's health and reproductive status as studies have shown

[7] Afimilk Ltd. 2018. Kibbutz Afikim, 1514800, Israel. URL https://www.afimilk.com.

(Schofield et al., 1991; MacArthur et al., 1992; Pemberton et al., 1998; Sloth et al., 2003; Mottram et al., 2007; Mottram, 2015). In general, biosensors are a growing field encompassing new areas in livestock as a prominent form of sensing technology cited in literature. As seen through multiple points in this section, biosensors have wide application. By implementing the use of biosensors in addition to other sensors, producers can potentially improve their management and care for livestock by forming a PLM-E of sensors to measure a wide range of livestock variables.

CONCLUSIONS

Sensor technology has been integrated into livestock management to collect valuable data from biometric signals. Reference to a variety of available sensors and technologies provides insight into the possibilities that lie ahead for precision livestock management (PLM). It is important to understand that not all sensors and sensor systems are appropriate for the commercial sector. For example, invasive sensors such as intra-vaginal (surgically implanted) thermometers are a prime example of sensors that raise ethical concerns and may not be practical for use within an operation. Surgical implantation of biosensors has ethical and health repercussions if not administered by a trained individual. Improper implementation can lead to infection and agitation that could result in an animal’s debilitation over time.

Along with ethical and practical worries of certain sensors, some technology may raise concerns about their effectiveness in collecting biometric signals. For example, rumen boluses have been researched for both temperature and contraction movements within cattle digestive tracts. Implementation procedure is invasive and once inside the animal have been reported to have the tendency of being inaccurate due to power failures, sinking to the rumen floor, or breaking after a short time period. Conceptually, these sensors correctly provide an appropriate understanding of the rumen when working. However, one must determine if time, cost, upkeep, implementation, and various expenditures of a sensor and its operation outweigh the benefits.

This is a major issue in the implementation of sensors and sensor-based systems because supporting evidence is deficient or in fledgling stages to show net returns for farms. Yet, it must be taken into consideration that the implementation of a technology may not have a direct economic benefit. Quality of life such as health and welfare at various points in an animal's life may not translate into a direct economic value. This should not deter individuals from using new technologies if a marketable return is not immediately identifiable.

Smart sensing as a whole, is the basis to understanding precision livestock management (PLM). Environmental sensors provide methods to understanding external factors that may affect an animal's productive life-cycle. Animal sensors (whether directly or indirectly sensing) provide insight to the productivity and general well-being of an animal which may not be visually observable. By using sensors to collect environmental and animal data, mathematical and statistical modelling paired with algorithms, software and analytical tools can achieve informative analysis for further control. Additionally, when this digital analysis component is embedded with a managing or control machine, such as robotics, true precision livestock management (PLM) is achieved. Overall, this chapter aimed to lay the groundwork for the research chapters to follow. By understanding currently available sensors and what they detect, key knowledge of their positives and negatives can be used when developing a new sensing technology. From this point, the problem aimed to be solved by the new sensing technology will be discussed. As such, the following chapter briefly covers the foundation of lameness and gait analysis for livestock production in which new optical sensing will be researched.

References

1. Afimilk Ltd. 2018. Kibbutz Afikim, 1514800, Israel. https://www.afimilk.com.

2. Al-Mashhadani, E., and M. M. Beck. 1985. Effect of atmospheric ammonia on the surface ultrastructure of the lung and trachea of broiler chicks. Poult. Sci. 64:2056-2061. doi: S1090-0233(13)00312-2/h0010.

3. Alsaaod, M., J. J. Niederhauser, G. Beer, N. Zehner, G. Schuepbach-Regula, and A. Steiner. 2017. Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows. J. Dairy Sci. 98:6236-6246. doi: 10.3168/jds.2015-9657.

4. Ambriz-Vilchis, V., N. S. Jessop, R. H. Fawcett, D. J. Shaw, and A. I. Macrae. 2015. Comparison of rumination activity measured using rumination collars against direct visual observations and analysis of video recordings of dairy cows in commercial farm environments. J. Dairy Sci. 98:1750-1758. doi: 10.3168/jds.2014-8565.

5. ASHRAE. 2013. 2013 ASHRAE handbook: Fundamentals. Amer. Soc. Heat. Refrig. Air-Cond. Engin. (ASHRAE) Atlanta, GA, USA.

6. Azadeh, M. 2009. Signal characterization and representation. In: B. Mukherjee, editor, Optical networks: Fiber optics engineering. Springer Science+Business Media LLC, New York, NY, USA. p. 61-93. doi: 10.1007/978-1-4419-0304-4_3.

7. Bach, A., M. Dinares, M. Devant, and X. Carre. 2007. Associations between lameness and production, feeding and milking attendance of Holstein cows milked with an automatic milking system. J. Dairy. Res. 74:40-46. doi: S0167-5877(14)00204-9/sbref0025.

8. Berckmans, D. 2017. General introduction to precision livestock farming. Anim. Front. 7:6-11. doi: 10.2527/af.2017.0102.

9. Berman, A., Y. Folman, M. Kaim, M. Mamen, Z. Herz, D. Wolfenson, A. Arieli, and Y. Graber. 1985. Upper critical temperatures and forced ventilation effects for high-yielding dairy cows in a subtropical climate. J. Dairy Sci. 68:1488-1495. doi: 10.3168/jds.S0022-0302(85)80987-5.

10. Borchers and Bewley. 2015. An assessment of producer precision dairy farming technology use, prepurchase considerations, and usefulness. J. Dairy Sci. 98:4198-4205. doi: 10.3168/jds.2014-8963.

11. Borderas, T. F., A. Fournier, J. Rushen, and A. M. B. de Passillé. 2008. Effect of lameness on dairy cows' visits to automatic milking systems. Can. J. Anim. Sci. 88:1-8. doi: S0167-5877(14)00204-9/sbref0080.

12. Braun, U., L. Trösch, F. Nydegger, and M. Hässig. 2013. Evaluation of eating and rumination behaviour in cows using a noseband pressure sensor. BMC Vet. Res. 9:164-170. doi: 10.1186/1746-6148-9-164.

13. Chapinal, N., A. M. de Passillé, J. Rushen, and S. Wagner. 2010. Automated methods for detecting lameness and measuring analgesia in dairy cattle. J. Dairy Sci. 93:2007-2013. doi: 10.3168/jds.2009-2803.

14. Chapinal, N., A. M. de Passillé, M. Pastell, L. Hanninen, L. Munksgaard, and J. Rushen. 2011. Measurement of acceleration while walking as an automated method for gait assessment in dairy cattle. J. Dairy Sci. 94:2895-2901. doi: 10.3168/jds.2010-3882.

15. Chateau, H., C. Degueurce, H. Jerbi, N. Crevier-Denoix, P. Pourcelot, F. Audigié, V. Pasqui-Boutard, and J. M. Denoix. 2001. Normal three-dimensional behavior of the metacarpophalangeal joint and the effect of uneven foot bearing. Equine Vet. J. (Suppl. 33):84-88. doi: S1871-1413(13)00263-1/sbref21.

16. Chedad, A., J. M. Aerts, E. Vranken, M. Lippens, J. Zoons, and D. Berckmans. 2003. Do heavy broiler chickens visit automatic weighing systems less than lighter birds? Br. Poult. Sci. 44:663-668. doi: 10.1080/00071660310001643633.

17. CIGR. 1999. Livestock housing and environment. In: E.H. Bartali, editor, CIGR handbook of agricultural engineering. Amer. Soc. Agric. Engin. (ASABE). St. Joseph, MI, USA. p. 31-88.

18. CIR Systems Inc. 2018. 12 Cork Hill Rd, BLDG 2, Franklin, NJ, 07416. https://www.gaitrite.com.

19. Clayton, H., and H. C. Schamhardt. 2001. Measurement techniques for gait analysis. In: W. Back and H. M. Clayton, editors, Equine locomotion. W. B. Saunders Co., Philadelphia, PA. p. 55-76. doi: S1871-1413(13)00263-1/sbref22.

20. Delagarde, R., and P. Lamberton. 2015. Daily grazing time of dairy cows is recorded accurately using the Lifecorder Plus device. Appl. Anim. Behav. Sci. 165:25-32. doi: 10.1016/j.applanim.2015.01.014.

21. De Mol, R. M., G. André, E. J. B. Bleumer, J. T. N. van der Werf, Y. de Haas, and C. G. van Reenen. 2013. Applicability of day-to-day variation in behavior for the automated detection of lameness in dairy cows. J. Dairy Sci. 96:3703-3712. doi: S0167-5877(14)00204-9/sbref0175.

22. De Wet, L., E. Vranken, A. Chedad, J. M. Aerts, J. Ceunen, and D. Berckmans. 2003. Computer-assisted image analysis to quantify daily growth rates of broiler chickens. Br. Poult. Sci. 44:524-532. doi: S1537-5110(16)30318-X/sref66.

23. DeVries, T. J., M. A. G. von Keyserlingk, D. M. Weary, and K. A. Beauchemin. 2003. Measuring the feeding behavior of lactating dairy cows in early to peak lactation. J. Dairy Sci. 86:3354-3361. doi: 10.3168/jds.S0022-0302(03)73938-1.

24. Doebelin, E. O. 1990. Measurement systems, application and design. McGraw-Hill. New York, NY, USA.

25. Donham, K. J., J. Yeggy, and R. R. Dague. 1988. Production rates of toxic gases from liquid swine manure – Health implications for workers and animals in swine confinement buildings. Biolog. Wastes. 24:161-173. doi: S1090-0233(13)00312-2/h0175.

26. Eigenberg, R. A., G. L. Hahn, J. A. Nienaber, T. M. Brown-Brandl, and D. E. Spiers. 2000. Development of a respiration rate monitor for cattle. Trans. ASAE. 43:723-728. doi: S1537-5110(16)30318-X/sref77.

27. Eigenberg, R. A., T. M. Brown-Brandl, and J. A. Nienaber. 2002. Development of a respiration rate monitor for swine. Trans. ASAE. 45:1599-1603. doi: S1537-5110(16)30318-X/sref73.

28. Eigenberg, R. A., R. A. Bucklin, and T. M. Brown-Brandl. 2009. Instrumentation for research and management in animal agriculture. In: J. A. DeShazer, editor, Livestock energetics and thermal environmental management. Amer. Soc. Agric. Engin. (ASABE). St. Joseph, MI, USA. p. 131-149. doi: S1537-5110(16)30318-X/sref76.

29. Flower, F. C., and D. M. Weary. 2009. Gait assessment in dairy cattle. Anim. 3:87-95. doi: S0167-5877(14)00204-9/sbref0240.

30. Fournel, S., A. N. Rousseau, and B. Laberge. 2017. Rethinking environment control strategy of confined animal housing systems through precision livestock farming. Biosyst. Engin. 155:96-123. doi: 10.1016/j.biosystemseng.2016.12.005.

31. Fraser, D., I. J. H. Duncan, S. A. Edwards, T. Grandin, N. G. Gregory, V. Guyonnet, P. H. Hemsworth, S. M. Huertas, J. M. Huzzey, D. J. Mellor, J. A. Mench, M. Špinka, and H. R. Whay. 2013. General principles for the welfare of animals in production systems: The underlying science and its application. Vet. J. 198:19-27. doi: 10.1016/j.tvjl.2013.06.028.

32. Frost, J. R., C. P. Schofield, S. A. Beaulah, T. T. Mottram, J. A. Lines, and C. M. Wathes. 1997. A review of livestock monitoring and the need for integrated systems. Comp. Electron. Agric. 17:139-159. doi: S1537-5110(16)30318-X/sref82.

33. George, W. D., R. W. Godfrey, R. C. Ketring, M. C. Vinson, and S. T. Willard. 2014. Relationship among eye and muzzle temperatures measured using digital infrared thermal imaging and vaginal and rectal temperatures in hair sheep and cattle. J. Anim. Sci. 92:4949-4955. doi: 10.2527/jas.2014-8087.

34. Grant, R. J., and J. L. Albright. 2000. Feeding behaviour. In: J. P. F. D'Mello, editor, Farm animal metabolism and nutrition. CABI Publishing, Wallingford, Oxon, UK. pp. 365-382.

35. GrowSafe Systems Ltd. 2018. GrowSafe Global Headquarters, #300-151 Canada Olympic Road SW, Calgary Alberta Canada, T3B 6B7. www.growsafe.com.

36. Hempstalk, K., C. R. Burke, and C. Kamphuis. 2013. Verification of an automated camera-based system of oestrus detection in dairy cows. Proc. New Zeal. Soc. Anim. Prod. 73:26-28.

37. Hoffman, G., M. Schmidt, and C. Ammon. 2015. First investigations to refine video-based IR thermography as a non-invasive tool to monitor the body temperature of calves. Anim. 10:1542-1546. doi: 10.1017/S1751731115001354.

38. IceRobotics Ltd. 2018. 5th Floor, 125 Princess Street, Edinburgh, EH2 4AD, United Kingdom. www.icerobotics.com.

39. Itin + Hoch Gmbh. 2018. Liestal, Switzerland. https://www.rumiwatch.ch.

40. Ito, K., D. M. Weary, and M. A. G. von Keyserlingk. 2009. Lying behavior: Assessing within- and between-herd variation in free-stall housed dairy cows. J. Dairy Sci. 92:4412-4420. doi: 10.3168/jds.2009-2235.

41. Ito, K., M. A. G. von Keyserlingk, S. J. LeBlanc, and D. M. Weary. 2010. Lying behavior as an indicator of lameness in dairy cows. J. Dairy Sci. 93:3553-3560. doi: 10.3168/jds.2009-2951.

42. Johnson, S. R., S. Rao, S. B. Hussey, P. S. Morley, and J. L. Traub-Dargatz. 2011. Thermographic eye temperature as an index to body temperature in ponies. J. Eq. Vet. Sci. 31:63-66. doi: 10.1016/j.jevs.2010.12.004.

43. Kammersgaard, T., J. Malmkvist, and L. Pedersen. 2013. Infrared thermography - a non-invasive tool to evaluate thermal status of neonatal pigs based on surface temperature. Anim. 7:2026-2034. doi: 10.1017/S1751731113001778.

44. Kamphuis, C., B. DelaRue, C. R. Burke, and J. Jago. 2012. Field evaluation of 2 collar mounted activity meters for detecting cows in estrus on a large pasture-grazed dairy farm. J. Dairy Sci. 95:3045-3056. doi: 10.3168/jds.2011-4934.

45. Koelsch, R. K., D. J. Aneshansley, and W. R. Butler. 1994. Analysis of activity measurement for accurate oestrus detection in dairy-cattle. J. Agric. Engin. Res. 58:107-114. Doi: 10.1006/jaer.1994.1040.

46. Kovács, L., V. Jurkovich, M. Bakony, O. Szenci, P. Póti, and J. Tözsér. 2014. Welfare implication of measuring heart rate and heart rate variability in dairy cattle: Literature review and conclusions for future research. Anim. 8:316-330. doi: S1537-5110(16)30318-X/sref124.

47. Leroy, T., E. Vranken, J. M. Aerts, M. Silva, E. Struelens, B. Sonck, and D. Berckmans. 2004. A real-time computer vision system for the quantification of animal behaviour and motor function. Proc. Book Abstr. Int. Works. Sma. Sens. Livest. Monit. 3:34-35.

48. Llobet, E., E. L. Hines, J. W. Gardner, P. N. Bartlett, and T. T. F. Mottram, T. T. F. 1999. Fuzzy ARTMAP based electronic nose data analysis. Sens. Act. B Chem. 61:183-190. doi: 10.1016/S0925-4005(99)00288-9.

49. Maertens, W., J. Vangeyte, J. Baert, A. Jantuan, K. C. Mertens, S. De Campeneere, A. Pluk, G. Opsomer, S. Van Weyenberg, and A. Van Nuffel. 2011. Development of a real time cow gait tracking and analyzing tool to assess lameness using a pressure sensitive walkway: The GAITWISE system. Biosyst. Engin. 110:29-39. doi: 10.1016/j. biosystemseng.2011.06.003.

50. MacArthur, A. J., M. P. Easdon, and K. Gregson. 1992. Milk temperature and detection of oestrus in dairy cattle. J. Agric. Engin. Res. 51:29-46. doi: 10.1016/0021-8634(92)80024-M.

51. McCafferty, D. J., S. Gallon, and A. Nord. 2015. Challenges of measuring body temperatures of free-ranging birds and mammals. Anim. Biotelem. 3:33. doi: S1537-5110(16)30318-X/sref149.

52. Middleton, L., A. A. Buss, A. I. Bazin, and M. S. Nixon. 2005. A floor sensor for gait recognition. Proc. IEEE Work. Auto. Ident. Adv. Tech. 4:171-176.

53. Moocall Ltd. 2018. Carraig House, Brookfield Terrace, Blackrock, Co. Dublin, Ireland, 01-9696038. https://www.moocall.com.

54. Mottram, T. F. F., R. M. Lark, A. Lane, D. C. Wathes, K. C. Persaud, M. Swan, and J. M. Cooper. 2000. Techniques to allow the detection of oestrus in dairy cows with an electronic nose. Proc. Int. Symp. Olfac. Elect. Noses. 7:201-208.

55. Mottram, T. F. F., A. Rudnitskaya, A. Legin, J. L. Fitzpatrick, and P. D. Eckersall. 2007. Evaluation of a novel chemical sensor system to detect clinical mastitis in bovine milk. Biosens. Bioelect. 22:2689-2693. doi: 10.1016/j.bios.2006.11.006.

56. Mottram, T. 2015. Animal board invited review: Precision livestock farming for dairy cows with a focus on oestrus detection. Anim. 10:1575-1584. doi: 10.1017/S1751731115002517.

57. Nalon, E., S. Conte, D. Maes, F. A. M. Tuyttens, and N. Devillers. 2013. Assessment of lameness and claw lesions in sows. Livest. Sci. 156:10-23. doi: 10.1016/j.livsci.2013. 06.003.

58. Neethirajan, S. 2017. Recent advances in wearable sensors for animal health management. Sens. Bio-Sens. Res. 12:15-29. doi: 10.1016/j.sbsr.2016.11.004.

59. Nielsen, P. P. 2013. Automatic registration of grazing behaviour in dairy cows using 3D activity loggers. Appl. Anim. Behav. Sci. 148:179-184. doi: 10.1016/j.applanim.2013. 09.001.

60. OMEGA. 2016. Introduction to temperature measurement. http://www.omega.com/ prodinfo/temperaturemeasurement.html. (Accessed 22 February 2017.)

61. Pastell, M., J. Kaihilahti, A. M. Aisla, M. Hautala, V. Poikalainen, and J. Ahokas. 2007. A system for contact-free measurement of respiration rate of dairy cows. Prec. Livest. Farm. doi: S1537-5110(16)30318-X/sref167.

62. Pedersen, S. 2005. Climatization of animal houses: A biographical review of three decades of research. Danish Inst. Agric. Sci., Tjele, Denmark.

63. Pemberton, R. M., J. P. Hart, and J. A. Foulkes. 1998. Development of a sensitive, selective electrochemical immunoassay for progesterone in cow's milk based on a disposable screen-printed amperometric biosensor. Electroch. Acta. 43:3567-3574. doi: 10.1016/S0013-4686(98)00104-2.

64. Peter, A. T., and W. T. K. Bosu. 1986. Postpartum ovarian activity in dairy cows: Correlation between behavioural estrus, pedometer measurements and ovulations. Theriogen. 26:111-115.

65. Rainwater-Lovett, K., J. M. Pacheco, C. Packer, and L. L. Rodriguez. 2009. Detection of foot-and-mouth disease virus infected cattle using infrared thermography. Vet. J. 180:317-324. doi: 10.1016/j.tvjl.2008.01.003.

66. Rutter, S. M., R. A. Champion, and P. D. Penning. 1997. An automatic system to record foraging behaviour in free-ranging ruminants. Appl. Anim. Behav. Sci. 54:185-195. doi: 10.1016/S0168-1591(96)01191-4.

67. Ruuska, S., S. Kajava, M. Mughal, N. Zehner, and J. Mononen. 2016. Validation of a pressure sensor-based system for measuring eating, rumination and drinking behaviour of dairy cattle. Appl. Anim. Behav. Sci. 174:19-23. doi: 10.1016/j.applanim.2015.11.005.

68. Saint-Dizier, M. and S. Chastant-Maillard. 2015. Methods and on-farm devices to predict calving time in cattle. Vet. J. 205:349-356. doi: 10.1016/j.tvjl.2015.05.006.

69. Schirmann, K., M. A. G. von Keyserlingk, D. M. Weary, D. M. Veira, and W. Heuwieser. 2009. Technical note: Validation of a system for monitoring rumination in dairy cows. J. Dairy Sci. 92:6052-6055 doi: 10.3168/jds.2009-2361.

70. Schofield, C. P. 1990. Evaluation of image analysis as a means of estimating the weight of pigs. J. Agric. Engin. Res. 47:287-296. doi: 10.1016/0021-8634(90)80048-Y.

71. Schofield, S. A., C. J. C. Phillips, and A. R. Owens. 1991. Variation in the milk-production, activity rate and electrical-impedance of cervical-mucus over the estrus period of dairy cows. Anim. Repro. Sci. 24:231-248. doi: 10.1016/S0378-4320(05)80007-7.

72. Scholten, M. C. Th., I. J. M. de Boer, B. Gremmen, and C. Lokhorst. 2013. Livestock farming with care: Towards sustainable production of animal-source food. NJAS-Wageningen J. Life Sci. 66:3-5. doi: 10.1016/j.njas.2013.05.009.

73. Schwartzkopf-Genswein, K. S., C. Huisma, and T. A. McAllister. 1999. Validation of a radio frequency identification system for monitoring the feeding patterns of feedlot cattle. Livest. Prod. Sci. 60:27-31. doi: 10.1016/S0301-6226(99)00047-0.

74. Schwartzkopf-Genswein, K. S., L. Faucitano, S. Dadgar, P. Shand, L. A. González, and T. G. Crowe. 2012. Road transport of cattle, swine and poultry in North America and its impact on animal welfare, carcass and meat quality: A review. Meat Sci. 92:227-243. doi: 10.1016/j.meatsci.2012.04.010.

75. Sellier, N., E. Guettier, and C. Staub. 2014. A review of methods to measure animal body temperature in precision farming. Amer. J. Agric. Sci. Tech. 2(2):74-99. doi: S1537-5110(16)30318-X/sref193.

76. Sloth, K. H. M. N., N. C. Friggens, P. Løvendahl, P. H. Andersen, J. Jensen, and K. L. Ingvartsen. 2003. Potential for improving description of bovine udder health status by combined analysis of milk parameters. J. Dairy Sci. 86:1221-1232. doi: 10.3168/jds.S0022-0302(03)73706-0.

77. Snowder, G. D., L. D. Van Vleck, L. V. Cundiff, and G. L. Bennett. 2006. Bovine respiratory disease in feedlot cattle: Environmental, genetic, and economic factors. J. Anim. Sci. 84:1999-2008. doi: S1090-0233(13)00312-2/h0710.

78. Stewart, M., J. R. Webster, G. A. Verkerk, A. L. Schaefer, J. J. Colyn, and K. J. Stafford. 2007. Non-invasive measurement of stress in dairy cows using infrared thermography. Phys. Behav. 92:520-525. doi: 10.1016/j.physbeh.2007.04.034.

79. Stevenson, J. S., M. W. Smith, J. R. Jaeger, L. R. Corah, and D. G. Lefever. 1996. Detection of estrus by visual observation and radiotelemetry in peripubertal, estrus-synchronized beef heifers. J. Anim. Sci. 74:729-735.

80. Stobbs, T. H., and L. J. Cowper. 1972. Automatic measurement of the jaw movements of dairy cows during grazing and rumination. Trop. Grassl. 6:107-112. doi: S0168-1591(15)00309-3/sbref0110.

81. Talukder, S., K. L. Kerrisk, L. Ingenhoff, P. C. Thomson, S. C. Garcia, and P. Celi. 2014. Infrared technology for estrus detection and as a predictor of time of ovulation in dairy cows in a pasture-based system. Theriogen. 81:925-935. doi: 10.1016/j.theriogenology.2014.01.009.

82. Thornton, P. K. 2010. Livestock production: Recent trends, future prospects. Philo. Trans. Roy. Soc. London B: Biolog. Sci. 365:2853-2867.

83. Tru-Test Inc. 2018. 528 Grant Road, Mineral Wells, TX, 76067. https://www.tru-testgroup.com.

84. Ueda, Y., F. Akiyama, S. Asakuma, and N. Watanabe. 2011. Technical note: The use of a physical activity monitor to estimate the eating time on cows in pasture. J. Dairy Sci. 94:3498-3503. doi: 10.3168/jds.2010-4033.

85. UNPD. 2017. World population prospects the 2015 revision. Accessed February 22, 2017 from https://esa.un.org/unpd/wpp/Publications/Files/Key_Findings_WPP_2015.pdf

86. Van der Fels-Klerx, H. J., H. S. Horst, and A. A. Dijkhuizen. 2000. Risk factors for bovine respiratory disease in dairy youngstock in the Netherlands: The perception of experts. Livest. Prod. Sci. 66:35-46. doi: S1090-0233(13)00312-2/h0780.

87. Van Hirtum, A., and D. Berckmans. 2004. Objective recognition of cough sound as a biomarker for aerial pollutants. Ind. Air. 14:10-15. doi: 10.1046/j.1600-0668.2003.00195.x.

88. Van Vliet, J. H., and F. J. C. M. Van Eerdenburg. 1996. Sexual activities and oestrus detection in lactating Holstein cows. Appl. Anim. Behav. Sci. 50:57-69. doi: 10.1016/0168-1591(96)01068-4.

89. Von Borell, E., J. Langbein, G. Després, S. Hansen, C. Leterrier, and J. Marchant-Forde. 2007. Heart rate variability as a measure of autonomic regulation of cardiac activity for assessing stress and welfare in farm animals a review. Physiol. Behav. 92:293-316. doi: B978-0-12-394586-0.00003-2/sbref17.

90. Von Wachenfelt, H., S. Pinzke, C. Nilsson, O. Olsson, and C. J. Ehlorsson. 2008. Gait analysis of unprovoked pig gait on clean and fouled concrete surfaces. Biosyst. Eng. 101:376-382. doi: S1871-1413(13)00263-1/sbref79.

91. Voronin, V., E. Brayer, and U. Ben-Menachem. 2011. Method and device for detecting estrus. Filed May 26. Patent Application No. US20110125065.

92. Wathes, C. M., H. H. Kristensen, J. M. Aerts, and D. Berckmans. 2008. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? Comp. Electron. Agric. 64:2-10. doi: 10.1016/j.compag. 2008.05.005.

93. West, J. W., B. G. Mullinix, and J. K. Bernard. 2003. Effects of hot, humid weather on milk temperature, dry matter intake, and milk yield of lactating dairy cows. J. Dairy Sci. 86:232-242. doi: 10.3168/jds.S0022-0302(03)73602-9.

94. White, R. P., C. P. Schofield, D. M. Green, D. J. Parsons, and C. T. Whittemore. 2004. The effectiveness of a visual image analysis (VIA) system for monitoring the performance of growing/finishing pigs. Anim. Sci. 78:409-418. doi: 10.1017/S1357729800058811.

95. Whittemore, C. T., and C. P. Schofield. 2000. A case for size and shape scaling for understanding nutrient use in breeding sows and growing pigs. Livest. Prod. Sci. 65:203-208. doi: 10.1016/S0301-6226(99)00136-0.

96. Wilson, J. S. 2005. Sensor technology handbook. 1st ed. Newnes., Burlington, MA. doi: 10.1016/B978-0-7506-7729-5.50081-1.

97. Wu, W., G. Zhang, and P. Kai. 2012. Ammonia and methane emissions from two naturally ventilated dairy cattle buildings and the influence of climatic factors on ammonia emissions. Atmos. Environ. 61:232-243. doi: 10.1016/j.atmosenv.2012.07.050.

98. Yazdanbakhsh, O., Y. Zhou, and S. Dick. 2017. An intelligent system for livestock disease surveillance. Info. Sci. 378:26-47. doi: 10.1016/j.ins.2016.10.026.

99. Zehner, N., J. J. Niederhauser, F. Nydegger, A. Grothmann, M. Keller, M. Hoch, A. Haeussermann, and M. Schick. 2012. Validation of a new health monitoring system (RumiWatch) for combined automatic measurement of rumination, feed intake, water intake and locomotion in dairy cows. Proc. Int. Conf. Agric. Engin. CIGR-AgEng2012. doi: S0168-1591(15)00309-3/sbref0135.

Chapter Three

Overview of lameness and development of the embedded-optical-base system

Lameness

A common evaluation tool for assessing live animal well-being is the observation of abnormalities in the musculoskeletal system (MS). MS impairments can be associated with motion deficits, functional disorders, lameness, primary muscular diseases, neurologic deficits, toxins, endocrine aberrations, metabolic disorders, infectious diseases, blood and vascular disorders, nutritional imbalances or deficits, and congenital defects (Adams, 2016). These abnormal afflictions which impair structural integrity can impact all livestock sectors, yet they are often an underreported factor for economic losses. In Wisconsin alone, a mean prevalence of 33.7% for lameness was reported in dairy herds resulting in involuntary cull losses (Shearer et al., 2013). Worldwide, lameness occurrence in dairy cattle ranged from 3% to 60% with respect to country, herd, season, and housing type (Garciá-Muñoz et al., 2016). Though lameness can be economically and physically crippling, pathogens causing MS impairment can also be security risks if infectious. Digital dermatitis (DD) is a global infectious hoof disease in sheep, dairy cattle and beef cattle causing severe lameness to infected animals (Sullivan et al., 2013). Recently, research has found bacteriological similarities between DD in sheep and cattle that has posed concern for cross species transmission (Sullivan et al., 2015). From this, identification of signs relating to MS impairments is critical so as to alleviate unnecessary pain, stress, death and potential contamination of livestock.

Lameness is deemed the most prevalent syndrome of MS impairments (Greenough et al., 2007). It is the clinical, pain-induced modification of gait occurring from differing diseases and disorders that can result in severe morbidity and mortality (Greenough et al., 2007). While clinically useful to distinguish between MS impairments, lameness has been noticed as an overlapping sign for most subtle and severe cases. However, detection and diagnosis of lameness is complex due to its multi-factorial nature. Lameness examination can be divided between the fore- and hind limbs and their respective hooves in quadrupeds. Bovine hoof disorders known to cause subclinical lameness have been reported to affect up to 70% of cattle in the dairy industry (Hedges et al., 2001; Van der Tol et al., 2003). The most prevalent of these disorders are lesions of the digital and interdigital spaces involving dermatitis, sole ulcers, white line disease, toe necrosis/apical syndrome, hyperplasia and sole hemorrhages (Adams, 2016). Disorders can also be found in the horn capsule and corium as a result of laminitis and foreign body exposure (Adams, 2016). Limb and upper-limb disorders can occur in the bone, joint or soft-tissue and are mostly due to issues in animal handling resulting in paralysis, neurological damage, dislocation or ruptures causing varying severity of lameness (Adams, 2016). Proper management to avoid these issues requires early detection as to the physical or pathogenic cause, extent of severity, and known location of an affliction. The focus of this research is on the assumption that lameness is a primary syndrome and sign for MS evaluation.

Commonly, diagnosis of lameness for MS impairment is subjective (i.e. qualitative) based on visual assessment of animal structure, locomotion and associated behaviors. Changes in behaviors to protect an affected limb are scored on either binomial, ordinal or analog scales by a trained observer. Posture of limbs is evaluated through angulation, position, and extension in an attempt to displace weight. Locomotive observation combines gait characteristics of stride, speed and tracking to evaluate pain mitigation during movement. The Sprecher lameness scoring system is the basis for most scoring scales (Sprecher et al., 1997; Shearer et al., 2016).

It associated signs of head bobbing, arching of spine and changes in stride length as rapid identifiers of affected animals (Sprecher et al., 1997; Shearer et al., 2016). Observational scoring systems vary between 3-, 4-, and 5-point gradings. Though common, observational analysis is dependent on intra-observer and inter-observer reliability that affects both repeatability and validity of tests (Dahl-Pedersen et al., 2018). This subjective variability has necessitated development of objective methods for assessment. As such, improvements to objectively detect incidence of animals being affected with lameness is the underlying intent of this research.

Overall, diseases and disorders of the MS that cause pain-induced lameness are biological and environmental risk factors that can result in significant morbidity and mortality for afflicted animals. Early diagnosis and treatment of the cause is crucial for animal recovery. Presently, visual subjective detection is the most accepted form of diagnostic standards. However, rapid detection for examination is challenging when relying on subjective analysis without the aid of objective measurement tools and requires personnel trained for evaluation. Additionally, current objective technologies are cumbersome relying on delicate sensors, direct attachment to an animal, compatible proprietary software and/or limited technical teams. An optical sensor for gait measurements may provide a unique method in detecting both minute and noticeable biomechanical metrics (i.e. biometrics) without future additional requirements. As such, technological advancements with optics could allow for rapid changes in how researchers and producers detect lameness and offer a viable objective option for onsite or remote gait analysis.

Embedded-Optical-Base System (EOBS)

Current gait analysis sensors (Table 3.1) rely on conventional sensor methods such as piezoresistive, strain gauge and/or complex solid-state units. However, these sensors can be miniaturized in nature with head diameters of 0.5 mm or smaller leading to problems of fragility, excessive drifting and long-term instability and inconsistency (Mignani and Baldini, 1996). Along with functional issues, the state of these sensors can limit output to minute areas that may require necessary expenditure for increased dimensions that in turn cause loss in flexibility (Arkwright et al., 2009). Minimizing these problems is a major factor in improving collection of gait biometrics for an eco-rich application in livestock operations. Research of a proof-of-concept embedded-optical-base system (EOBS) with high performance while operating under harsh production conditions may provide a solution to these problems.

Optical sensors are classified based on their working principles (Roriz et al., 2012). General intensity modulated schemes are applied most abundantly within mature solutions and simple interrogations for optical sensors (Udd, 1991; Roriz et al., 2012). Two major configurations of intensity modulated schemes applied are based on (1) reflecting membrane and (2) curvature. Additionally, two major light sources applied in optical sensors are (1) white light and (2) infrared. The Ag Tech Optics' LLC (ATO) EOBS was based on a multi-beam device in which output is dependent on reflections from an input source between two formed interfaces. Resonant space was developed from previous ATO optic-based research. Two dielectric interfaces were formed within a single-mode construct (Xie et al., 2006). Magnitude of signal (P_r) was based on signal interference where P_i is the incident power, R_1 and R_2 are reflections from the two interfaces, L is length, and φ is the beam's phase shift.

$$P_r = P_i * (R_1 + R_2 - 2\sqrt{R_1 * R_2} * \cos\varphi) \tag{2.1}$$

If $R=R_1=R_2$, equation (2.1; 2.2) will become

$$P_r = 2RP_i(1 - \cos\varphi) \tag{2.2}$$

Phase shift is based on the equation (2.3)

$$\varphi = \frac{4\pi n v L}{c} = \frac{4\pi n L}{\lambda} \tag{2.3}$$

where n is the beam's propagative value, v is frequency, L is length, and c is the beam's free space. Magnitude in power (P_r) is then changed in response to phase shift (φ) variation where φ is expressed as equation (2.4).

$$\varphi = \varphi_0 + \Delta\varphi_L + \Delta\varphi_v + \Delta\varphi_T \tag{2.4}$$

Where φ_0 is the initial shift and $\Delta\varphi_L$ (2.5) is change in length, $\Delta\varphi_v$ (2.6) is change in frequency, and $\Delta\varphi_T$ (2.7) is change in temperature.

$$\Delta\varphi_L = \frac{4\pi}{\lambda}(n\Delta L + L\Delta n) \tag{2.5}$$

$$\Delta\varphi_v = \frac{4\pi L}{c}\left(n + v\frac{dn}{dv}\right) \tag{2.6}$$

$$\Delta\varphi_T = \frac{4\pi}{\lambda}\left(L\frac{dv}{dT} + n\frac{dL}{dT}\right) \tag{2.7}$$

Power is the summation of waves from the two dielectric interfaces in which the optical signal is converted to an electrical signal. This electrical signal can be used to determine physical fluctuations such as temperature, pressure and strain.

From an optical design provided by ATO, the research hoped to improve on current collection methods of gait biometrics. The optical sensor was modified for spectral manipulation brought on by physical fluctuations affecting optical phase shifts. This signal surface distribution (R) was then monitored as a sinusoidal modulation of output current. One limiting factor of optical sensors and their spectral sources is attenuation. Attenuation (i.e. transmission loss) is a limiting factor in optical sensing that is brought on by scattering or in-homogeneities in beam source. To resolve this, the novel ATO sensor utilized optical time-domain reflectometers (OTDRs) to evaluate both quality of medium and connector as a means of measuring backscatter from a beam source. The novel ATO EOBS focused on collecting signal fluctuations (e.g. amplitudes) for objective analysis of livestock gait biometrics.

Implementation was based on ATO specifications with the following concepts and designs provided by ATO (Figure 3.1). Application of the ATO EOBS was centered around encapsulation and a panel design to withstand harsh livestock variables such as manure and urine. To safely encapsulate the EOBS, a metal box was constructed to securely hold the sensor while also providing a standard rating of protection from external particles such as dust and water. An anchored surface mounting was utilized involving bolt-on, grout-in and weldable bracketing. A recycled rubber base was applied to the outer-bottom surface of the capsule to eliminate impact vibration from contact with concrete flooring. Panel design was based on a low-degradating metal sheet of specific dimensions (width x height x length) derived from previous research and evaluation of industry standards that adhere for livestock compatibility. Proprietary metal sheeting was utilized based on reduced noise and vibrational error at greater efficiencies than other material. Thus, low interference in signal collection was beneficial during gait collection. For traction and friction, a commercialized rubber layer of specific dimensions (width x height x length) was applied as a top layer to the metal sheeting. Special attention to animal safety was made to provide a sufficient surface area and footing while moving across the EOBS.

A signal-base-unit (SBU) was provided by ATO that primarily focused on the natural behavior of the system. Common commercial SBUs for sensing require differential operating components to acquire and analyze output. These units are not beneficial for optical designs however, evaluation of physical dimensions, tolerances and material selection are proper to perform. For optical enhancement, ATO devised an SBU around a standard optical system, operational scheme. The ATO SBU contained a single micrometer communication grade semiconductor beam with thermoelectric cooler (TEC). The TEC provided stable temperature operation of the beam. Beam operation was driven by a current driver (CD) while being modulated by a microprocessor. Optical coupling was applied to distribute the beam to the sensors. Once received, sensor splitters directed signals to corresponding channel detectors. The beam was then converted to an electrical signal and a microprocessor tracked the change. A digital timing scheme was used to track changes allowing for the optical shifts in each sensor to be determined. From there signals were analyzed with a comparator (CP) and information was passed to an output terminal. Beam drift caused by system linearization was compensated for. Modulation can be used for normal sample rates equaling to repetitive frequencies. The ATO SBU was constructed on integrated, multifunctional hardware capable of high performance in a compact package for significant readings without compromising performance. SBU circuitry was centered around multiple output boards, master and slave microprocessor boards, a power supply board, a detector board, and a beam board. Other components consisted of internal micro controllers, separated analog-digital-analog converters, and memory storage. In its entirety, the ATO SBU consisted of blocked diagrams for hosting output, processing, detecting, and beam driving. In combination with the ATO SBU hardware, commercial and open-source software was used for initial integration and interface control. Software is vast and numerous with differentiations in architecture, purpose and function. ATO provided insight into software that worked in tandem with hardware to ensure ubiquitous behavior of the EOBS operation.

Design and development of the EOBS construction devised a usable prototype (Figure 3.2). Prior work was accomplished by ATO personnel at ATO's facilities in Texas. Complex integration was needed for incorporation in livestock testing. Items that did not meet functional standards required a substitute to be created. Once the system was established and set, experimentation of the device's functional and operational behavior was performed to assess the EOBS's future utilization in a precision livestock management ecosystem (PLM-E).

Table 3.1 General gait biometrics and prior technologies used for quantitative and qualitative gait analysis and lameness detection along with a short list of pros and cons associated with each technology.

Gait Biometric	Technologies	General Pros and Cons
Stride Length	Pressure Mat [8]	**Pros:** Portable and provides contact point asymmetry analysis; **Cons:** Limited in dynamic range.
Stride Duration	Force Plate [5] Pressure Mat [8]	**Pros:** Both are accurate; **Cons:** Limited use outside of research or clinics.
Tracking (Step Overlap)	Video Imaging [7] Observational [*]	**Pros:** Provides additional measures for evaluation; **Cons:** Additional cameras required for greater input cost.
Abduction and Adduction	Observational [*]	
Stance and Swing Phase	Observational [*]	
Peak Loading	Force Plate [5]	**Pros:** Accurate and fast; **Cons:** Installation adjustments of facilities required.
Ground Reaction Force	Force Plate [5, 7] Pressure Mat [8]	**Pros:** Accurate and fast; **Cons:** Installation adjustments of facilities required.
Step Frequency and Limb Weight Drift	Single Point Load Cell [4, 7]	**Pros:** Fast evaluation of hoof contacts; **Cons:** Requires complex implementation.
Locomotion Speed	Accelerometer [2]	**Pros:** Low input cost; Small to large repeatability; **Cons:** Limited in ground range and additional handling of animals and lacking practicality on all limbs for accurate measurements.
Locomotion Score	3D Imaging [1] Observer [7]	**Pros:** Fast evaluation; **Cons:** Large input cost on additional camera and workers to observe scoring.
Spine Arch and Head Position	Lameness Algorithm [3] Observer [7]	**Pros:** Fast evaluation; **Cons:** Large input cost on additional camera and workers to observe scoring.

* Observational evaluations are utilized in various studies to observe a variety of animal biometrics.
[1] Jabbar et al., 2017
[2] Pastell et al., 2009
[3] Viazzi et al., 2013
[4] Pastell and Madsen, 2008
[5] Walker et al., 2010
[6] Chapinal et al., 2010
[8] Maertens et al., 2011

Note: *1. Additional variables to take into consideration are live weight, parity, diet and additional management records to provide a comprehensive understanding of the animal while analyzing gait biometrics; 2. References are cited in the References section.*

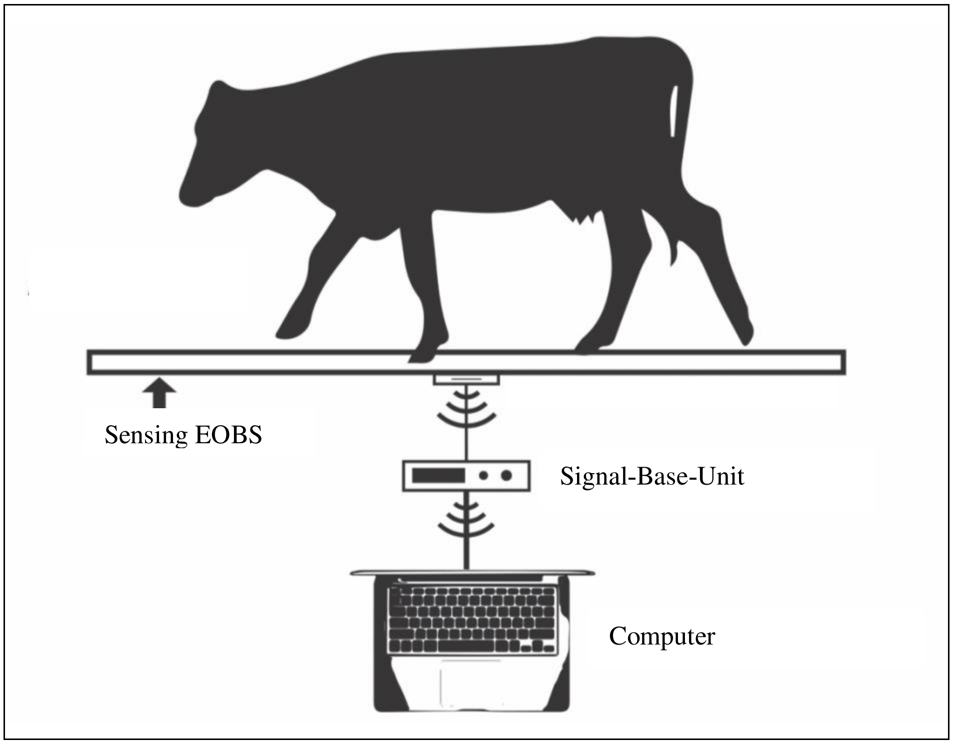

Figure 3.1 Diagram of embedded-optical-base system (EOBS) and its connection between the signal-base-unit (SBU) and computer. Animals walk across the EOBS in which the SBU receives the signal fluctuation and returns the received interruption to a computer for real-time graphing and analysis.

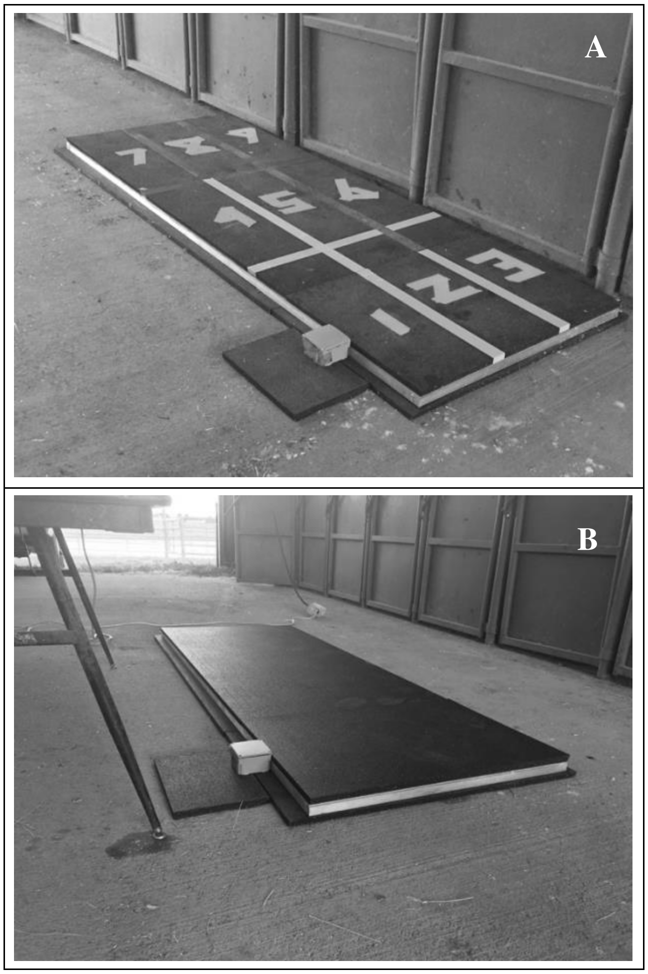

Figure 3.2 Images of the embedded-optical-base system (EOBS). Image A shows EOBS with initial column and row grid layout for first round testing. Image B shows EOBS without grid layout. The EOBS platform measured 0.914 m (width) x 2.438 m (length).

References

1. Adams, S. B. 2016. Overview of musculoskeletal system. Merck Veterinary Manual (11th ed.). http://www.merckvetmanual.com/mvm/ musculoskeletal _system/Musculoskeletal system introduction/overview of musculoskeletal system.html (Accessed 10 August 2017.)

2. Arkwright, J. W., N. G. Blenman, I. D. Underhill, S. A. Maunder, M. M. Szczesniak, P. G. Dinning, and I. J. Cook. 2009. In-vivo demonstration of a high-resolution optical fiber manometry catheter for diagnosis of gastrointestinal motility disorders. Opt. Expr. 17:4500-4508. doi: 10.1364/OE.17.004500.

3. Dahl-Pedersen, K., L. Foldager, M. S. Herskin, H. Houe, and P. T. Thomsen. 2018. Lameness scoring and assessment of fitness for transport in dairy cows: Agreement among and between farmers, veterinarians and livestock drivers. Res. Vet. Sci. 119:162-166. doi: 10.1016/j.rvsc.2018.06.017.

4. García-Muñoz, A., G. Vidal, N. Singh, and N. Silva-del-Río. 2016. Evaluation of two methodologies for lameness detection in dairy cows based on postural and gait abnormalities observed during milking and while at headlock stanchions. Prev. Vet. Med. 128:33-40. doi: 10.1016/j.prevetmed.2016.04.005.

5. Greenough, P. R. 2007. Bovine laminitis and lameness: A hands on approach. 1st ed. Saunders Elsevier, Philadelphia, PA.

6. Hedges, J., R. W. Blowey, A. J. Packington, C. J. O'Callaghan, and L. E. Green. 2001. A longitudinal field trial of the effect of biotin on lameness in dairy cows. J. Dairy Sci. 84:1969-1975. doi: 10.3168/jds.S0022-0302(01)74639-5.

7. Jabbar, K. A., M. F. Hansen, M. L. Smith, and L. N. Smith. 2017. Early and non-intrusive lameness detection in dairy cows using 3-dimensional video. Biosyst. Engin. 153:63-69. doi: 10.1016/j.biosystemseng.2016.09.017.

8. Maertens, W., J. Vangeyte, J. Baert, A. Jantuan, K. C. Mertens, S. De Campeneere, S. Pluk, G. Opsomer, S. Van Weyenberg, and A. Van Nuffel. 2011. Development of a real time cow gait tracking and analyzing tool to assess lameness using a pressure sensitive walkway: The GAITWISE system. Biosyst. Engin. 110:29-39. doi: 10.1016/j.biosystemseng.2011.06.003.

9. Mignani, A. G., and F. Baldini. 1996. Biomedical sensors using optical fibres. Rep. Prog. Phys. 59:1-28. doi: 10.1088/0034-4885/59/1/001.

10. Pastell, M. and H. Madsen. 2008. Application of CUSUM charts to detect lameness in a milking robot. Exp. Syst. Appl. 35:2032-2040. doi: 10.1016/j.eswa.2007.08.087.

11. Pastell, M., J. Tiusanen, M. Hakojärvi, and L. Hänninen. 2009. A wireless accelerometer system with wavelet analysis for assessing lameness in cattle. Biosyst. Engin. 104:545-551. doi: 10.1016/j.biosystemseng.2009.09.007.

12. Roriz, P., A. Ramos, J. Santos, and J. Simões. 2012. Fiber optic intensity-modulated sensors: A review in biomechanics. Phot. Sens. 2:315-330. doi: 10.1007/s13320-012-0090-3.

13. Shearer, J. K., M. L. Stock, S. R. Van Amstel, and J. F. Coetzee. 2013. Assessment and management of pain associated with lameness in cattle. Vet. Clin. North Amer. Food Admin. Pract. 29:135-156. doi: 10.1016/j.cvfa.2012.11.012.

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

15. Sullivan, L. E., S. D. Carter, R. Blowey, J. S. Duncan, D. Grove-White, and N. J. Evans. 2013. Digital dermatitis in beef cattle. Vet. Rec. 173:582. doi: 10.1136/vr.101802.

16. Sullivan, L. E., S. R. Clegg, J. W. Angell, K. Newbrook, R. W. Blowey, S. D. Carter, J. Bell, J. S. Duncan, D. H. Grove-White, R. D. Murray, and N. J. Evans. 2015. High-level association of bovine digital dermatitis Treponema spp. with contagious ovine digital dermatitis lesions and the presence of Fusobacterium Necrophorum and Dichelobacter Nodosus. J. Clin. Micro. 53:1628-1638. doi: 10.1128/JCM. 00180-15. doi: 10.1128/JCM.00180-15.

17. Udd, E. 1991. Fiber optic sensors: An introduction for engineers and scientists. John Wiley and Sons, Inc. Hoboken, NJ.

18. Van der Tol, P. J., J. M. Metz, E. N. Noordhuizen-Stassen, W. Back, C. R. Braam, and W. A. Weijs. 2003. The vertical ground reaction force and the pressure distribution on the claws of dairy cows while walking on a flat substrate. J. Dairy Sci. 86:2875-2883. doi: 10.3168/jds.S0022-0302(03)73884-3.

19. Viazzi, S., C. Bahr, A. Schlageter-Tello, T. Van Hertem, C. E. B. Romanini, A. Pluk, I. Halachmi, C. Lokhorst, and D. Berckmans. 2013. Analysis of individual classification of lameness using automatic measurement of back posture in dairy cattle. J. Dairy Sci. 96:257-266. doi: 10.3168/jds.2012-5806.

20. Walker, A. M., T. Pfau, A. Channon, and A. Wilson. 2010. Assessment of dairy cow locomotion in a commercial farm setting: The effects of walking speed on ground reaction forces and temporal and linear stride characteristics. Res. Vet. Sci. 88:179-187. doi: 10.1016/j.rvsc.2009.05.016.

21. Xie, Z., O. Eknoyan, H. F. Taylor, C. B. Su, and G. L. Cote. 2006. Two applications of the fabry-perot interferometric sensor (Doctoral dissertation). Retrieved from Texas A&M University Libraries.

Chapter Four

In-motion optical sensing as an objective assessment for gait examination [8]

SUMMARY

The primary objective of this investigative field study was to establish initial feasibility in using an optical sensor for detecting hoof contacts and calculating kinematic variables. An embedded-optical-base system (EOBS) was attached to a constructed platform and used to collect signal amplitude (0 to 1 arbitrary units (au)) from cattle hoof contact. The EOBS platform was divided into 3 sectors and 9 sub-sectors. Mechanical flex of the platform (recorded as signal outputs; S_O) occurred from an animal's walk over the EOBS. Signal outputs (S_O) correlated to points on a linear time-series for animal passes over the EOBS platform. Eight steers (n = 8) weighing between 680 and 1134 kg, of British and Continental influence were tested. Cattle were herded 2 times across the platform over 1 d. Prior to testing, initial body weights were collected along with fore- and hind limb hoof circumferences. Each steer's pass over the platform was video recorded and later evaluated by a trained observer during data analysis. Hoof contacts from each animal were recorded. A total of 58 strides (complete limb swings) were obtained. Approximately 2 complete strides per animal were observed. Estimated mean steer velocity ($\sim v$) was 2.6 m/s, with a range of 2.0 to 4.0 m/s. Outliers consisted of 0.9 m/s and 6.6 m/s due to shift in speed during a pass over the EOBS platform.

Overall, aperiodic (i.e. asymmetric; uneven) linear hoof contact measurements from fore- and hind limbs were detectable by the EOBS. Uniform and non-uniform hoof contact signal

---

[8] Part of this chapter was published as: *Colton A. Atkins, Kevin R. Pond, and Christi K. Madsen. 2017. In-motion optical sensing for assessment of animal well-being. Proc. SPIE 10217, Sensing for Agriculture and Food Quality and Safety IX, 1021709. doi: 10.1117/12.2262194.*

fluctuations from fore- and hind limbs were also detectable. Additionally, qualitative analysis showed that hoof contact with the EOBS platform could be correlated to video recordings. First fore- and hind limb contact proved to have the largest signal amplitude when located within sectors 1 and 2. Flex within the platform's metal showed muting in the signal output (S_O) when hoof contacts where located in sector 3. Animal speed showed correlation to hoof contact signal amplitude. Initial video and data analysis suggested detectable lameness in 1 of the 8 steers. Veterinary examination occurred roughly a week after the suggestion and confirmed lameness was developing. Overall, the system detected animal hoof contact with the embedded-optical-base system (EOBS) platform.

Key words: Optics, steers, gait analysis, sensors

INTRODUCTION

Biomechanical Load Measuring

Biomechanical load measuring is used for objective acquisition of biometric gait data through the use of connected sensor systems. Ground reaction forces and vertical pressure distributions (Van der Tol et al., 2003) of hoof impacts in contact with sensor surfaces provide topographical measurements during an animal's stride cycle. Specifically, these sensor systems give information about the stance phase when the animal's hoof is in contact with the ground. From these methods and their collected measurements, automatic lameness detection could be achieved (Pastell et al., 2008). As such, automated sensor methods have detected hind limb lameness from vertical forces of cows walking across parallel force plates; explained right-left limb symmetry of vertical forces from heifers without hoof lesions; and separated mildly lame cows from healthy cows (Rajkondawar et al., 2006; Almeida et al., 2007; Van Nuffel et al., 2013; Thorup et al., 2014). Further research also found that kinematic analysis of recorded passes by reflective markers over a pressure-sensitive walkway provided adequate sensitivity and specificity in analyzing gait measurements from cows to indicate lameness (Van Nuffel et al., 2009; Maertens et al., 2011; Nalon et al., 2013). Thus, gait analysis by means of sensors could be viewed as a diagnostic choice for objective lameness detection.

Force and pressure sensor systems are common methods employed in veterinary and academic laboratories and a small set of large-scale operations for obtaining objective data. Despite published results, current systems are based on electrical sensors such as thin-film electric force nodes, pressure-sensitive load cells and strain gauge force plates. All of which, can require substantial manual labor, extensive costs and considerable setup to properly function. Commercially available instruments measuring weight distribution between limbs, weight shifting and weight pressure on claws are limited in design adaptability due to corrosion vulnerability in rugged environments, electromagnetic interference and calibration instability (National Instruments, 2016). To incorporate these systems, developers are required to address noise, isolation and shielding parameters to make an adaptable sensing unit (National Instruments, 2016).

The primary objective of this proof-of-concept study was to establish initial feasibility in using an optical sensor for measuring hoof contacts. The second objective was to assess the system's functionality in withstanding rugged environments as well as large animals. The third objective was to test the system's initial capabilities in providing useful gait data for analysis.

MATERIALS AND METHODS

The research protocol for this study and all procedures involving animal handling were approved by the Colorado State University (CSU) Institutional Animal Care and Use Committee (IACUC; approval number 16-6611AA). The study was conducted in August 2016.

Animals and Housing

Eight crossbred steers (n = 8), of predominantly British and Continental breeding, weighing between 680 and 1134 kg were tested. Animals were representative of feedlot beef cattle in Colorado. All animals were worked multiple times in the Agriculture Research, Development and Education Center's (ARDEC) facilities prior to data extraction.

Embedded-Optical-Base System (EOBS)

An embedded-optical-base system (EOBS) developed around a point sensor was provided by Ag Tech Optics, LLC (ATO; Bryan, TX). The EOBS was attached to a constructed metal platform (2.4 m (length) x 0.9 m (width)) and used to collect signal amplitude (0 to 5 voltage (V)) from cattle hoof contact. The EOBS platform was divided into 3 sectors and 9 sub-sectors (Figure 4.1). Hoof contacts on the EOBS platform resulted in mechanical flex which resulted in signal fluctuations recorded as signal outputs (S_O). Signal outputs (S_O) correlated to deviations from a signal baseline on a linear time-series for animal passes over the EOBS.

Experimental Design

Field testing was performed in an environment that closely mimicked a working cattle operation so as to analyze the EOBS platform's performance. The testing period was for 1 d with multiple passes of the EOBS platform allowing for repeated gait examination. The EOBS platform was installed on a level concrete pathway with careful consideration given to spacing and utility access. Portable panels were aligned prior, on the sides and after the EOBS platform to ensure steers moved across the system. Prior to gait analysis, body weights were determined using a commercial static scale, along with fore- and hind limb hoof circumferences. In addition, a simple health examination was performed by a trained worker for ARDEC's records. Once evaluations and measurements were done, steers were herded into a holding pen and individually passed over the EOBS platform for gait collection. A total of 2 passes over the EOBS platform for each steer were obtained.

Each animal's pass over the platform was recorded with a video camera for later comparison. An interval of at least 1 min was spaced between each steer to allow for separation of individual signal readings. Videos were evaluated during data analysis. Each pass over the EOBS platform was considered a valid complete gait pass (CGP) if an animal did not slip, stop or jump while on the system. Signal output (S_O) data were recorded via integrated cabling, a microcontroller [9] and laptop. Once an animal made its last pass over the system it was herded back to its pen. A trained observer provided locomotion analysis of each animal from collected videos. Locomotion measurements obtained included CGP time (T), approximate limb strides (i.e., swing counts), number of hoof contacts (i.e., step counts), and limb differentiations per stance/swing phase (i.e., qualitative, visual observations). Additionally, potential signal amplitudes per hoof contact (ΔS) were measured as peak and trough signal fluctuations. The signal was digitized [10] at a sufficient sampling rate to accurately characterize details of hoof contact. The EOBS's S_O was measured in arbitrary units (au). A simple Pearson correlation was run between ΔS and T. A p-value of ≤ 0.05 was considered significant.

RESULTS AND DISCUSSION

Gait analysis was performed by analyzing hoof contact and additional gait events during locomotion. Sixteen passes over the EOBS were completed with a total of 22 fore- and hind limb strides obtained (Table 4.1). A stride, obtained from video data, was correlated to 2 hoof contacts with the EOBS platform for a single limb's swing phase. Approximately 2 complete strides were

---

[9] Arduino Uno. 2016. Arduino. https://www.arduino.cc.

[10] MATLAB and Signal Processing Toolbox Release 2017b. 2017 The MathWorks, Inc., Natick, Massachusetts, US. URL https://www.mathworks.com. (Version 9.3.0)

observed for each animal's pass. Figure 4.2A shows 1 steer's hoof placement on the platform, platform segmentation and a steer's complete gait pass (CGP) over the platform. Hoof contact was analyzed by observing signal output (S_O) fluctuations from a corrected baseline. Increasing and decreasing fluctuations from hoof contact were reported as signal output (S_O) differences (i.e., signal inversion associated with amplitude; ΔS). Limb contact with the EOBS platform was determined by visually correlating video hoof contact/impact time (IT) to S_O inversion (ΔS) and time signatures. A single ΔS was associated to hoof contact for a given limb, measured in arbitrary units (au), and reported as an absolute value (Figure 4.2B). A total of 17 hoof contacts for right forelimb, 17 hoof contacts for left forelimb, 18 hoof contacts for right hind limb, and 16 hoof contacts for left hind limb were recorded during the 16 CGPs over the EOBS platform. Hoof contact signal amplitude (ΔS) were adjusted and normalized. An average ΔS for each steer (ΔS_{avg}) was calculated and total ΔS_{avg} of 0.18 ± 0.0135 (mean ± SD; au) reported (Table 4.2).

Initial gait signal patterns were evaluated by analyzing the number of hoof contacts, ΔS per limb and animal time duration per CGP (T). Animal time duration per CGP (T) was evaluated based on the time interval from a steer's first hoof contact to last hoof break-over. An average T for all 8 steers (T_{avg}^{ttl}) of 2.25 s was calculated. Velocity (v) was an approximate measure based on EOBS platform length and estimated time from first hoof contact to when the last hoof came off the plate. Passes over the EOBS platform were correlated to video using commercial editing software [11]. A time delay, from recording the signal to computer graphing, of roughly half a second was corrected for each reading between CGP and ΔS. Hoof contact was marked by an identifiable time signature and cross validated with ΔS readings.

[11] Adobe Premiere Pro CC. 2017. Adobe Systems, Inc. 345 Park Avenue, San Jose, California 95110-2704. URL https://adobe.com.

Gait was categorized as either a walk or run and hoof contacts (i.e., step counts) were counted for each pass. Steers had an overall average of 5.67 hoof contacts. Steers moved at inconsistent speeds over the EOBS platform with an overall estimated average velocity ($\sim v_{avg}$) of 1.32 m/s. Estimated velocity ($\sim v$) for steer CGP had a range from 0.5 to 3.0 m/s. A $\sim v$ of 2.709 m/s was reported as caused by hesitation and shift in gait speed, but still within range. From video data, a total estimated number of 2.7 strides per steer was recorded with a majority of stride lengths greater than 0.813 m from first to second hoof contact per limb. An estimated swing phase time of 1.26 s for the 22 complete strides was calculated (Table 4.1). Stride differences were measured in units of seconds (s) and milliseconds (ms) from video timestamps. The EOBS's ability to collect multiple hoof contacts on a single platform was beneficial when estimating $\sim v$. Along with this, multiple collection of an animal's hoof contacts during a CGP provided the ability to extract gait differentiations when compared to a corrected baseline. Table 4.1 shows stride swing phase time from video data, number of hoof contacts and approximated velocity ($\sim v$; m/s) collected from each animal's pass over the EOBS platform.

Gait pattern was determined based on ΔS in combination with T per CGP. Animal time duration per CGP (T) was used for primarily determining gait pattern due to time's relation with gait differences. However, time does not truly determine gait, but the two variables tend to be related with walks being longer in time duration than runs, trots and lopes. Two steers (i.e., C and E) had a T of 0.9 s for their second passes over the EOBS platform indicating a variation of a run (Table 4.2). EOBS placement on the platform was a key factor for ΔS as location was shown to affect amplitude strength of S_O. Hoof contact closer to the EOBS resulted in a larger signal amplitude on average. EOBS placement was used in interpreting ΔS. Hoof contact located within sectors 2 and 3, and sub-sectors 4 through 8 exhibited a slight muting in ΔS. First fore- and hind limb hoof contacts have the largest ΔS when located in sectors 1 and 2. Additional graphical analysis of collected hoof contact data provided evidence for the use of location, T and ΔS as adequate variables for initial gait analysis.

A simple Pearson correlation coefficient between ΔS and T was performed using R [12,13]. In a linear direction, weak correlation (r = 0.24) was shown as T did not have a convincing relationship with ΔS strength during increased or decreased fluctuations. No statistical significance (P = 0.4468) was observed for T and ΔS. Eliminating any external noise (error or influence) on ΔS could provide greater accuracy in hoof contact readings.

Hoof ΔS_{avg} with average hoof contact/impact time (IT_{avg}; associated with ~v) were recorded for each steer. Observational analysis of ΔS_{avg} correlated to IT_{avg} providing an assumption that ~v affects readings as seen with Steers C and E (Table 4.2). A connection between T, IT and ΔS was also suspected to exist. Noticeable decreased IT on the EOBS platform exhibited potential reduction in ΔS. However, though small trends were visible, these assumptions require further analysis to understand if they are significant or mere anomalies during the field test. Observations from Table 4.2 exhibited strong repeatability of the EOBS's ability in detecting ΔS_{avg}, IT and IT_{avg} between animals' passes over the platform. Steers A, B and D exhibited the greatest differentiation in ΔS_{avg} between passes. Steers C, E and F exhibited the lowest differences in ΔS_{avg} between passes. Steers C and E had greater differences in T between passes 1 and 2. Animal time duration per CGP (T) in combination with IT and ΔS may add to gait detection in combination with hoof contact location. Further understanding of these variables and their interaction with each other is required to validate current assumptions.

---

[12] R Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. URL https://www.R-project.org.

[13] RStudio Team. 2017. RStudio: Integrated Development for R. RStudio, Inc. Boston, MA. URL http://www.rstudio.com.

Repeated ΔS is represented in Figures 4.3 and 4.4 during 2 CGP for steer A. Figures 4.3 and 4.4 show time signatures and signal fluctuations from hoof contacts for each pass. Signal output (S_O) fluctuates from decreasing to increasing depending on the number of limbs on the platform and the location of hoof landings. Highlighted areas in Figures 4.3 and 4.4 represent initial assumptions of individual hoof contacts. Due to multiple limbs on the EOBS platform, signal overlap occurred. Thus, hoof impact signals for each figure are not fully separate during CGP as seen by flushed sections (e.g., 1, 2, 3 and 4). Beyond signal differences (ΔS) for each hoof contact, there are additional signal variations from the baseline that may be due to hoof signal micro-fluctuations during contact.

Of the 8 steers tested, readings suggested a problem with the left hind limb of steer A. Figure 4.3 represents steer A's first pass over the EOBS platform with the fifth contact exhibiting a reduced ΔS and IT for the left hind limb. Additionally, steer A's second pass (Figure 4.4) exhibits the same trend in low ΔS and IT. It should be noted that the high third ΔS in Figure 4.4 is due to contact location on the EOBS platform. Steer A's sixth ΔS for both passes are slightly lower due to the 2 contacts hitting the edge of the EOBS platform. These were taken into consideration and veterinary examination later confirmed lameness was developing.

The distribution of ΔS from individual hoof contacts on the EOBS sensing surface (within a detection zone) offered the ability to determine when hoof contacts occur. Overall, the preliminary investigative field study of the proof-of-concept EOBS showed that the optical sensor has robust sensitivity for detecting hoof contacts. The study also demonstrated that ΔS (signal amplitude) and relative timing of hoof contacts (IT and T) is observable by the EOBS.

CONCLUSIONS

The investigative field study of the proof-of-concept embedded-optical-base system (EOBS) addressed whether optical sensing could be utilized for detecting hoof contacts. The study established initial feasibility in using an optical sensor for detecting hoof contacts. From signal readings, the study collected signal output (S_O) and correlated time signatures (i.e., T and IT) that could be potentially associated with gait. In turn, this capability allowed for assessment of the sensor's functional operability for gait analysis. The EOBS did operate under cattle passes and though data were not robust enough to draw statistically significant conclusions, the study opened the door for further research on assumptions and observations made. Additionally, the study showed that the EOBS was capable of obtaining hoof contact signals (e.g., ΔS). This provided insight into the potential viability of optical sensing to obtain animal gait biometrics. However, though semi-controlled passes over the EOBS platform led to noticeable signal fluctuations from hoof contacts, further research is needed to understand the true state of the collected data. Furthermore, additional research and potential enhancements may increase detecting and determining signal variables. With this, kinetic and kinematic research on the EOBS needs to be greatly expanded. The study provided quantifiable grounds to expanding studies on objective optical sensing. Overall, the field study demonstrated that optical sensors have potential use in detecting and measuring animal biometrics, such as gait measurements (e.g., hoof contact and kinematic variables), for future analysis and assessment of lameness.

Table 4.1 Observations of steers' hoof contact counts (i.e., step(s)), estimated stride differences (i.e., stride) for limbs and estimated velocity (~v) for 2 passes over the embedded-optical-base system (EOBS) per steer during 1 d.

	Round 1				Round 2			
Steer	**Step(s)** [1]	**Limb** [2]	**Stride** [3]	**Velocity** [4]	**Step(s)** [1]	**Limb** [2]	**Stride** [3]	**Velocity** [4]
A	6	FR	1.5	0.975	6	FL	1.3	1.219
		HR	1.5			HL	0.9	
B	6	FL	1.8	0.739	5	FR	1.6	0.797
		HL	1.6			NA	NA*	
C	4	FL	1.0	1.876	5	HR	0.4	2.709
		NA	NA*			FR	0.6	
D	7	FR	1.1	1.219	6	HL	1.4	0.938
		HR	1.2			FL	1.7	
E	6	FR	1.9	0.677	6	FR	0.7	2.709
		HR	1.5			HR	0.5	
F	6	FR	1.6	1.06	6	FL	1.6	0.95
		HR	1.1			HL	1.3	

* A secondary complete stride for steers C and B were not recorded.
[1] Step(s) = Number of hoof contacts on the embedded-optical-base system (EOBS).
[2] Limb: FR = Fore Right; HR = Hind Right; FL = Fore Left; HL = Hind Left; NA = Not available.
[3] Stride = Seconds (s) from initial hoof contact to last hoof contact per limb.
[4] Velocity = Approximate velocity measured in meters per second (m/s) with combined swing/stance phase.

Table 4.2 Steer observations for average signal strength (ΔS_{avg}), average time per impact (IT_{avg}) and overall time duration (T) for 2 complete gait passes (CGP) over the embedded-optical-base system (EOBS) during 1 d.

	Round 1			Round 2		
Steer	**Signal [1]**	**Impact Time [2]**	**Overall Time [3]**	**Signal [1]**	**Impact Time [2]**	**Overall Time [3]**
A	0.198	0.392	2.5	0.086	0.3	2.0
B	0.277	0.5	3.3	0.135	0.602	3.06
C	0.144	0.275	1.3	0.187	0.18	0.9
D	0.183	0.3	2.0	0.387	0.417	2.6
E	0.171	0.567	3.6	0.124	0.1	0.9
F	0.155	0.367	2.3	0.147	0.406	2.57

[1] Signal: ΔS_{avg} = Average ΔS for hoof contact collected.
[2] Impact Time: IT_{avg} = Average impact time for hoof contacts collected.
[3] Overall Time: T = Time duration for complete gait pass (CGP).

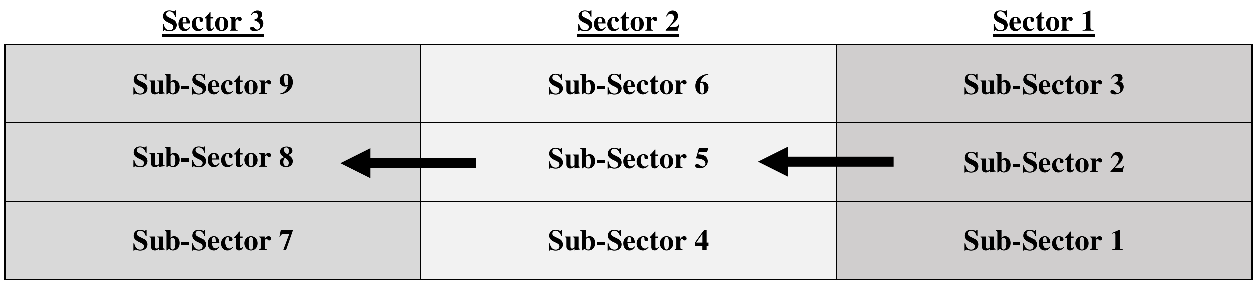

Figure 4.1 Embedded-optical-base system (EOBS) platform sectors (n = 3) and sub-sectors (n = 9). Arrows indicate direction of cattle movement.

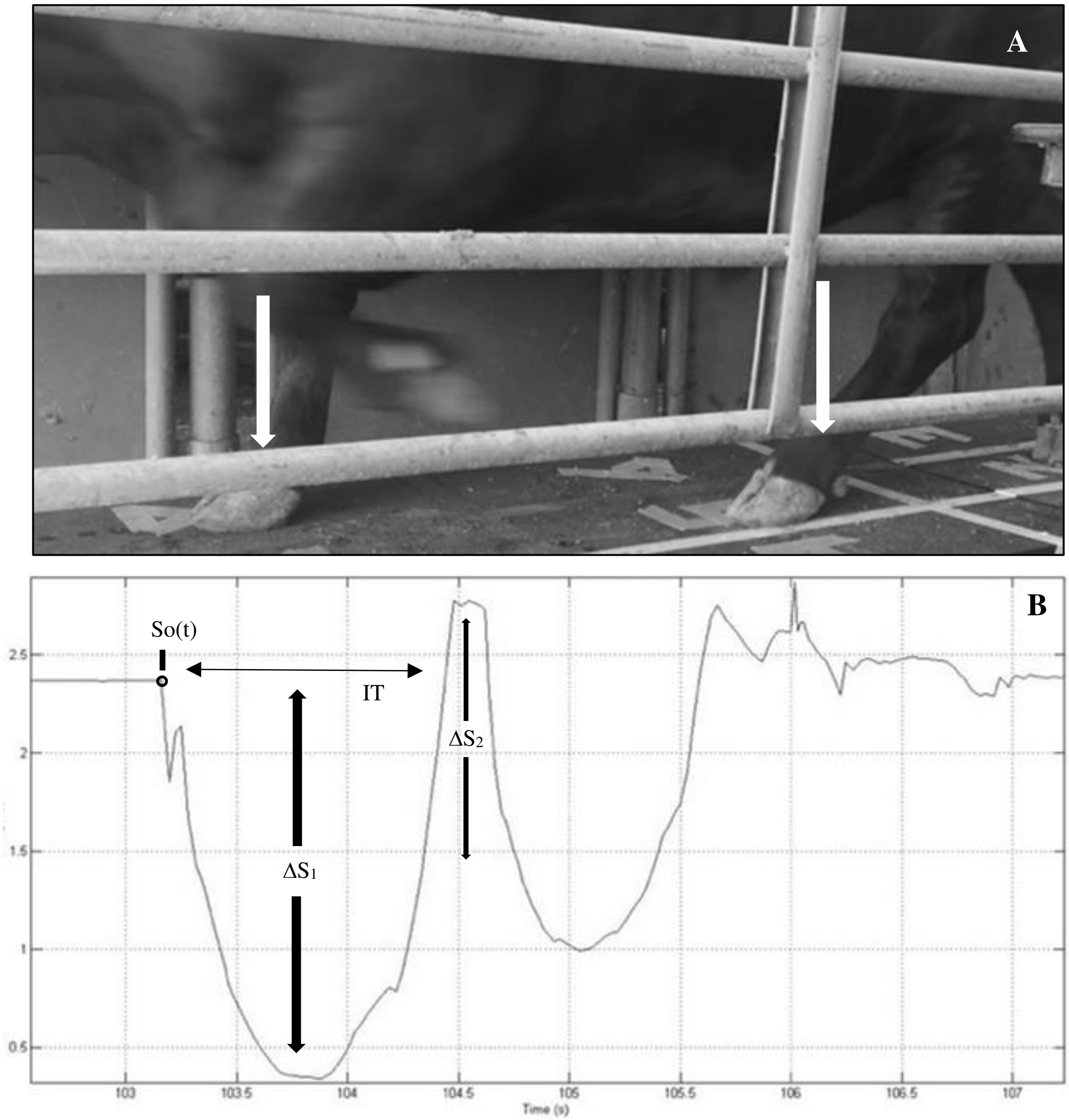

Figure 4.2 A) Individual steer's complete gait pass (CGP) over the embedded-optical-base system (EOBS) exhibiting hoof placement and platform segmentation. B) Individual steer's complete gait pass (CGP) reading; $S_O(t)$ = Signal output at a given time in seconds (s); ΔS_1 = Signal difference for first hoof impact; ΔS_2 = Signal difference for second hoof impact; IT = Impact time for single hoof that could be correlated to ΔS_1; X-axis based on time in seconds (s) with y-axis based on signal in arbitrary units (au).

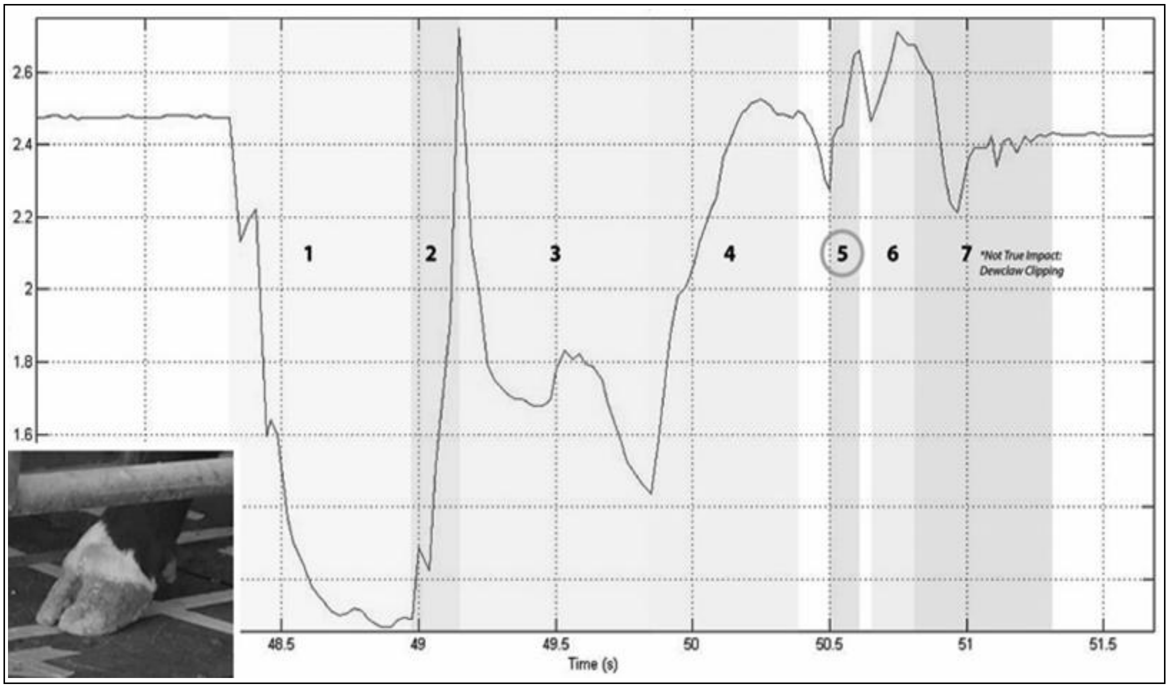

Figure 4.3 Steer A's first complete gait pass (CGP) over the embedded-optical-base system (EOBS); X-axis based on time in seconds (s) and y-axis based on non-normalized signal in arbitrary units (au); ΔS_5 (circled; left hind limb) exhibits unique signal fluctuation ($\Delta S_5 = 0.0772$ normalized arbitrary units (au); $\Delta IT_5 = 0.11$ seconds (s)). Additional information: First right forelimb hoof contact on EOBS sectors 1 and 2; Second left forelimb hoof contact on sectors 2 and 5; Third right hind limb hoof contact on sectors 1, 3 and 2; Fourth right forelimb hoof contact on sectors 3, 8 and 9; Fifth left hind limb on sectors 2, 4, and 5; Sixth right hind limb hoof contact on sectors 3 and 8; Seventh left hind limb on sectors 3 and 8 (Note: *Note on graph states "Not true impact; Dewclaw clipping"*).

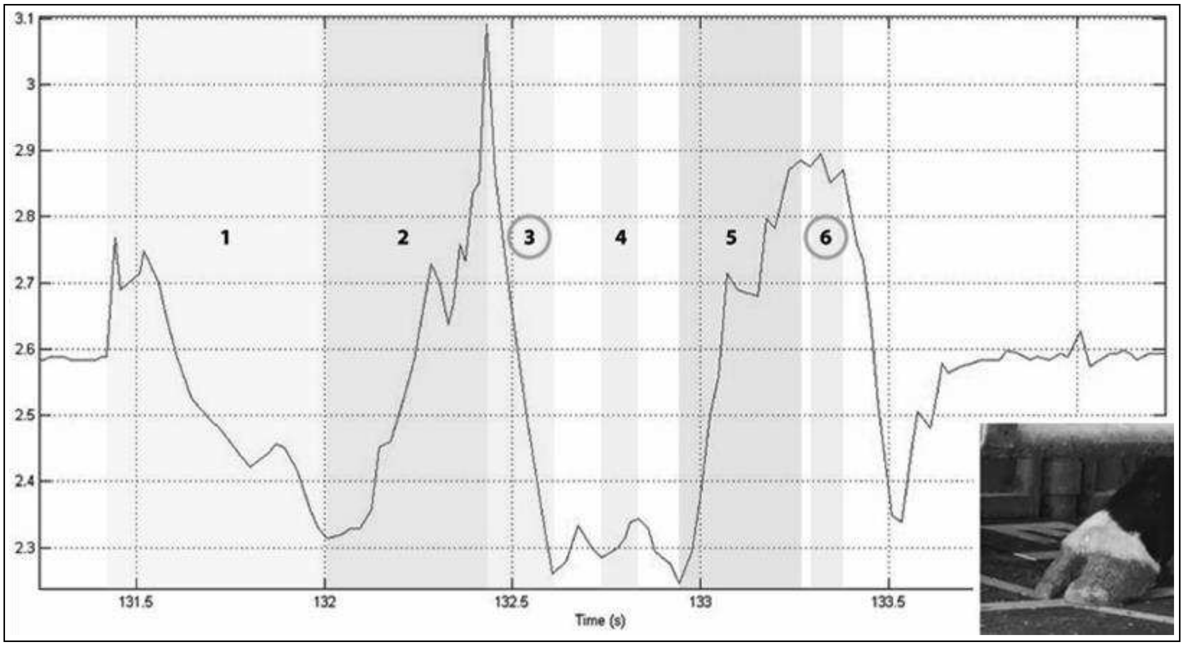

Figure 4.4 Steer A's second complete gait pass (CGP) over the embedded-optical-base system (EOBS); X-axis based on time in seconds (s) and y-axis based on non-normalized signal in arbitrary units (au); ΔS_3 and ΔS_6 (circled; left hind limb) show unique signal fluctuations ($\Delta S_3 = 0.166$ normalized arbitrary units (au); $\Delta IT_3 = 0.2$ seconds (s); $\Delta S_6 = 0.001$ normalized arbitrary units (au); $\Delta IT_6 = 0.1$ seconds (s)); Additional information: First right forelimb hoof contact on EOBS sectors 1 and 2; Second left forelimb hoof contact on sectors 2, 5 and 8; Third right hind limb hoof contact on sectors 1 and 2; Fourth right forelimb hoof contact on sectors 3 and 8; Fifth left hind limb hoof contact on sectors 2, 5, and 6; Sixth right hind limb hoof contact on sectors 3 and 8.

References

1. Almeida, P. E., D. R. Mullineaux, W. Raphael, C. Wickens, and A. J. Zanella. 2007. Early detection of lameness in heifers with hairy heel warts using a pressure plate. Anim. Welf. 16:135-137.

2. Atkins, C. A., K. R. Pond, and C. K. Madsen. 2017. In-motion optical sensing for assessment of animal well-being. Proc. SPIE Sens. Agric. Food Qual. Saf. IX 1021709. doi: 10.1117/12.2262194.

3. Maertens, W., J. Vangeyte, J. Baert, A. Jantuan, K. C. Mertens, S. De Campeneere, A. Pluk, G. Opsomer, S. Van Weyenberg, and A. Van Nuffel. 2011. Development of a real time cow gait tracking and analyzing tool to assess lameness using a pressure sensitive walkway: The GAITwise system. Biosyst. Eng. 110:29-39. doi: 10.1016/j.biosystemseng. 2011.06.003.

4. National Instruments. 2011. Overview of fiber optic sensing technologies. http://www.ni.com/white-paper/12953/en/. (Accessed 20 September 2016.)

5. Pastell, M., M. Hautala, V. Poikalainen, J. Praks, I. Veermae, M. Kujala, and J. Ahokas. 2008. Automatic observation of cow leg health using load sensors. Comput. Electron. Agric. 62:48-53. doi: 10.3168/jds.2014-8410.

6. Rajkondawar, P. G., M. Liu, R. M. Dyer, N. K. Neerchal, U. Tasch, and A. M. Lefcourt. 2006. Comparison of models to identify lame cows based on gait and lesion scores, and limb movement variables. J. Dairy Sci. 89:4267-4275. doi: 10.3168/jds.S0022-0302(06)72473-0.

7. Thorup, V. M., O. F. do Nascimento, F. Skjøth, M. Voigt, M. D. Rasmussen, T. W. Bennedsgaard, and K. L. Ingvartsen. 2014. Short communication: Changes in gait symmetry in health and lame dairy cows based on 3-dimensional ground reaction force curves following claw trimming. J. Dairy Sci. 97:7679-7684. doi: 10.3168/jds.2014-8410.

8. Van der Tol, P. J., J. M. Metz, E. N. Noordhuizen-Stassen, W. Back, C. R. Braam, and W. A. Weijs. 2003. The vertical ground reaction force and the pressure distribution on the claws of dairy cows while walking on a flat substrate. J. Dairy Sci. 86:2875-2883. doi: 10.3168/jds.S0022-0302(03)73884-3.

9. Van Nuffel, A., M. Sprenger, F. A. M. Tuyttens, W. Maertens. 2009. Cow gait scores and kinematic gait data: can people see gait irregularities? Anim. Welf. 18:433–439. doi: S0168-1591(17)30031-X/sbref0150.

10. Van Nuffel, A., J. Vangeyte, K. C. Mertens, L. Pluym, S. De Campeneere, W. Saeys, and S. Van Weyenberg. 2013. Exploration of measurement variation of gait variables for early lameness detection in cattle using the GAITWISE system. Livest. Sci., 156:88-95. doi: 10.1016/j.livsci.2013.06.013

Chapter Five

Sensor analysis and initial classification of optical signals to assess commercial steer and heifer gait patterns

SUMMARY

The primary objective was to assess the functional capability of an embedded-optical-base system (EOBS) for rapid, real-time assessment of gait patterns in cattle. Gait patterns were categorized into 3 classifications: walk (A_W), run (A_R) and other variations (B_{WR}; jump, stop, slip, kick, etc.). Gait signal patterns were measured (0 to 1 arbitrary units (au)) using 1 EOBS platform. Fifty commercial (n = 20, Angus; n = 10, Hereford; n = 20, Angus x Hereford) cattle (n = 50; average BW = 292.5 kg) were used. Signal and kinematic data were collected during 2 d over a 1-wk period. Cattle passed over the EOBS platform a total of 6 times per animal. Cattle exited through a hydraulic chute and passed down a walkway over the EOBS platform. A signal-base unit (SBU) and laptop were connected to the EOBS to collect real-time data. Signal amplitudes from hoof contacts and kinematics (e.g., estimated speed and time duration) were recorded from each animal's pass. Steer and heifer signalment were also recorded. A linear mixed model with animal and day as repeated measures was used for statistical analysis. Signal measurements, visual observations and video data were used for classifying patterns. Walk (A_W; $P < 0.05$; 0.398 ± 0.072; Estimate ± SD) and other classifications (B_{WR}; $P = 0.0134$; 0.113 ± 0.045; Estimate ± SD) were significant whereas run (A_R) was not significant ($P = 0.436$; -4.825 ± 6.186; Estimate ± SD). Overall, data suggests the EOBS functioned properly and could detect unique gait patterns based on signal fluctuations in a repeated measures study.

Key words: Biomechanical patterns, cattle gait cycle, optical sensors

INTRODUCTION

Sensor technologies for automated collection and analysis of behavioral and physiological animal measurements are desired as practical tools in supporting human observations for livestock management (Rushen et al., 2011; Alsaaod et al., 2016;). In using these automated systems, subtle changes and fluctuations in typical animal movement patterns can be detected (Van Nuffel et al., 2015; Alsaaod et al., 2016;). This method allows for continual gait data to be acquired for real-time monitoring of animals. However, quantification of these sensor-collected fluctuations requires varying statistical, mathematical and computational methods of proving a signal's representation of a detected event. Previous methods used to classify sensor-obtained behaviour patterns vary from empirical calculation of threshold values and dynamic linear modelling with multi-process Kalman filtering to canonical discriminate analysis (Martiskainen et al., 2009). Current methods have utilized support vector machines (SVM), random forests and neural network machine learning for determining signal classifiers and event prediction (Borchers et al., 2016). Due to an animal's influence and interaction with the sensor, pattern recognition within these studies lacks direct assessment of a sensor's functioning. However, by observing the technology within animal-based studies, indirect assessment of a sensor's functional behavior can be achieved. From this concept, precision livestock technology is a field of study in which animal science and engineering intertwine by determining both animal behavior and the functionality of the tools, technologies or systems. As such, the objective of this study was to evaluate whether the embedded-optical-base system (EOBS) functioned properly and could detect unique gait patterns based on signal fluctuations and times in a repeated measures study.

MATERIALS AND METHODS

The research protocol for this study and all procedures involving animal handling were approved by the Colorado State University (CSU) Institutional Animal Care and Use Committee (IACUC; approval number 16-6611AA). Experiments were conducted on 2 d. The study spanned 1 wk and occurred in December 2016.

Cattle, Housing and Test Area

The field study utilized 50 commercial steers and heifers (n = 20, Angus; n = 10, Hereford; n = 20, Angus x Hereford; n =50) with no perceptible lameness. Cattle were approximately 1- to 2-yr of age with an average BW of 292.5 kg. Cattle were fed a diet of more than 60% carbohydrates at the time of study. Excessive carbohydrate diets in ruminants have been shown to exacerbate lameness from diseases such as laminitis. Thus, it is worth mentioning when proceeding with gait analysis. Cattle were separated into 4 mixed groups of 10 (2 groups) and 15 (2 groups) animals. Cattle were assumed to be representative of the various population of feedlot beef cattle in Colorado. All animals were worked multiple times in the Agriculture Research, Development and Education Center's (ARDEC) cattle handling facilities prior to data being collected.

Optical-Sensing System and Modifications

The embedded-optical-base system (EOBS) platform utilized an optical point sensor provided by Ag Tech Optics, LLC (ATO; Bryan, TX). The EOBS was encapsulated and integrated into a durable metal platform to withstand livestock impacts, manure and urine. Three 0.914 m (width) x 2.438 m (length) x 0.051 m (height) wooden platforms were constructed (2 non-sensing and 1 sensing platform). The embedded-optical-base system (EOBS) metal platform was embedded in 1 of the wooden platforms to create an enclosed sensing unit.

Wooden platforms were designed for robust corrosion/abrasion tolerance and built for durability under strenuous testing conditions at the ARDEC cattle handling facilities. Dimensions were based on previous research (Atkins et al., 2016). Reflective markers were placed along the sensing platform to create 3 visually detectable sectors. Platforms were aligned directly after a hydraulic squeeze chute from which animals exited. A non-sensing platform was placed before and after the sensing platform. These non-sensing platforms allowed cattle to have a level surface with an area to adjust their gait after exiting the chute and crossing the sensing platform. Each non-sensing platform and the sensing platform were covered with several, commercially-available synthetic rubber layers [14] for traction and friction. The sensing platform held a recycled synthetic rubber base underneath to allow for elimination of signal vibration noise (i.e., error) from contact with interior flooring. The combined platform system was set on concrete levelled with impacted dirt to form an even path. Portable, commercial livestock panels were installed prior to testing. Panels were aligned on both sides of the platforms forcing cattle to pass over the EOBS while protecting equipment from hoof contacts. Special attention to animal safety was given in concerns to providing cattle with sufficient surface area to pass over the system while ensuring animals did not step off or disrupt signal readings.

An optical signal-base unit (SBU) was used to generate, detect and collect differentiations in signal readings from fluctuations made during cattle passes. The optical SBU was calibrated to a pre-determined baseline (i.e., 3.14 au). Optical signal readings were digitized at a pre-specified sampling rate (i.e., ~50 average samples per second (s)) to sufficiently analyze contact details. The optical SBU was connected to a commercially-available laptop via an open-source microcontroller [15] which read and converted the optical signal for compatible crosstalk.

[14] Utility Rubber Matting. 2016. Tractor Supply Co. Fort Collins, CO. URL https://tractorsupply.com.
[15] Arduino Uno. 2016. Arduino.URL https://www.arduino.cc.

The microcontroller was equipped to the optical SBU with a memory capacity of 32 kB, allowing for a minimum sampling frequency of roughly 9600 baud-rate at a clock speed of 16 MHz (dependent on bit and prescalers). Temperature measurements were recorded to see if failure might be associated with temperature should it occur during collection. A commercial software package [16] obtained through CSU was used for data logging, real-time graphing and interface control. Lastly, a commercial video camera [17] was used to collect video data of cattle exiting the chute, passing over the platforms and exiting off the secondary non-sensing platform.

Experimental Design

Investigation and evaluation of the EOBS was accomplished by analyzing overall field performance in an environment that closely mimicked a commercial livestock operation. A completely randomized design was utilized for selection of cattle group passes. Approximately 6 passes over the EOBS per animal were collected for 2 d over a 1-wk period for repeated signal measurements. Prior to testing, routine health exams on cattle were performed. Cattle groups were guided through an open lane and guided over the platform system. Groups were spaced approximately 1 min or greater between grouped signal readings. An interval of at least 30 s was attempted for spacing between each animal to allow for easier analysis of separated animal readings within each group. Cattle passes over the EOBS platform were recorded electronically and with a standard two-dimensional (2D) video camera. Videos were evaluated concurrently with signal readings after the testing period. Cattle were allowed to pass over the platform at their own pace. Signal readings were collected via an integrated logging scheme. After collection, cattle were taken back to their pens.

---

[16] MATLAB and Statistical Toolbox Release 2017b. 2017. The MathWorks, Inc. Natick, Massachusetts, US. URL https://www.mathworks.com. (Version 9.3.0)

[17] Raspberry Pi 3 and Camera Module. 2016. Raspberry Pi Foundation. URL https://www.raspberrypi.org.

Video and Signal Data

Cattle passes over the embedded-optical-base system (EOBS) platform were identified using signal and video timestamps. Mechanical flex of the platform recorded as signal outputs (S_O), occurred from an animal's pass over the EOBS. Signal outputs (S_O) correlated to points on a linear time-series for animal passes over the EOBS platform. Signal output (S_O) readings were normalized to an arbitrary threshold allowing for calculation of S_O descriptive statistics. Complete gait pass (CGP) time duration (T), number of hoof contacts and visual limb differentiations (i.e., symmetry of hoof contacts) per combined stance and swing phases were recorded. Additionally, signal output differences (i.e., signal amplitude per fluctuation; ΔS) were recorded for animal passes over the EOBS platform. Data were analyzed and correlated to linear, time signatures for each animal. Sampling measurements of peak and trough points per fluctuation for each ΔS per animal were recorded (i.e., max-min sampling count (ΔS_C^{HL}) and max-min sampling average (ΔS_{avg}^{HL})). Maximum and minimum sampling counts per fluctuation (ΔS_C^{HL}) were extracted from unit-time plots and associated sampling rates. Kinematic measurements with time signatures allowed for observation of signal deviations and differentiations per animal.

Detailed Visual Gait Evaluation and Data Classification

Heifers and steers were unrestrained when released from the chute causing variations in gait and pace over the platforms. Signal readings were described as fluctuations (i.e., peak and trough interruptions) within the baseline forming quantifiable fluctuations in amplitude (i.e., peak-to-peak signal strength and reflected power). Signal readings were compiled to observe contact and toe-off points for each hoof impact with the EOBS platform so as to define gait events and durations in seconds (s). Video data was used in correlating gait patterns to associated fluctuations as signal output difference (ΔS) readings. Detailed descriptions of passes over the platforms were recorded by a trained observer. Three classification groups along with specific criteria were noted to identify standard symmetrical or asymmetrical (i.e., run or walk), and unique (i.e., other) gait events (Table 5.1). A pass was defined as the length of time an animal took to move across the sensing platform from its first hoof contact to its last break-over. Deviations in time signatures and corresponding signal fluctuations were classified as either A_W (walk), A_R (run), or B_{WR} (other). Passes over the EOBS platform were considered valid and acceptable for normal classification if an animal exhibited symmetrical or asymmetrical four-beat (i.e., walk), two-beat (i.e., trot) or three-beat (i.e., run/lope) patterns. Two-beat and three-beat patterns were lumped into A_R however, they are different. Gait patterns were classified as other if slipping, stopping, jumping or edge-clipping occurred during an animal's pass over the EOBS platform. If multiple animals were on the platform at the same time, video and signal readings were re-analyzed to determine whether there was enough separation for individual standard classifications, unique classification or be combined as 1 unique classification.

Statistical Analysis

Data were statistically analyzed using multiple commercial and open-source software programs [18,19,20]. Measurements calculated from cattle included complete gait pass (CGP) time duration per animal (T), average (± SD) T per animal (T_{avg}), max-min sampling count (ΔS_C^{HL}) and max-min signal average (ΔS_{avg}^{HL}) from signal amplitude peaks and troughs (Table 5.2). Linear trending was first analyzed using the *interact_plot* function found in the *jtools* package [18,19]. Complete gait pass (CGP) time duration (T) data were not normally distributed.

---

[18] R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. URL https://www.R-project.org/. (Version 3.5.0 - "Joy in Playing")

[19] RStudio Team. 2018. RStudio: Integrated Development for R. RStudio, Inc. Boston, MA. URL http://www.rstudio.com/. (Version 1.1.453)

[20] MATLAB and Statistical Toolbox Release 2017b. 2017. The MathWorks, Inc. Natick, Massachusetts, US. URL https://www.mathworks.com. (Version 9.3.0)

A natural log transformation (T_{log}) was performed to try to meet normality assumptions for modelling. A linear mixed model was established using the *lme4* package [21,22] for Welch-Satterthwaite's t-tests to observe differences between signal classifications based on T_{log}. The model (5.2) was fitted and expressed as

$$Y_{ijk} = a + C_i + S_l + R_m + (CD)_{lm} + H_{jk} + e_{ijk} \tag{5.2}$$

where, Y_{ijk} represents time duration (T_{log}) observed in day k in animal j; a is the intercept; C_i is the fixed effect of classification i (A_W, A_R and B_{WR}); S_l represents the max-min signal fluctuation l (ΔS^{HL}_{avg}); R_m is the fixed effect of max-min sampling count m (ΔS^{HL}_{C}); $(CD)_{lm}$ is the interaction effect of the m^{th} ΔS^{HL}_{avg} with l^{th} ΔS^{HL}_{C}; H_{jk} is the repeated measures term for j^{th} animal within day k; e_{ijk} is the residual term. Cattle nested within test day (H_{jk}) was used due to animals having multiple passes over the EOBS platform within a single test day. Estimates, standard errors, and *p*-values for classification on T_{log} were reported. A pairwise comparison test (*lsmeans* package) was used to further analyze differences between A_W (walk), A_R (run) and B_{WR} (other) classifications. A p-value of ≤ 0.05 was considered significant.

RESULTS AND DISCUSSIONS

Repeatability Study

Prior to examination, cattle did not exhibit any musculoskeletal abnormalities. There were no prior conceptions of animals which mitigated potential bias during analysis. Health exams were performed by trained personnel with none of the cattle exhibiting signs of clinical disease or sickness during the testing period. Five passes over the EOBS per 50 animals (n = 50)

---

[21] R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. URL https://www.R-project.org/. (Version 3.5.0 - "Joy in Playing")

[22] RStudio Team. 2018. RStudio: Integrated Development for R. RStudio, Inc. Boston, MA. URL http://www.rstudio.com/. (Version 1.1.453)

were tested on 2 d over a 1-wk period. One round was eliminated from the analysis due to lacking video data. Videos were analyzed with signals to determine which hoof contacts corresponded to signal fluctuations. Complete gait grouping (CGG) within the linear signal was observed by assessing the pattern of disruption for grouped fluctuations and approximate vicinity of neighboring disruptions (Figure 5.2). Hoof contact with the platform was reported as signal output (S_O) by observing increased and decreased inversions (i.e., peaks and troughs in signal baseline). A change in signal output (S_O) occurred with hoof contact and measured as signal output difference (ΔS). Signal output difference (ΔS) was measured in arbitrary units (au) and reported as absolute values (Figure 5.3 and Figure 5.4).

Analysis of Signal Classifications

Gait classification was performed by analyzing signal readings cross-validated with video data to assess an animal's pass over the EOBS platform. A total of 65 runs (A_R; n = 65), 28 walks (A_W; n = 28), and 157 other passes (B_{WR}; n = 157) over the EOBS platform were collected. Passes were grouped by visual assessment. Signals were normalized between 0 and 1 arbitrary units (au) using an averaged signal amplitude. Interaction plotting was performed to determine if any trends in the EOBS's functioning could be observed based on time (T_{log}), classification (A_W, A_R and B_{WR}) and the interaction between average max-min signal and max-min sampling count ($\Delta S_{avg}^{HL} \times \Delta S_C^{HL}$; Table 5.2). Summary of ΔS_{avg}^{HL} exhibited 2 descriptive signal markers (i.e., 0.61 to 0.63 and 0.63 to 0.65 (au)) based on T_{log} (-0.887 to 1.983). Max-min sampling count (ΔS_C^{HL}) had an average of ~39 sampled measures for all cattle ranging from 11 (min) to 167 (max). From Figure 5.5, an increasing linear trend can be observed between ΔS_C^{HL} and ΔS_{avg}^{HL} based on T_{log}. Classification influenced ΔS_C^{HL} and T_{log} by adding an additional fixed effect of grouping to the model which led to an increase in deviation within larger time durations and corresponding signal points (Figures 5.6 and 5.7). This trend is presumably typical for ΔS_C^{HL} and T_{log} to increase with ΔS_{avg}^{HL}. An interaction effect between ΔS_{avg}^{HL} and ΔS_C^{HL} was not significant ($P = 0.493$; -0.207 ± 0.301; Estimate ± SD) with both variables having a weak positive correlation ($r = 0.042$). From the interaction plot data, it was inferred that the EOBS exhibited standard functional operability considered to be normal as signal deviations increased when time duration increased. The scope of the field study was to infer the sensor's operability while excluding animal analysis. Addition of the interaction term and associated animal variables were included to reduce residual error and increase normal gaussian distribution.

Significance for A_W ($P < 0.05$; 0.412 ± 0.072; Estimate ± SD) and B_{WR} ($P < 0.005$; 0.127 ± 0.045; Estimate ± SD) classifications was found. Max-min signal average (ΔS_{avg}^{HL}), max-min sampling count (ΔS_C^{HL}) and the interaction factor ($\Delta S_C^{HL} \times \Delta S_{avg}^{HL}$) were not statistically significant ($P = 0.492$; $P = 0.459$; $P = 0.518$; respectively). An estimated 64% of variability ($R^2 = 0.641$; Fixed) in the model was explained by fixed effects ($\Delta S_C^{HL} + \Delta S_{avg}^{HL} + (\Delta S_C^{HL} \times \Delta S_{avg}^{HL})$) while 5% of variability ($R^2 = 0.690$; Fixed + Random) was due to random effects (animal + (test day × animal)). Pairwise comparisons of classifications (Table 5.3) showed a significant difference between A_R and B_{WR} ($P = 0.014$; -0.127 ± 0.045; Estimate ± SE). Run (A_R) and A_W were considered different ($P < 0.001$; -0.412 ± 0.072; Estimate ± SE). However, classification between A_R and A_W was not statistically large enough to consider the two as uniquely different based on signal readings alone. Comparison of A_W and B_{WR} classifications were significantly different ($P < 0.001$; 0.285 ± 0.066; Estimate ± SE). Observed inflated p-value for A_W and B_{WR} comparison is assumed to be due to the small number of A_W classifications compared to B_{WR} classification. However, A_W and B_{WR} classifications are considered uniquely different and usable as classifiers based on T_{log}.

Conclusions

Sensor technology and their algorithmic backends typically implement statistical process controls requiring trial and error testing with development of deviations from baseline values (MacGregor and Kourti, 1995; Borchers et al., 2016). Standard workflow involves partitioning time-series data into short windows for extracting sets of statistical features that can be correlated and corresponded to ordered moments (Rahman et al., 2018). This basic strategy was the starting point for determining the EOBS's operability for analyzing gait biometrics. The focus of the research was on evaluating the functionality of the EOBS to measure gait variables by examining pre-determined classifying groups. The preliminary field study aimed to improve understanding of the EOBS's ability to detect correlated signal readings derived from animal hoof contact.

The following conclusions were drawn from the study: 1) the EOBS platform works in detecting hoof contact; 2) the EOBS platform measured continuous and repeatable measurements of signal fluctuations (S_O) based on T (T_{log}) that were unique and sensitive enough for use in the application of identifying individual gait patterns as standard (i.e., run and walk classifications) or unique (i.e., other classification); and 3) the system exhibited robustness to withstand a larger sample size under field conditions. As such, the study demonstrated for the first time that the EOBS can be utilized for measuring and detecting signal patterns (e.g., gait classifications). Further research is needed in observing a broader set of cattle. Additionally, studies in repeatability, accuracy, precision, sensitivity and specificity are needed within controlled environments to validate the EOBS. However, data suggests the optical sensor has potential for assessment of variable gait measurements based on signal gait patterns. Overall, the EOBS is a promising tool for future implementation in providing automated gait analysis and potential lameness detection.

Table 5.1 Gait pattern classifications along with descriptive characteristics for visual observations of individual cattle as they moved across the embedded-optical-base system (EOBS). [1]

Pattern Classification	Description
Class A_W	Walk - Time duration greater than approximately 2 s; Clear and distinguishable hoof contacts and break-overs; Obvious time separation in hoof contacts; No presumable alterations in gait while crossing the platform.
Class A_R	Run - Time duration less than approximately 2 s; Clear and distinguishable hoof contacts and break-overs; Noticeable bilateral impact of fore- and hindlimbs during platform crossing; No presumable alterations in gait.
Class B_{WR}	Other - Indistinguishable hoof contacts during platform crossing; Prominent hesitation or stopping on platform; Slipping on or clipping the platform during passes; Prominent jumping during any moment on platform; Low energy hoof contacts [2] and break-overs influenced by impacting outside sensing zone.

[1] Pattern classifications were recorded by a trained observer during video analysis. Discrepancies in classification were verified by a secondary observer for classification.
[2] Low amplitude (i.e., low energy) hoof contacts were associated with hoof impacts that did not fully register in the optical sensor's detection zone.

Table 5.2 Total descriptive measurements (i.e., min, max, mean ± SD and totals) from 5 complete gait passes (CGP) over the embedded-optical-base system (EOBS) [1] for 50 cattle on 2 d over a 1-wk period.

EOBS Variable	Min	Max	Mean ± SD	Total
Time Duration [2]	0.412	7.264	1.512 ± 1.09	377.944
Sampling Count [3]	11	167	38.69 ± 20.70	9673
Signal Amplitude [4]	0.599	0.666	0.6273 ± 0.006	156.825

[1] The embedded-optical-base system (EOBS) platform was constructed around the Ag Tech Optics' (ATO) optical-point sensor for assessing gait patterns in livestock.
[2] Time duration calculated from total seconds (s) and milliseconds (ms).
[3] Sampling count calculated from total sampled points recorded per peak or trough signal fluctuation (ΔS_{C}^{HL}).
[4] Signal amplitude calculated from total average signal (ΔS_{avg}^{HL}).

Table 5.3 LSMeans (± SE) and 95% confidence intervals (CI; upper and lower bounds) for visual classifications based on 5 complete gait passes (CGP) over the embedded-optical-base system (EOBS) [1] for 50 cattle on 2 d over a 1-wk period.

		95% CI	
Classification [2]	**LSMeans ± SE**	**Lower**	**Upper**
A_R	0.135 ± 0.039	0.058	0.212
A_W	0.546 ± 0.062	0.424	0.668
B_{WR}	0.262 ± 0.026	0.210	0.313

[1] The embedded-optical-base system (EOBS) platform was constructed around the Ag Tech Optics' (ATO) sensor for assessing gait patterns from livestock.

[2] Classifications: A_R = run; A_W = walk; B_{WR} = other.

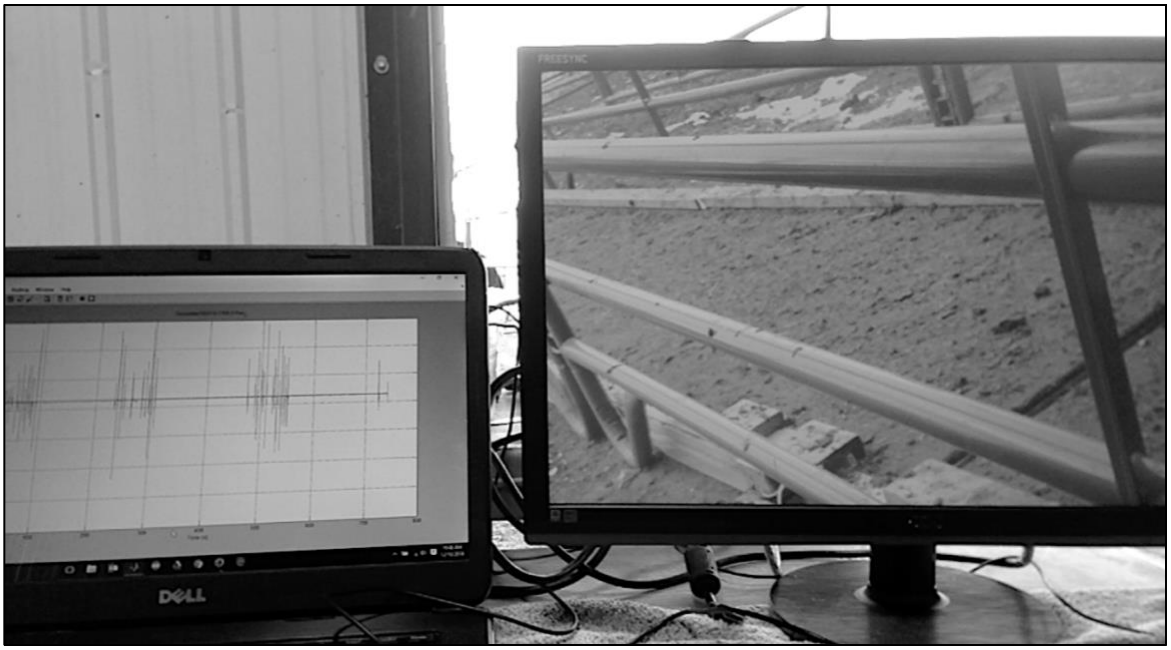

Figure 5.1 Image of embedded-optical-base system (EOBS) platform and signal readings.

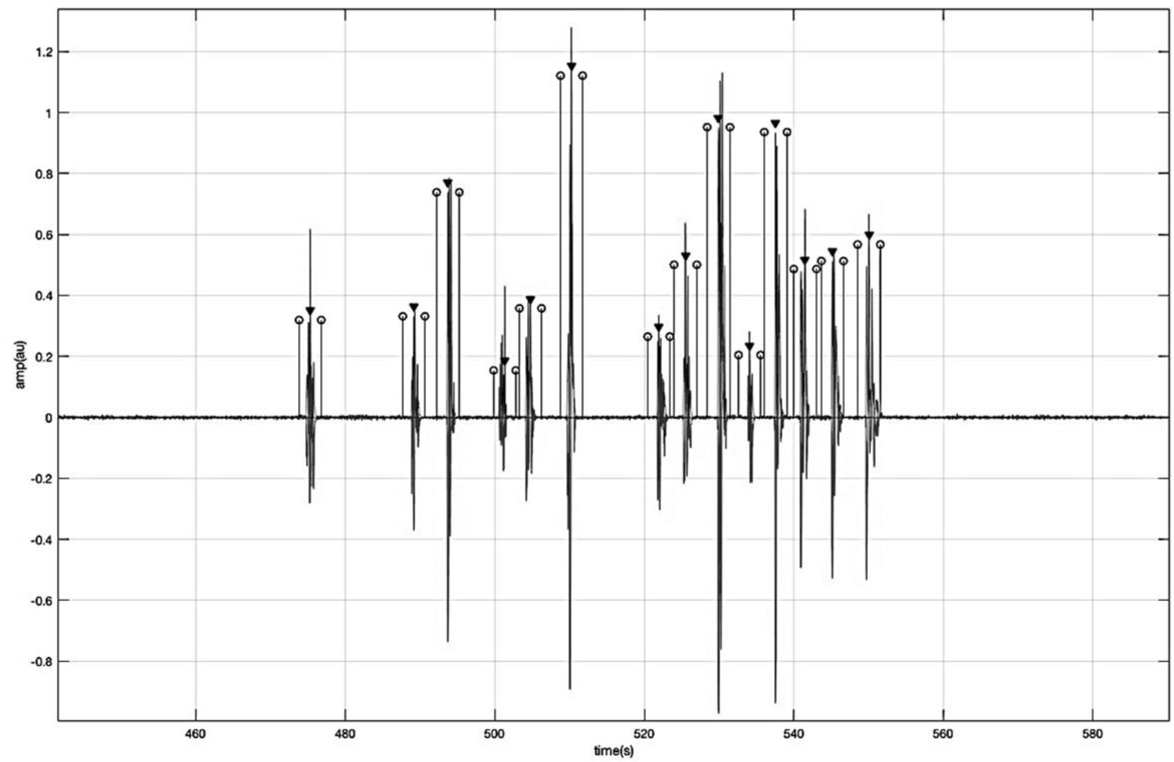

Figure 5.2 Subsection of 15 commercial steer and heifer passes over the embedded-optical-base system (EOBS). X-axis based on signal amplitude measured in arbitrary units (au) from 1.3 au to -0.9 au and y-axis based on time (T) in seconds (s). Main line represents optical signal baseline at 0 au. Signal fluctuations (ΔS) due to animal contact with EOBS represented as upward and downward deviations from the baseline. Vertical lines with circles show the start and finish of individual animal passes. Triangle positioned over peak max point of largest impact during an animal's contact on the EOBS. Signals measured from 50 commercial steers and heifers for 2 d over a 1-wk period. Signal readings recorded in Matlab (MATLAB and Signal Processing Toolbox Release 2017b. 2017. The MathWorks, Inc. Natick, Massachusetts, USA).

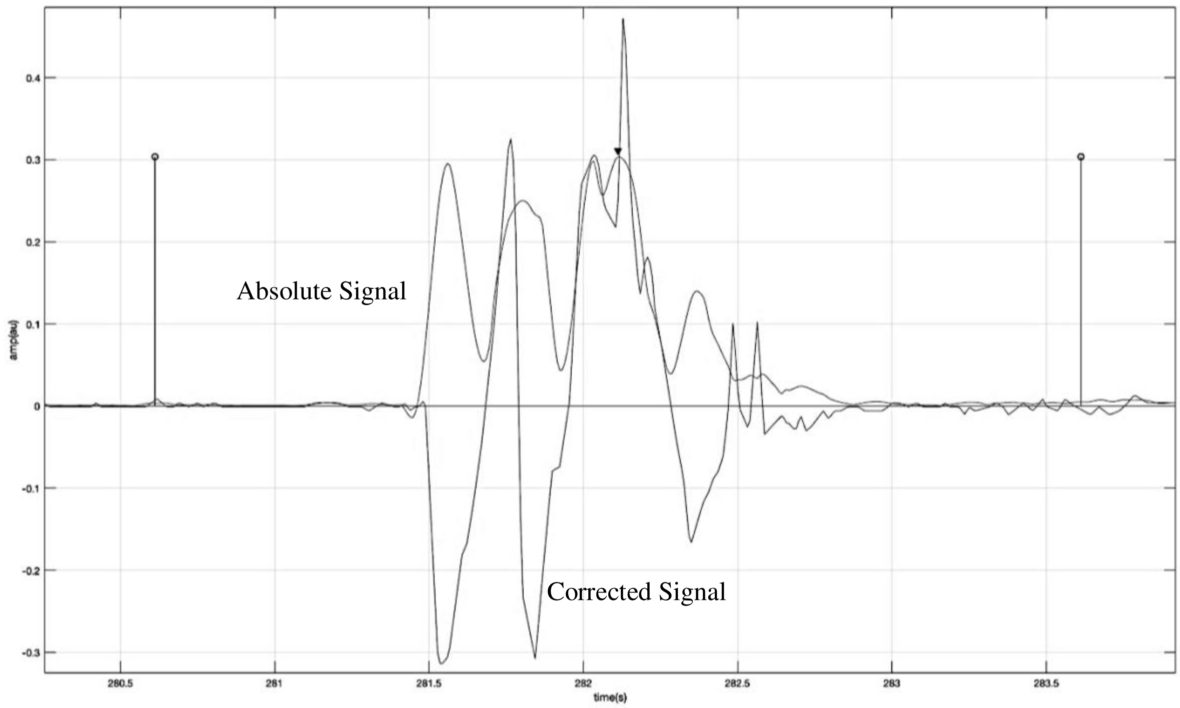

Figure 5.3 Section of 1 complete animal pass over the embedded-optical-base system (EOBS). X-axis based on signal amplitude measured in arbitrary units (au) from 0.65 au to -0.6 au and y-axis based on time (T) from 27.5 s to 30.55 s. Primary line represents corrected optical signal with a baseline at 0 au. Secondary line represents smoothed signal based on absolute (positive) sampled values. Signal fluctuations (ΔS) due to animal contact with the EOBS represented as peak and trough deviations from the baseline. Triangle positioned over peak max point of largest impact. Signal extracted from 50 commercial steer and heifer passes for 2 d over a 1-wk period. Signal readings recorded in Matlab (MATLAB and Signal Processing Toolbox Release 2017b. 2017. The MathWorks, Inc. Natick, Massachusetts, USA).

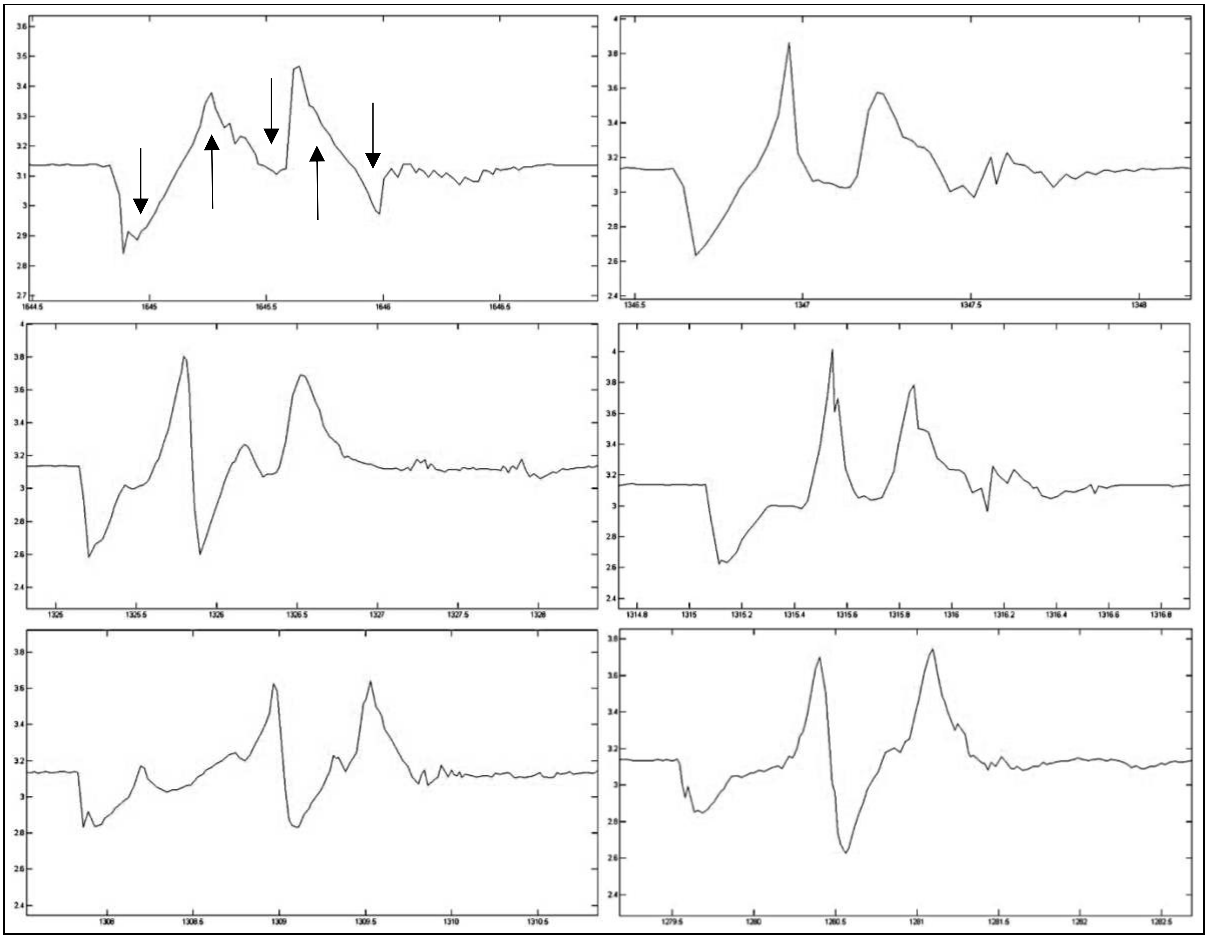

Figure 5.4 Repeatable cattle patterns obtained from gait passes over the embedded-optical-base system (EOBS) for 6 animals. X-axis based on time (s) and y-axis based on signal (non-adjusted) in arbitrary units (au). Arrows represent the repeatable range of primary and secondary signal hoof contact and break-over (i.e., peaks and troughs) patterns during an animal's pass over the EOBS.

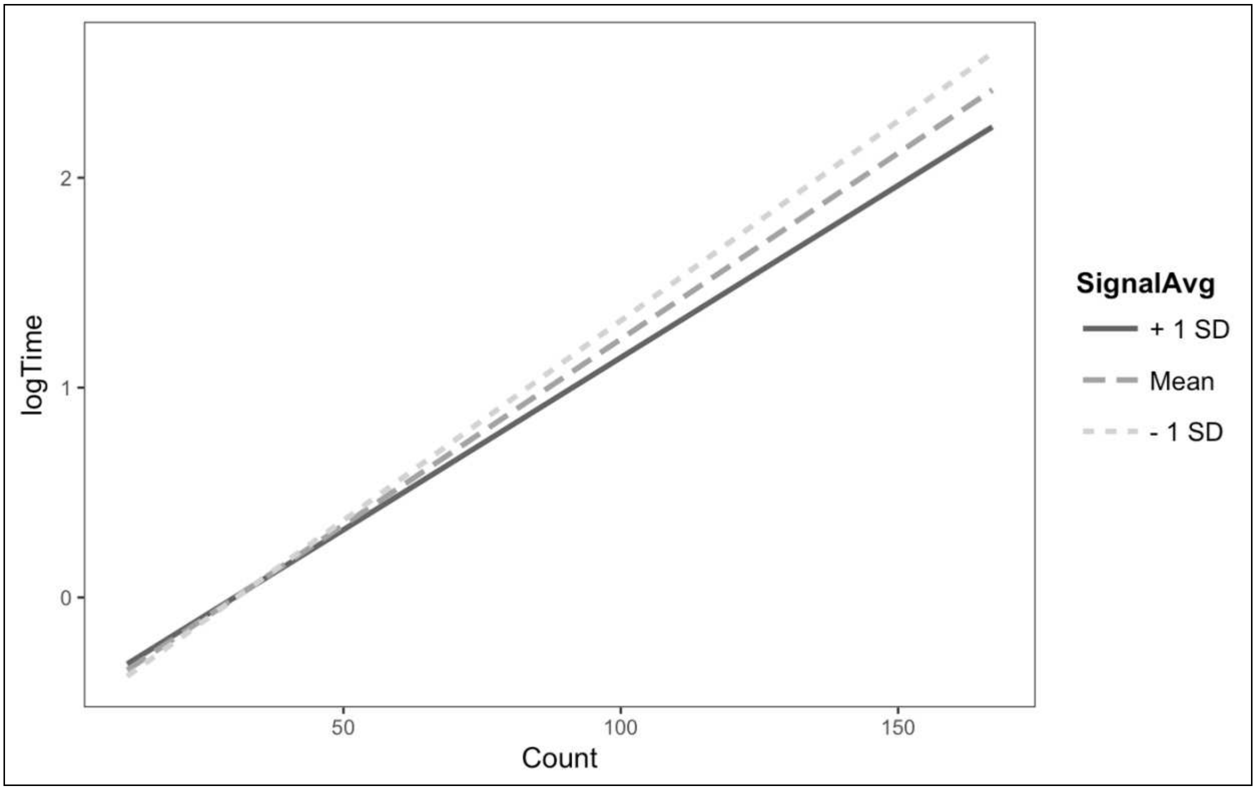

Figure 5.5 Plot between time (T_{log}; log transformed) per complete gait pass (CGP) and max-min sampling count (ΔS_{C}^{HL}) based on average signal (ΔS_{avg}^{HL}) per individual animal with classification type (A_W, A_R and B_{WR}) added to account for deviations between gait patterns. Expected linear trend represented due to increasing time (T_{log}) and sampling count (ΔS_{C}^{HL}). Additionally, deviations increase concurrently with average signal (ΔS_{avg}^{HL}) and classification type (A_W, A_R and B_{WR}) added. As such, signal readings operate within standard time constraints and represent a functional behavior that is within normal ranges.

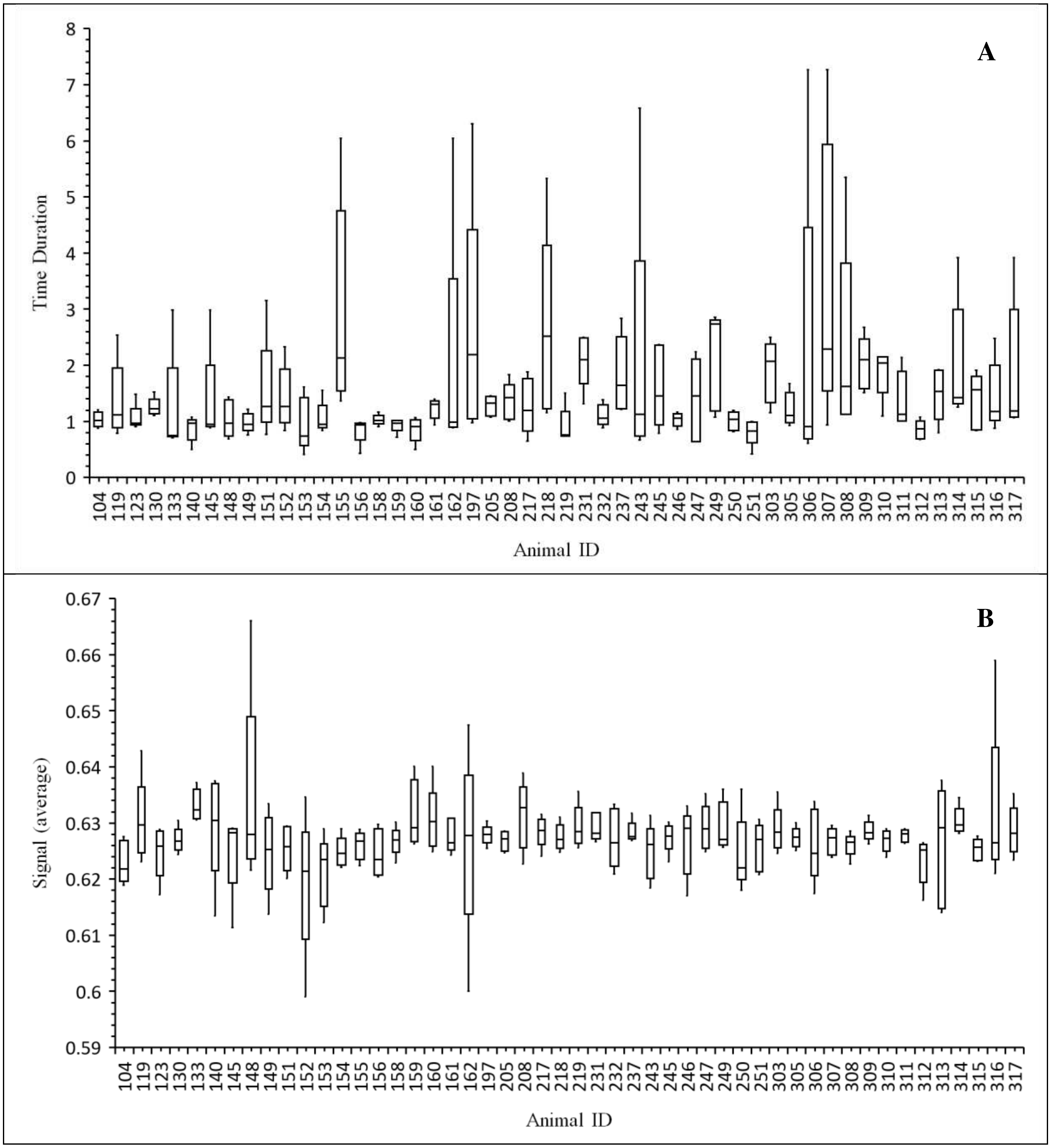

Figure 5.6 A) Box and whisker plots of total time duration (T) distributions for individual cattle (n = 50) based on 5 passes across the embedded-optical-base system (EOBS) for 2 d over a 1-wk period. X-axis represents individual animals and Y-axis represents total time duration (T) with time distributions with cattle ranging from 0.4 seconds (s) to 7.3 s. B) Box and whisker plot of max-min signal average (ΔS_{avg}^{HL}) distributions for individual cattle (n = 50) based on 5 passes across the embedded-optical-base system (EOBS) for 2 d over a 1-wk period. X-axis represents individual animals and Y-axis represents signal averages with cattle ranging from .59 arbitrary units (au) to .66 au.

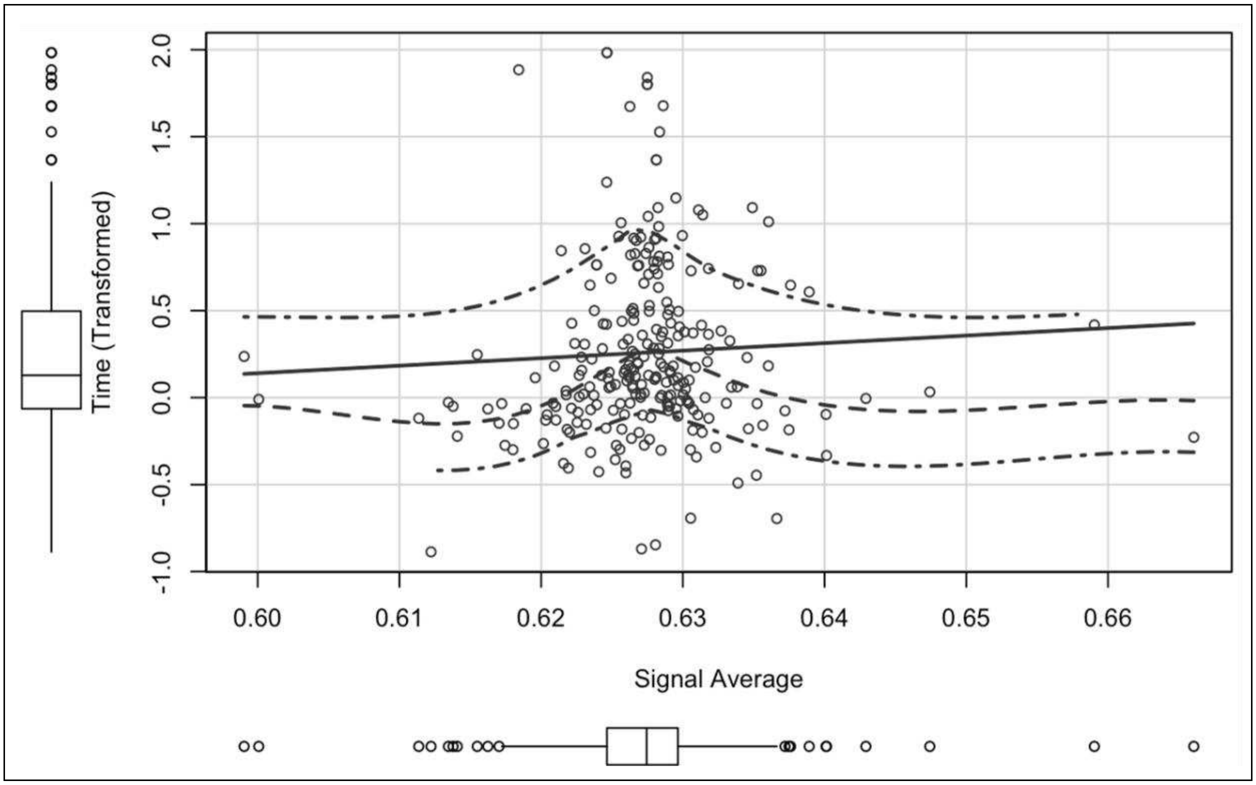

Figure 5.7 Scatter plot between average time durations (T_{log}; log transformed) and max-min signal averages (ΔS_{avg}^{HL}) for steers and heifers (n = 50). X-axis box plot represents distribution of max-min signal averages (ΔS_{avg}^{HL}) and y-axis box plot represents distribution of average time durations (T_{log}). Solid line represents linear trend and dashed lines represent deviations from linear trend.

References

1. Alsaaod, M., M. Luternauer, T. Hausegger, R. Kredel, and A. Steiner. 2016. The cow-pedogram – Analysis of gait cycle variables allows the detection of lameness and foot pathologies. J. Dairy Sci. 100:1417-1426. doi: 10.3168/jds.2016-11678.

3. Atkins, C. A., K. R. Pond, and C. K. Madsen. 2017. In-motion optical sensing for assessment of animal well-being. Proc. SPIE Sens. Agric. Food Qual. Saf. IX 1021709. doi: 10.1117/12.2262194.

4. Borchers, M. R., Y. M. Chang, K. L. Proudfoot, B. A. Wadsworth, A. E. Stone, and J. M. Bewley. 2016. Machine-learning-based calving prediction from activity, lying, and ruminating behaviors in dairy cattle. J. Dairy Sci. 100:5664-5674. doi: 10.3168/jds.2016-11526.

5. MacGregor, J. F., and T. Kourti. 1995. Statistical process control of multivariate processes. Control Eng. Pract. 3:403-414. doi: 10.1016/0967-0661(95)00014-L.

6. Martiskainen, P., M. Järvinen, J. P. Skön, J. Tiirkainen, M. Kolehmainen, and J. Mononen. 2009. Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines. Appl. Anim. Behav. Sci. 119:32-38. doi: 10.1016/j.appl.anim.2009.03.005.

8. Rahman, A., D. V. Smith, B. Little, A. B. Ingham, P. L. Greenwood, and G. J. Bishop-Hurley. 2018. Cattle behaviour classification from collar, halter, and ear tag sensors. Inf. Proc. Agric. 5:124-133. doi: 10.1016/j.inpa.2017.10.001.

12. Rushen, J., A. Butterworth, and J. C. Swanson. 2011. Animal behavior and well-being symposium: Farm animal welfare assurance: Science and application. J. Anim. Sci. 89:1219-1228. doi: 10.2527/jas.2010-3589.

14. Van Nuffel, A., W. Saeys, B. Sonck, J. Vangeyte, K. C. Mertens, B. De Ketelaere, and S. Van Weyenberg. 2015. Variables of gait inconsistency outperform basic gait variables in detecting mildly lame cows. Livest. Sci. 177:125-131. doi: 10.1016/j.livsci.2015.04.008.

Chapter Six

Assessment of detectable first hoof contacts and last break-overs

as unique signal fluctuations for horse gait analysis

SUMMARY

The primary objective of the control study was to assess 2 prominent fluctuations in a single optical signal as being either true first hoof contact or last break-over based on descriptive measures. Hoof contacts were measured (0 to 1 au; arbitrary units) using a 2.4 m (length) x 0.9 m (width) platform containing 1 embedded-optical-base system (EOBS). The study consisted of 3 mixed-breed horses (n = 3) that were blocked with saline or either 100 IU or 200 IU for a 2.5 mL final volume solution. Injections were made in the deep digital flexor muscle at the motor end plates of the forelimb. Electromyography (EMG) was used to determine end plate locations. Horses were observed for 3 d (pre-, post and recovery test days) over the span of a 4-mo period. Signal fluctuations (i.e., amplitude of hoof-impacts based on true first hoof contacts (ΔS_{TS}) and true last break-overs (ΔS_{TL})) and kinematics (i.e., complete gait pass (CGP) time duration (T)) were recorded from each horse. Visual observations and video analysis were used for determining gait pattern categories. Individual horse measurements were analyzed for each trial, compared to video data and classified. Comparison of primary signal fluctuations (i.e., ΔS_{TS} vs. ΔS_{TL}; forelimb vs. hind limb) exhibited significant difference between hoof contacts and break-overs ($P < 0.05$). Overall, data showed that the EOBS can collect unique primary signal fluctuations as prominent and different gait measurements in a repeated study.

Key words: Optics, sensors, equine, gait analysis

INTRODUCTION

Animal stepping, tracking and various gait behaviors are sensitive indicators of welfare and welfare-oriented problems, such as lameness (Krohn and Munksgaard, 1993; Haley et al., 2001). Lameness represents an animal welfare issue due to the prolonged pain and discomfort that can occur (Scott, 1989; Pluk et al., 2012). In horses, musculoskeletal injuries and diseases represent a significant economic impact on owners and the equine industry due to loss in sales and fees (USDA, 2001; Moorman et al., 2013). While in cattle, lameness can have a significant impact on milk yield (Ouared et al., 2015) and reproductive performance (Morris et al., 2011) to name a few. Early detection is an effective preventative of lameness developing into a chronic condition (Clarkson et al., 1996). The use of electronic, sensor-oriented techniques is a growing field for lameness detection in several species such as horses and cattle. High-speed cameras to investigate locomotion and hoof contact (Herlin and Drevemo, 1997; Meyer et al., 2007) and systems for ground reaction force detection (Tasch and Rajkondawar, 2004) coupled with motion analysis software (Flower et al., 2005) have provided sensitive indicators for fore- and hind limb assessment (Pluk et al., 2012). With the advancement of these systems, new technologies are advancing based on their concepts and findings.

However, when working with new automated technologies for gait analysis and detection of lameness, discriminant measures should be analyzed to ensure their reliability, accuracy and precision. Determining the functionality and operability of a technology requires in-depth analysis of its principal concepts and variables for further research to build on. From this standpoint, the objective of this research study was to assess two primary signal fluctuations as being uniquely different within a single linear optical signal. The second objective was to describe the fluctuations as either true (i.e., anomaly free) first hoof contacts or last break-overs from descriptive statistical analysis. Video and signal data collected during animal walks over the EOBS were compared for validating signal fluctuations with respect to time.

MATERIALS AND METHODS

The research protocol for this study and all procedures involving animal handling were approved by the Colorado State University (CSU) Institutional Animal Care and Use Committee (IACUC; approval number 16-6611AA). Experiments were conducted over 3 d; test 1 and 2 occurred in January 2017, and test 3 was completed in May 2017.

Animals and Housing

A total of 3 clinically normal, mixed breed horses (2 geldings and 1 mare) [23] were obtained. Horses were housed individually and provided ad libitum access to water with feedings twice a day. Facilities and horses were inspected daily. Horses lacked visually perceptible lameness at a walk. Horses were between 2- and 10-yr of age with varying degrees of height, weight and frame. Horses did not have their feet trimmed and balanced prior to evaluation. All horses were acclimated to the Equine Orthopaedic Research Center (EORC) Gait Analysis Laboratory prior to data being collected.

Platform Design and Procedure

The EOBS platform was based on current commercial dimensions (0.914 m (width) x 2.438 m (length) x 0.051 m (height)) found in standard livestock scales. An adjustment feature of an additional 1.219 m of 1¼ inches rubber matting at the start and rear of the platform was implemented. The EOBS platform was constructed of 1 optical sensor attached and protected within a metal case. The EOBS platform had an approximate holding capacity of 1361 kg. A protective rubber matting was placed underneath to eliminate noise in signal readings.

---

[23] Note: *Four horses were initially obtained. However, prior to the start of the study 1 horse was removed due to complications that led to its inability to properly complete the tests for data collection.*

A signal-base-unit (SBU) logged hoof contact as signal fluctuation and time with a rate greater than ~50 average samples per second (s). A laptop with commercial software was used to graph and analyze readings. Data was saved offsite using custom code. A single standard camera system was used to record the position of the horses' limbs during walks over the EOBS platform. Videos were synchronized with the signal readings. Signal observations were initiated when a horse placed its first forelimb on the EOBS platform and ended once the final hind limb lifted off the platform.

Experimental Design

An experimental, repeated measures design was used to compare multiple horse signal readings for 3 d over a 124-d period. Horses were acclimated to the EORC facility, tools and handling for approximately 1 wk prior to commencement of the study. Individual horses were evaluated by the research veterinarian before gait analysis. All 3 horses were included in the data and compared to themselves before and after intra-muscular injection. The experimental design was a 3 (days) x 3 (horses) x 3 (treatments) factorial arrangement, and horse was the experimental unit. Experimental design allowed for control of intra- and inter-animal and day variations in signal readings. Utilizing a random number generator, horses were randomly allocated to 1 of 3 treatments (100 IU, 200 IU or saline) and blocked in either the left or right forelimb. The study was not balanced due to 1 animal removed prior to testing. Three test days were compared: D-4 (sound/baseline, defined as 4-d pre-treatment), D+3 (peak treatment, defined as 3-d post-treatment), and D+124 (recovery period, defined as 124-d post-treatment). Days were compared along with fore- and hind limb primary signal fluctuations (true first hoof contact or last break-over). Days D-4, D+3 and D+124 were based on previous treatment models validated by Carter and Renfroe (2013), Wijnberg et al. (2013), and Hardeman et al. (2013).

Additionally, horses were used in a companion study with data collected on the same days after the proceeding test sessions.

Data Processing

Data were collected from all 3 horses walking over the embedded-optical-base system (EOBS). Video observations were analyzed to detect and determine both valid and invalid periods of recorded hoof impacts. Hoof contacts which hit within the sensor's detection zone (i.e., detectable 3 (column) x 4 (row) gridded sector and 1-inch dead zone border; Figure 6.1) were kept as they corresponded to either a hoof contact or break-over reading. Video observations allowed for removal of inaccurate hoof readings during the recording periods (e.g., hoof placement half off the platform). Analysis was performed using varying methods from Pastell et al. (2006), Chapinal et al. (2010) and Conte et al. (2014).

Data measured were first hoof contact (i.e., when hoof impacted the platform; ΔS_{TS}) and last break-over (i.e., when hoof lifted from the platform; ΔS_{TL}). Signal amplitude (i.e., peak-to-peak curves) was measured from signal fluctuations. Limb placement on the EOBS platform was also evaluated. Stance time (i.e., when a hoof was in contact with the platform prior to being lifted) was recorded for future analysis. Additionally, swing time (i.e., when a limb was in movement from the platform to its next impact) was not analyzed with initial analysis though it is an influencing factor on hoof contact and break-over. First hoof contacts and last break-overs were considered true (i.e., anomaly free) signal fluctuations and analyzed for any significant trends as to their difference. Horses walked at a steady pace on the platform (Figure 6.2) with additional detailed descriptions of the gait recorded by a trained observer. Specific criteria were utilized to determine signal data for each horse. Horse signals for each pass were classified either valid or invalid. Valid signals were analyzed.

Statistical Analysis

Primary signal fluctuation data (i.e., true first hoof contact (ΔS_{TS}) and true last break-over (ΔS_{TL})) were tested for normality using the *pearson.test* function from the *nortest* package in R [24,25]. Due to random occurrences during walks over the EOBS, data were not normally distributed; thus, data were analyzed by running a log transformation. Signal readings were continuous and fit to a linear mixed model to assess differences between primary signal fluctuations. Left and right fore- and hind limbs were not reported separately but categorized together. Initial correlation tests were measured between time (T), platform grid (P_R = row; P_C = column) and primary signal fluctuations (ΔS_{TS} and ΔS_{TL}). The *lme4* package was used for Welch-Satterthwaite's t-tests to look at the difference between ΔS_{TS} and ΔS_{TL} to assess their usability as signal markers for walks over the EOBS. The model (6.1) was fitted and expressed as

$$Y_{pjk} = a + T_i + C_p + Hj_k + e_{pjk} \tag{6.1}$$

where, Y_{pjk} represents primary signal fluctuation (ΔS; log transformed) observed in day k, in animal j, and by ΔS classification p (ΔS_{TS} or ΔS_{TL}); a is the intercept; T_i is the fixed effect of time i (T); C_p is the fixed effect of p^{th} ΔS classification (ΔS_{TS} or ΔS_{TL}); H_{jk} is the repeated measures term for j^{th} horse within day k due to horses performing multiple walks over the EOBS platform within a test day; e_{pjk} is the residual term. Estimates, standard errors and p-values for fixed effects of primary signal fluctuations (ΔS_{TS} or ΔS_{TL}) and time (T) were reported for the model (6.1). Proportion of variance (R^2) for fixed and random effects for the model (6.1) were determined using the *MuMIn* package in R [24,25].

---

[24] R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. URL https://www.R-project.org/. (Version 3.5.0 - "Joy in Playing")

[25] RStudio Team. 2018. RStudio: Integrated Development for R. RStudio, Inc. Boston, MA. URL http://www.rstudio.com/. (Version 1.1.453)

A secondary linear mixed model was constructed to assess limb (left or right; forelimb or hind limb) and treatment (Botox or saline injection) differences. Treatments of 100 IU and 200 IU were combined (i.e., Botox group) for analysis. The model (6.2) was fitted and expressed as

$$Y_{pjk} = a + T_i + L_t + R_p + H_{jk} + e_{pjk} \quad (6.2)$$

where, Y_{pjk} represents primary signal fluctuation (ΔS; log transformed absolute value) observed in day *k,* in animal *j*, and by treatment method *p* (Botox or saline); *a* is the intercept; T_i represents the fixed effect of time *i* (T); L_t represents the fixed effect of limb *t* (left or right; forelimb or hind limb); R_p represents the fixed effect of treatment method *p* (Botox or saline); H_{jk} is the repeated measures term for j^{th} horse within day *k*; e_{pjk} is the residual term. Estimates, standard errors and *p*-values for fixed effects of limb, treatment and T were also reported for the model (6.2). Pairwise comparisons using the *lsmeans* package compared differences between primary fluctuations (ΔS_{TS} or ΔS_{TL}), limbs and treatments. A *p*-value of ≤ 0.05 was considered significant. A single model should have been utilized during analysis however, due to related variables found in the first model the study required analysis of multiple models.

RESULTS AND DISCUSSIONS

Repeatability Study

Prior to blocking, all 3 horses were found clinically sound. Soundness was defined as the ability to move freely using 4 limbs and showing no evidence of abnormal weight-shifting, non-weight-bearing behavior and/or reluctance to walk on any limb (Pairis-Garcia et al., 2015). Horses demonstrated no additional signs of clinical disease or sickness during the testing period. Peak treatment effects were assumed to be exhibited on D+3. No noticeable signs of lameness were observed between treatments and no horses became non-weight-bearing during the testing period. Horse limbs for all treatments exhibited minute differences in signal fluctuation strength.

It was also noted that due to the location of the treatments in each limb and the EOBS's sampling threshold at the time of study, noticeable gait fluctuations in the signal may have been reduced. Thus, sensor fluctuations between saline and treated limbs were not reported separately in the initial analysis but utilized as a factor within horse and day to explain deviations within the model. However, changes to a limb (proximal or distal) may change how an animal places it, resulting in noticeable deviations. Observed variables were then calibrated on the basis of animal's gait characteristics to eliminate horse effects as suggested by Zhao et al. (2018).

Distribution of Signals

A total of 53 normal ΔS_{TS} (n = 53; Table 6.1) and 53 normal ΔS_{TL} (n = 53; Table 6.1) for horses A, B and C were collected and used for analysis (Figures 6.3 and 6.4). A Savitzky-Golay lowpass filtering was used for adjusting the signal baseline. Average hoof contacts and break-overs were observed (total average of ΔS_{TS} = -0.426; total average ΔS_{TL} = -0.045). Ratio means (± SD) were used to standardize values and determine variation between ΔS_{TS} and ΔS_{TL} (Table 6.2). Horse C's ΔS_{TL} exhibited greater deviation (0.132 ± 0.084; Ratio mean ± SD). Due to Horse C's small number of recorded passes over the EOBS, extremes in deviations and/or variability may be noticeable as inflated differences. Individual horses crossed the EOBS at a consistent speed during each walk with an average hoof impact time (ST_{avg}) of 0.67 s and an average break-over time (LT_{avg}) of 0.79 s. Average hoof impact time (ST_{avg}) and LT_{avg} were based on ΔS_{TS} and ΔS_{TL} variables as an assumption that animals will maintain a symmetrical pattern for each secondary hoof contact and break-over while walking across the EOBS. Normal animals exhibit left-right symmetry of limb placement and motion during a walking gait while asymmetry is expressed by differences in stride duration, stride length and number of spacing frames (Maertens et al., 2011; Zhao et al., 2018). Thus, a single horse was used as its own control for determining soundness. Any noticeable deviations would allow for the assumption that the animal was lame as studies on horses with induced lameness have reported within-animal changes for various gait variables (Buchner et al., 1996; Keegan et al., 2001; Pluk et al., 2012). Observable differences between horses were found across the 3 d. For ΔS_{TS}, horses A and C increased in signal amplitude over the testing period while horse B dipped during D+3 and increased again for D+124 in signal amplitude (Figure 6.5). For ΔS_{TL}, horses A and C decreased in signal amplitude over the testing period while horse B decreased during D+3 and increased again for D+124 in signal amplitude (Figure 6.6). As seen by figures 6.5 and 6.6, ΔS_{TL} and ΔS_{TS} are closely associated to each other. From these observable trends, horses A and C may have incurred slight functional changes in limb integrity due to treatments causing deviations in variability found in ΔS_{TS} and ΔS_{TL}. However, additional factors such as velocity, hoof impact location and limb (i.e., right vs. left) may have influenced deviations in variability.

Evaluation of Signal Correlations

Simple correlations were examined based on time (T), primary signals (ΔS_{TS} and ΔS_{TL}), and platform grid (P_R = row; P_C = column) to examine initial relationship trends in the data. Weak positive correlation ($r = 0.085$) between T and ΔS_{TS} was observed. Additionally, a weak negative correlation ($r = -0.148$) was observed between T and ΔS_{TL}. Both observations indicated that T does not have a linear relationship with ΔS_{TS} and ΔS_{TL} allowing for their use without noticeable interference. However, time and velocity are traditionally related with faster velocities resulting in larger impact forces. Thus, lacking variability may have reduced any noticeable differences for T with ΔS_{TS} and ΔS_{TL} (Goodwin and Leech, 2006). Platform row (P_R) had a moderately positive correlation ($r = 0.5142$) to ΔS_{TS} and moderately correlated ($r = 0.457$) to ΔS_{TL}. Both ΔS_{TS} ($r = 0.336$) and ΔS_{TL} ($r = -0.507$) were moderately correlated to platform column

(P_C). Last break-over (ΔS_{TL}) was stronger in correlation to P_C related to sensor position and mechanical flex. However, ΔS_{TS} was strongly correlated to P_R due to proximity within the sensor's detection zone. Both moderate correlations between signal strength for ΔS_{TS} and ΔS_{TL} with P_R and P_C are expected trends based on the EOBS platform construction.

Analysis of First Hoof Contact and Last Break-Over Signals

Primary signal fluctuations were significant ($P < 0.05$; -3.434 ± 0.382, ΔS_{TS}; 2.209 ± 0.102, ΔS_{TL}; Estimate ± SE, Figure 6.7) whereas T was not significant ($P = 0.441$; 0.368 ± 0.475; Estimate ± SE) within the model (6.1). True ΔS_{TS} exhibited moderate negative estimated correlation with ΔS_{TL} ($r = -0.595$). Time (T) exhibited negative estimated correlation with ΔS_{TL} ($r = -0.966$). Moderate positive estimated correlation between ΔS_{TS} and T was observed ($r = 0.514$). Roughly 84% of variability ($R^2 = 0.836$; Fixed) in the model (6.1) is explained by ΔS_{TS}, ΔS_{TL}, and T. Additionally, ~2% of variability ($R^2 = 0.858$; Fixed + Random) in the model (6.1) was accounted for due to horse within day and horse. By including the effects of horse and day, primary fluctuations with respect to animal influence were considered more accurate. True first hoof contact (ΔS_{TS}) and last break-over (ΔS_{TL}) values may have differed due to asymmetry (i.e., unevenness) in weight bearing (i.e., limb shifting). The center of gravity is closer to a quadruped's forelimbs (i.e., ~60% of weight) and could result in larger fluctuations. Limb placement on the platform relative to the embedded sensor's location or outside of the sensor's detection zone also influenced signal strength. Signal fluctuation strength was shown to be associated with contact location in previous studies and may result in greater deviations between passes. Animal hesitation when passing over the EOBS may have also contributed to horse deviations. However, comparison between right and left limb hoof contacts and break-overs from model 6.2 were not significantly different for fore- or hind limbs ($P = 0.966$; 0.063 ± 0.135;

Estimate ± SE; $P = 0.606$; -0.176 ± 0.142; Estimate ± SE, respectively). Additionally, treatment (i.e., Botox) versus saline forelimbs did not exhibit significant difference ($P = 0.7407$; -0.098 ± 0.279; Estimate ± SE). It was noted that limb stance phase while in contact with the EOBS and secondary limb's swing phase contributed to weight shifting causing first hoof contact signals to deviate on the tail-end. As such, implementing animal body weights to attributed shifting could allow insight into understanding the relative quality of primary fluctuations. Lastly, both models 6.1 and 6.2 lacked statistical power due to insufficient samples sizes to assess anything but the largest differences. Although there are limited significant results, there are existing patterns that could result in significance and be useful for future research (Tsang et al., 2009).

Conclusions

In conclusion, the embedded-optical-base system (EOBS) proved a reliable source for continuous automatic recording of unique signal fluctuations. The EOBS was found to be able to detect the 2 primary signal fluctuations as being uniquely different within the linear optical signal. Video and signal data collected during complete gait passes (CGP) over the EOBS platform were compared for validating signal fluctuations with respect to time (T). As such, the 2 primary signal fluctuations were described as either true (i.e., anomaly free) hoof contacts (ΔS_{TS}) or break-overs (ΔS_{TL}). Additionally, the 2 observed gait variables (ΔS_{TS} and ΔS_{TL}) provided segmentation between animal passes. Horses' estimated velocities ($\sim v$) were not calculated but could be determined from observed segmentation. Lastly, differences between ΔS_{TS} and ΔS_{TL} resulted in mechanical thresholds between CGP that provided individual horse evaluation.

Further research should be conducted to evaluate the signal's detection and representation of multiple secondary hoof contacts and break-overs within an animal's CGP over the EOBS. Number of fluctuation deviations reflected within the data limits inference to the EOBS's practical use at this time. Also, evaluating horses' pain sensitivity (i.e., pain threshold before gait deviations are exhibited) during CGP over the EOBS is needed to understand various degrees of lameness such as transient lameness (i.e. short-lived gait issue; internal pain not exhibited as a long-term gait deviation). However, the research provided information on the potential use of optics for gait analysis and future lameness detection. Lastly, by analyzing prominent signal fluctuations such as first hoof contacts (ΔS_{TS}) and last break-overs (ΔS_{TL}), observed signal fluctuations in the linear optical signal proved reliable discriminant measures.

Table 6.1 Observations (i.e., visual counts) of total true first hoof contacts (ΔS_{TS}; forelimb) and true last break-overs (ΔS_{TL}; hind limb) along with left and right limb counts for individual horses (n = 3) at a walking gait for 3 d (pre-, post, and recovery) over a 4-mo period.

	First Hoof Contact (ΔS_{TS}; Forelimb)			Last Break-over (ΔS_{TL}; Hind Limb)		
Animal	**Normal** [1]	**Left** [2]	**Right** [3]	**Normal** [1]	**Left** [2]	**Right** [3]
Horse A	16	8	8	16	5	11
Horse B	22	5	17	22	5	17
Horse C	15	9	6	15	5	10
Total	53	19	34	53	15	38

[1] Total normal hoof contact (fore- or hind limb) with embedded-optical-base system (EOBS). Normal was considered an impact or break-over that did not show signs of deviation or error during its contact with the EOBS.
[2] Left hoof contact (fore- or hind limb) with embedded-optical-base system (EOBS).
[3] Right hoof contact (fore- or hind limb) with embedded-optical-base system (EOBS).

Table 6.2 Overall descriptive statistics of true first hoof contacts (ΔS_{TS}; forelimb) and true last break-overs (ΔS_{TL}; hind limb) for individual horses (n = 3) at a walking gait for 3 d (pre-, post, and recovery) over a 4-mo period. Max, min, range, median and ratio mean (± SD) based on signal output (S_O) in arbitrary units (au) from a corrected baseline.

Animal	Min	Max	Range	Median	Ratio Mean (± SD)
First Hoof Contact [1]					
Horse A	-0.899	-0.187	0.711	-0.485	0.924 ± 0.033
Horse B	-0.815	-0.103	0.712	-0.278	0.865 ± 0.046
Horse C	-0.829	-0.137	0.692	-0.435	0.868 ± 0.084
Last Break-over [2]					
Horse A	-0.056	-0.021	0.035	-0.035	0.076 ± 0.033
Horse B	-0.080	-0.020	0.060	-0.043	0.135 ± 0.046
Horse C	-0.088	-0.024	0.064	-0.043	0.132 ± 0.084

[1] True first hoof contact (ΔS_{TS}) recorded during animal hoof impact on the embedded-optical-base system (EOBS).
[2] True last break-over (ΔS_{TL}) recorded during animal toe-off from the embedded-optical-base system (EOBS).

R4 | C3	**R3 | C3**	**R2 | C3**	**R1 | C3**
R4 | C2	**R3 | C2**	**R2 | C2**	**R1 | C2**
R4 | C1	**R3 | C1**	**R2 | C1**	**R1 | C1**

Figure 6.1 Example of embedded-optical-base system (EOBS) platform grid rows (P_R) and columns (P_C). White border represents platform's signal dead zone. Shaded areas represent signal detection zone.

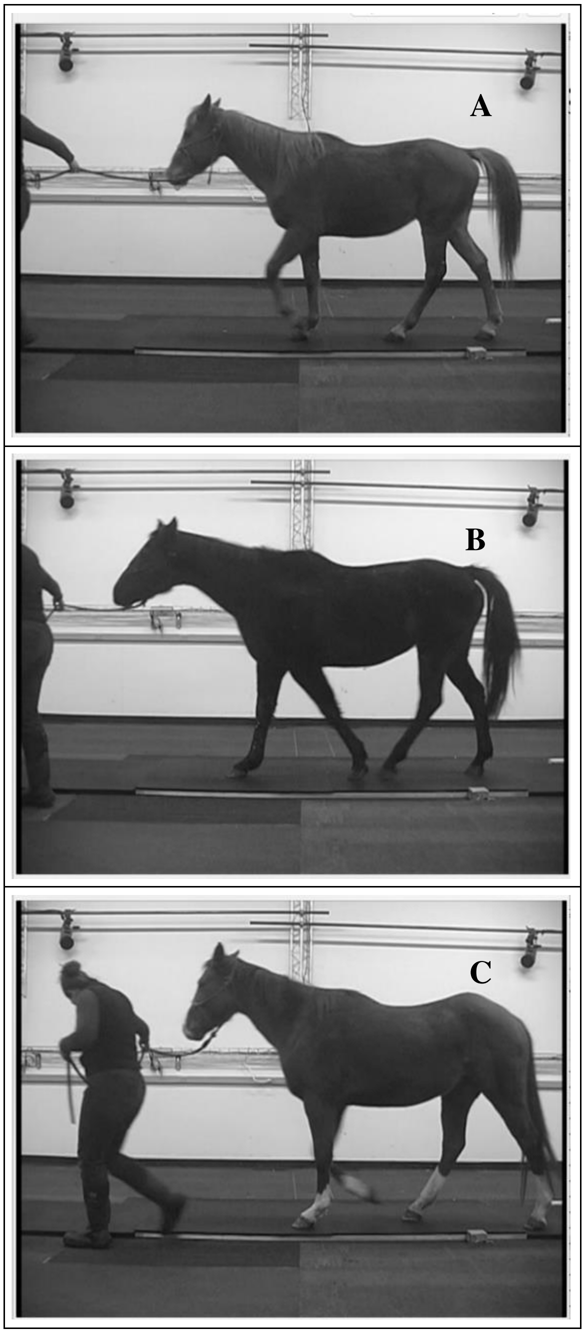

Figure 6.2 Images of horses walking across the embedded-optical-base system (EOBS) during a single test day.

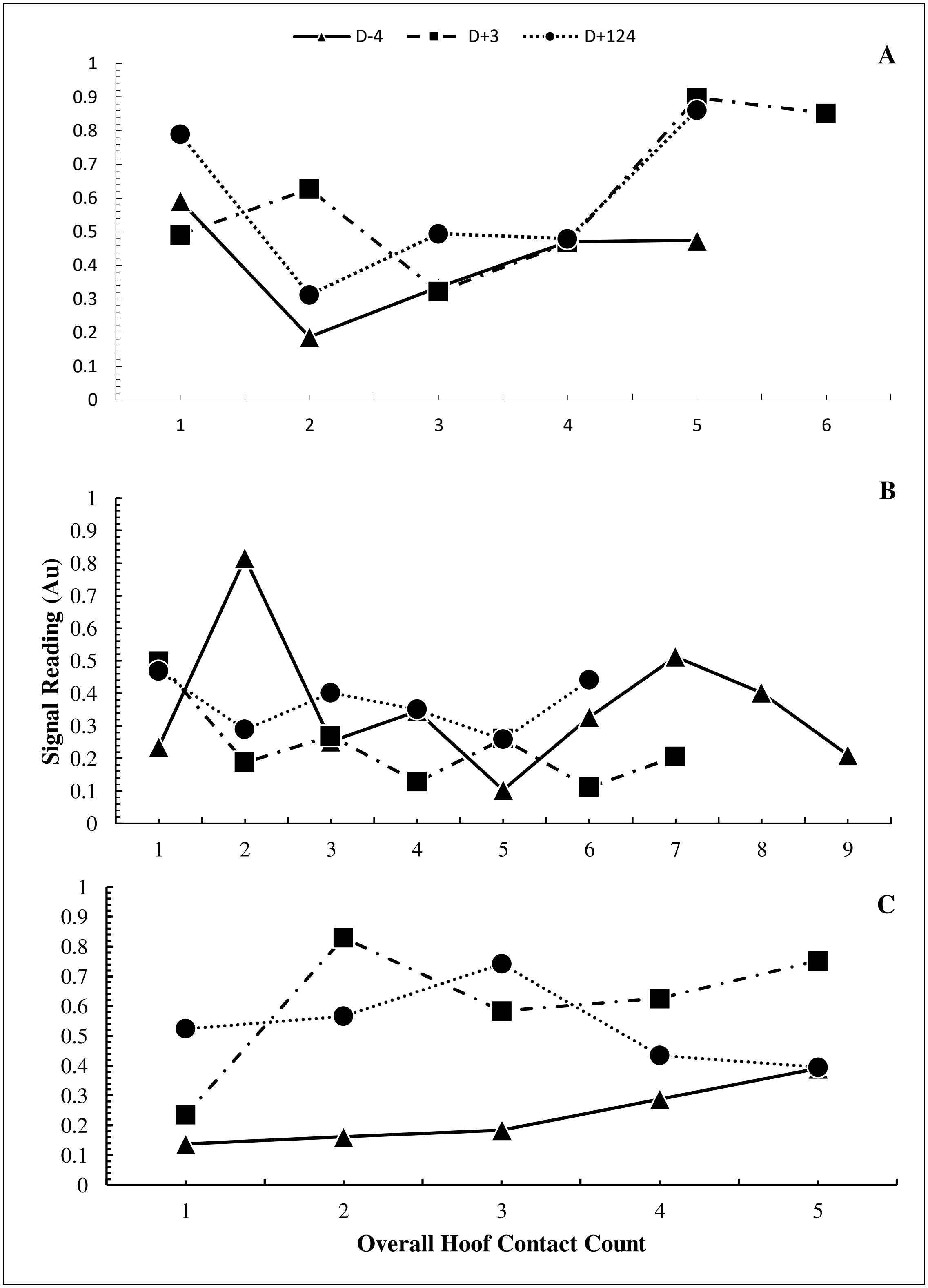

Figure 6.3 Plots of true first hoof contact signal amplitudes (ΔS_{TS}; arbitrary units (au)) for visual trend analysis between pre-treatment (D-4; solid line), peak treatment (D+3; dashed line) and post-treatment (D+124; dotted line) days per horse (A, B and C) reported over a 4-mo period.

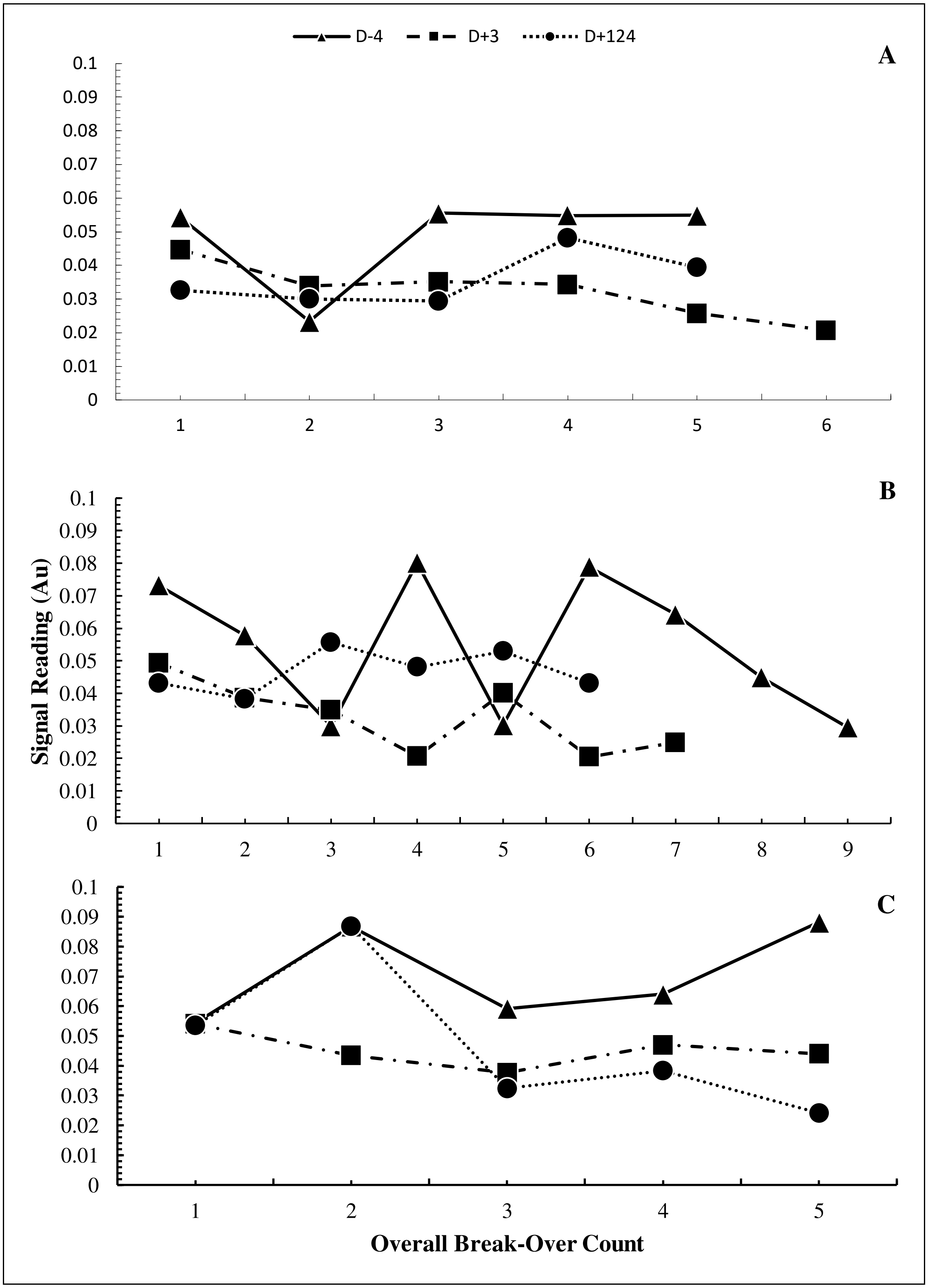

Figure 6.4 Plots of true last break-over signal amplitudes (ΔS_{TL}; arbitrary units (au)) for visual trend analysis between pre-treatment (D-4; solid line), peak treatment (D+3; dashed line) and post-treatment (D+124; dotted line) days per horse (A, B and C) reported over a 4-mo period.

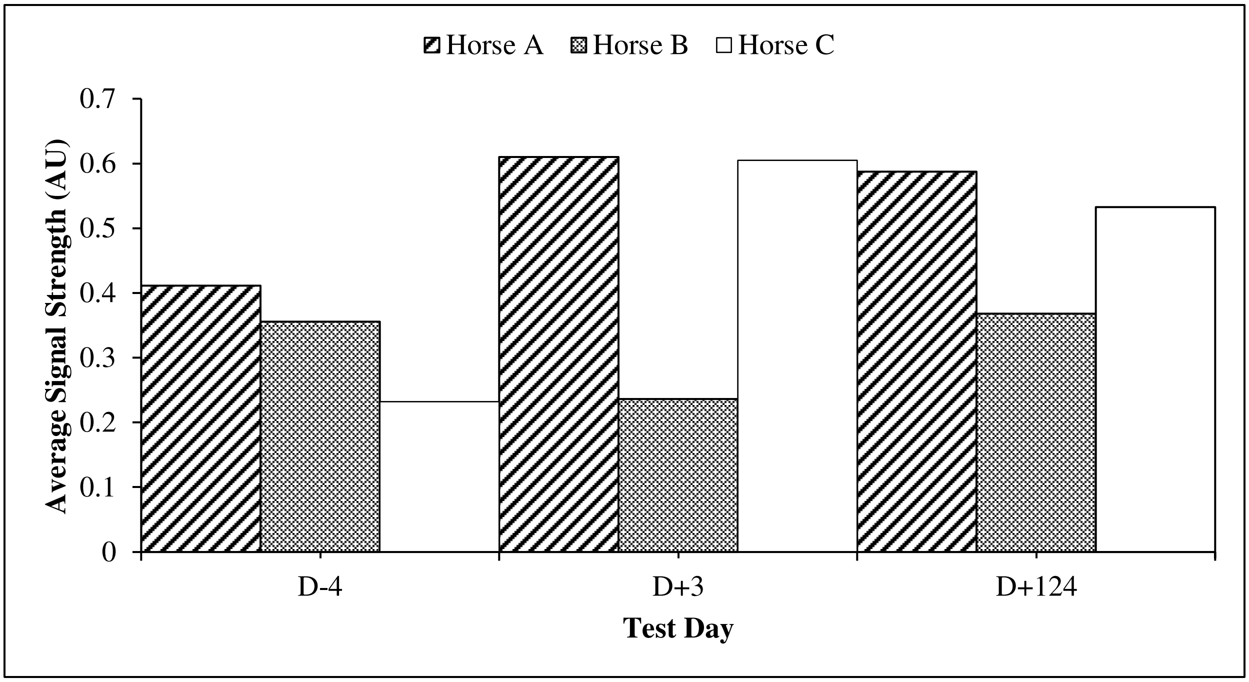

Figure 6.5 Histogram of average true first hoof contact signal amplitude (measured in arbitrary units (au)) between horses relative to 3 d (pre-, peak and post-treatment) over a 4-mo period. Horses A and C increased in signal amplitude over the study period while horse B dipped during D+3 and increased again for D+124 in signal amplitude. Horse B followed an inverted trend compared to horses A and C.

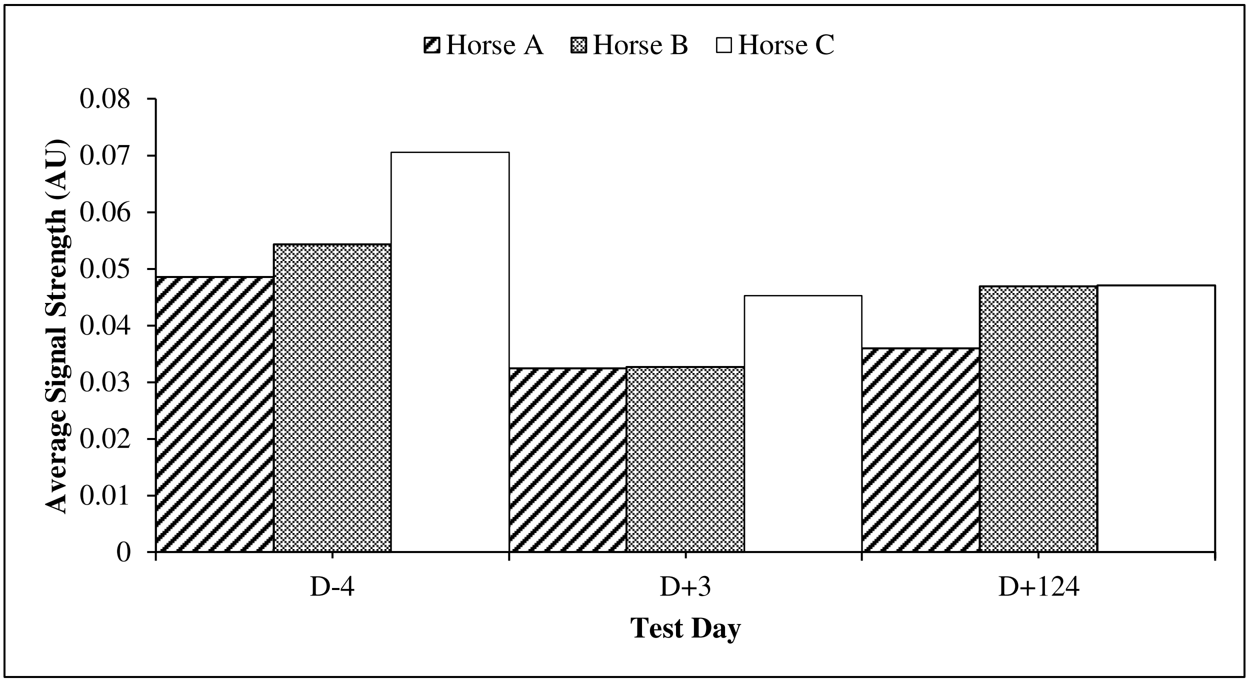

Figure 6.6 Histogram of average true last break-over signal amplitude (measured in arbitrary units (au)) between horses relative to 3 d (pre-, peak and post-treatment) over a 4-mo period. Horses A and C decreased in signal amplitude over the study period while horse B dipped during D+3 and increased again for D+124 in signal amplitude. Horse B followed an inverted trend compared to horses A and C.

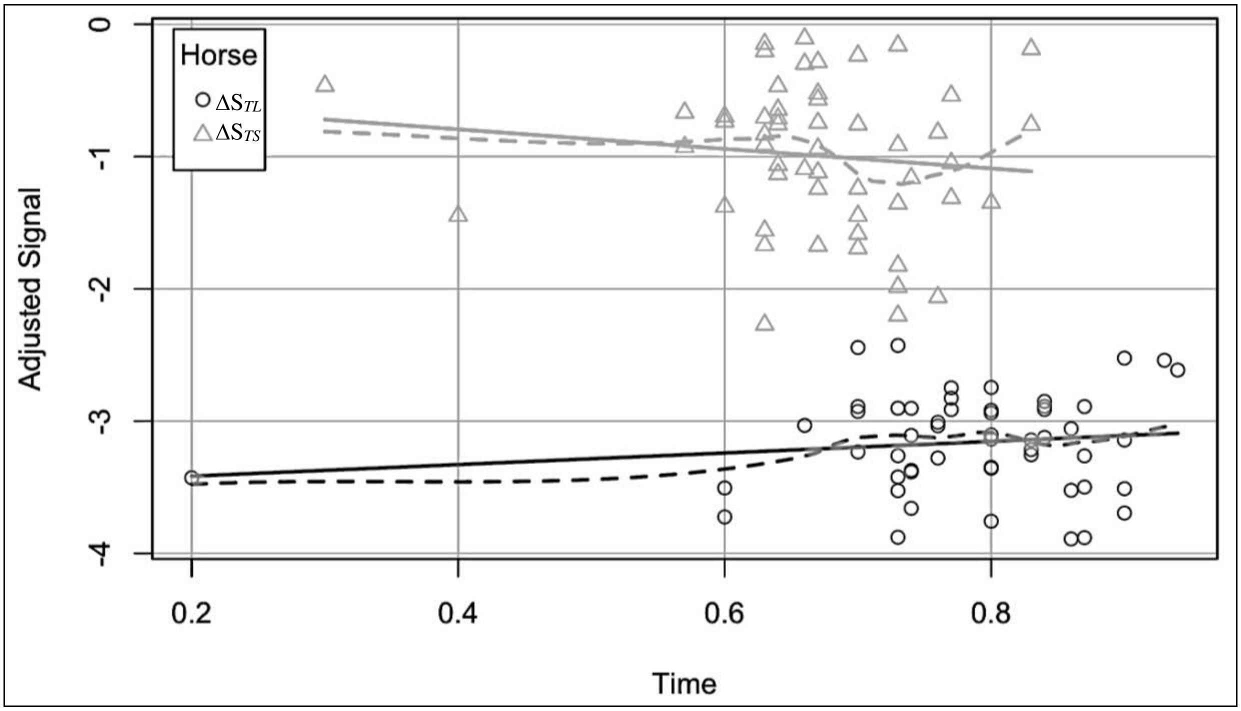

Figure 6.7 Scatter plot comparison between adjusted signal amplitude (y-axis) for horse break-overs (ΔS_{TL}) and hoof contacts (ΔS_{TS}) and time duration (T; x-axis). Solid lines represent linear trends and dashed lines represent moving mean trends. Open circles represent break-overs (ΔS_{TL}) and open triangles represent hoof contacts (ΔS_{TS}) per horse. True break-overs and hoof contacts exhibit clear separation indicating difference between primary signal fluctuations.

References

1. Buchner, H. F., H. H. C. M. Savelberg, H. C. Schamhardt, and A. Barneveld. 1996. Limb movement adaptations in horses with experimentally induced fore- or hindlimb lameness. Equine Vet. J. 28:63-70. doi: 10.1111/j.2042-3306.1996.tb01592.x.

2. Carter, D. W., and J. B. Renfroe. 2013. A novel approach to the treatment and prevention of laminitis: Botulinum toxin type A for the treatment of laminitis. J. Equine Vet. Sci. 29:595-600. doi: 10.1016/j.jevs.2009.05.008.

3. Chapinal, N., A. M. de Passillé, J. Rushen, and S. Wagner. 2010. Automated methods for detecting lameness and measuring analgesia in dairy cattle. J. Dairy Sci. 93:2007-2013. doi: 10.3168/jds.2009-2803.

4. Clarkson, M. J., D. Y. Downham, W. B. Faull, J. W. Hughes, F. J. Manson, J. B. Merritt, R. D. Murray, W. B. Russell, J. E. Sutherst, and W. R. Ward. 1996. Incidence and prevalence of lameness in dairy cattle. Vet. Rec. 138:563-567. doi: 10.1136/vr.138.23.563.

5. Conte, S., R. Bergergon, H. Gonyou, J. Brown, F. C. Rioja-Lang, L. Connor, and N. Devillers. 2014. Measure and characterization of lameness in gestating sows using force plate, kinematic, and accelerometer methods. J. Anim. Sci. 92:5693-5703. doi: 10.2527/jas.2014-7865.

6. Flower, F. C., D. J. Sanderson, and D. M. Weary. 2005. Hoof pathologies influence kinematic measures of dairy cow gait. J. Dairy Sci. 88:3166-3173. doi: 10.3168/jds.S0022-0302(05)73000-9.

7. Goodwin, L. D., and N. L. Leech. 2006. Understanding correlation: Factors that affect the size of r. J. Exp. Edu. 74:251-266.

8. Haley, D. B., A. M. de Passillé, and J. Rushen. 2001. Assessing cow comfort: Effects of two floor types and two tie stall designs on the behaviour of lactating dairy cows. Appl. Anim. Behav. Sci. 71:105-117.

9. Hardeman, L. C., B. R. van der Meij, M. Oosterlinck, S. Veraa, J. H. van der Kolk, I. D. Wijnberg, and W. Back. 2013. Effect of Clostridium botulinum toxin type A injections into the deep digital flexor muscle on the range of motion of the metacarpus and carpus, and the force distribution underneath the hooves, of sound horses at the walk. Vet. J. 198: e152-e156. doi: 10.1016/j.tvjl.2013.09.051.

10. Herlin, A. H., and A. Drevemo. 1997. Investigation of locomotion of dairy cows by use of high speed cinematography. Equine Vet. J. Suppl. 23:106-109.

11. Keegan, K. G., R. Pai, D. Wilson, and B. Smith. 2001. Signal decomposition method of evaluating head movement to measure induced forelimb lameness in horses trotting on a treadmill. Am. J. Vet. Res. 61:612-619. doi: 10.2746/042516401776254781.

12. Krohn, C. C. and L. Munksgaard. 1993. Behaviour of dairy cows kept in extensive (loose housing/pasture) or intensive (tie stall) environments. II. Lying and lying-down behaviour. Appl. Anim. Behav. Sci. 37:1-16. doi: 10.1016/0168-1591(93)90066-X.

13. Maertens, W., J. Vangeyte, J. Baert, A. Jantuan, S. De Campeneere, A. Pluk, G. Opsomer, S. Van Weyenberg, and A. Van Nuffel. 2011. Development of a real time cow gait tracking and analyzing tool to assess lameness using a pressure sensitive walkway: The GAITWISE system. Biosyst. Eng. 110:29-39. doi: 10.1016/j.biosystemseng.2011.06.003.

14. Meyer, S., M. A. Weishaupt, and K. A. Nuss. 2007. Gait pattern of heifers before and after claw trimming: A high-speed cinematographic study on a treadmill. J. Dairy Sci. 90:670-676. doi: 10.3168/jds.S0022-0302(07)71549-7.

15. Moorman, V. J., R. F. Reiser, M. L. Peterson, C. W. McIlwraith, and C. E. Kawcak. 2013. Effect of forelimb lameness on hoof kinematics of horses at a walk. Am. J. Vet. 74:1192-1197. doi: 10.2460/ajvr.74.9.1192.

16. Morris, M. J., K. Kaneko, S. L. Walker, D. N. Jones, J. E. Routly, R. F. Smith, and H. Dobson. 2011. Influence of lameness on follicular growth, ovulation, reproductive hormone concentrations and estrus behavior in dairy cows. Theriogen. 76:658-668. doi: 10.1016/j.theriogenology.2011.03.019.

17. Ouared, K., K. Zidane, H. Aggad, and A. Niar. 2015. Impact of clinical lameness on the milk yield of dairy cows. J. Anim. Vet. Adv. 14:10-12. Doi: 10.3168/jds.S0022-0302(02)74304-X.

18. Pairis-Garcia, M. D., A. K. Johnson, C. A. Abell, J. F. Coeztee, L. A. Karriker, S. T. Millman, and K. J. Stadler. 2015. Measuring the efficacy of flunixin meglumine and meloxicam for lame sows using a GAITFour pressure mat and an embedded microcomputer-based force plate system. J. Anim. Sci. 93:2100-2110. doi: 10.2527/jas2014-8796.

19. Pastell, M., H. Takko, H. Grohn, M. Hautala, V. Poikalainen, J. Praks, I. Veermae, M. Kujala, and J. Ahokas. 2006. Assessing cow's welfare: Weighing the cow in a milking robot. Biosyst. Eng. 93:81-87. doi: 10.1016/j.biosystemseng.2005.09.009.

20. Pluk, A., C. Bahr, A. Poursaberi, W. Maertens, A. van Nuffel, and D. Berckmans. 2012. Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques. J. Dairy Sci. 95:1738-1748. doi: 10.3168/jds.2011-4547.

21. Scott, G. B. 1989. Changes in limb loading with lameness for a number of Friesian cattle. Br. Vet. J. 145:28-38. doi: 10.1016/0007-1935(89)90005-5.

22. Tasch, U., and P. Rajkondawar. 2004. The development of a SoftSeparator™ for a lameness diagnostic system. Comput. Electron. Agric. 44:239-245. doi: 10.1016/j.compag.2004.04.001.

23. Tsang, R., L. Colley, and L. D. Lynd. 2009. Inadequate statistical power to detect clinically significant differences in adverse event rates in randomized controlled trials. J. Clinic. Epidem. 62:609-616. doi: 10.1016/j.jclinepi.2008.08.005.

24. USDA. 2001. National economic cost of equine lameness, colic, and equine protozoal myeloencephalitis in the United States. https://www.aphis.usda.gov/animal_health/nahms/equine/downloads/equine98/Equine98_is_EconCost.pdf. (Accessed 11 October 2018.)

25. Wijnberg, I. D., L. C. Hardeman, B. R. van der Meij, S. Veraa, W. Back, and J. H. van der Kolk. 2013. The effect of Clostridium botulinum toxin type A injections on motor unit activity of the deep digital flexor muscle in healthy sound Royal Dutch sport horses. Vet. J. 198:e147-e151. doi: 10.1016/j.tvjl.2013.09.050.

26. Zhao, K., J. M. Bewley, D. He, and X. Jin. 2018. Automatic lameness detection in dairy cattle based on leg swing analysis with an image processing technique. Comput. Electron. Agric. 148:226-236. doi: 10.1016/j.compag.2018.03.014.

Chapter Seven

In-motion optical sensing to assess deviations in signal patterns from commercial beef bulls with varying musculoskeletal abnormalities

SUMMARY

The primary objective of this small investigative field study was to provide detectable and observable patterns of true abnormal and normal embedded-optical-base system (EOBS) signal readings from commercial bulls to validate groundwork for future optical sensing research. An EOBS with an optical-point sensor was attached to a constructed metal platform and used to collect signal readings from cattle hoof contact. Fluctuations in readings correlated to signal amplitude (0 to 1 arbitrary units (au)). The EOBS platform was divided into 2 sectors. Induced mechanical flex recorded as signal outputs (S_O) were obtained from cattle fore- and hind limb hoof contacts on the EOBS platform. Signal outputs (S_O) correlated to points on a linear time-series for animal passes over the EOBS platform. Eight commercial, 2-yr old crossbred and purebred bulls (n = 4, Red Angus; n = 4, Stabilizers; n = 8) with a mean BW of 588.54 kg (± 70.92 kg) were tested. Bull signal readings were obtained during a 3-hr sampling period for 1 d with 3 complete gait passes (CGP) over the EOBS platform recorded. Each bull's pass over the EOBS platform was video recorded and evaluated concurrently. Bulls exhibited a total average complete gait pass (CGP) time duration (T) of 2.105 ± 1.288 (mean ± SD), a total average signal amplitude (ΔS_{avg}^{ttl}) of 0.642 ± 0.002 (mean ± SD), a total max signal average (ΔS_{avg}^{mx}) of 0.721 ± 0.050 (mean ± SD) and a total min signal average (ΔS_{avg}^{mn}) of 0.571 ± 0.045 (mean ± SD). Linear model fixed effects of time ($P < 0.05$; 0.0029 ± 7.406e^{-4}; mean ± SD; T) and max-min signal difference ($P = 0.033$; 0.00824 ± 3.575e^{-3}; mean ± SD) were found to be significant. No

significance in residual differences was observed. However, bulls exhibited observable signal variation in passes over the EOBS platform. Overall, the small field study allowed for both qualitative and quantitative analysis to be performed to validate future optical sensing research.

Key words: bovine, optical sensors, gait analysis, musculoskeletal structure

INTRODUCTION

On commercial beef cattle operations such as North American feedlots, lameness accounts for 16% of morbidity and up to 70% lost revenue due to premature slaughter (Griffin et al., 1993; Terrell et al., 2017). Lameness can have negative effects on welfare, health and overall performance of cattle making it imperative to identify and understand its risk factors and pathogenesis (Terrell et al., 2017). However, farmers and ranchers tend to underestimate economic effects along with herd prevalence and severity of lameness (Wells et al., 1993; Whay et al., 2003; Leach et al., 2010; Van De Gucht et al., 2018). As such, making it a complicated underlying problem for livestock producers.

Lameness, as a whole, affects gait parameters in quadrupeds with lame cattle walking slower, exhibiting shortened stride length, negative overlap (i.e., overtracking) and decreases in vertical peak forces, average forces, stance time, vertical impulse and horizontal forces (Scott, 1989; Telezhenko and Bergsten, 2005; Rajkondawar et al., 2006; Skjøth et al., 2013). Additionally, equine studies found that animals exhibit reduced vertical forces and altered horizontal forces on affected limbs with ipsilateral limbs showing compensatory changes (Merkens and Schamhardt, 1988; Clayton et al., 2000). When gait is affected, animal productivity and welfare are inherently reduced. By observing these parameters, novel methods for automatic detection of lameness can be developed. Therefore, the primary objective of this small field study was to determine if detectable differences in embedded-optical-base system (EOBS) signal patterns from sound and unsound commercial bulls could be identified to validate groundwork for future in-motion optical sensing research. With this data, livestock industry stakeholders ranging from nutritionists and geneticists to veterinarians and managers may begin to comprehend the recent developments of optical sensing technology for monitoring lameness.

MATERIALS AND METHODS

The Colorado State University Institutional Animal Care and Use Committee (CSU IACUC) reviewed and approved all research procedures (approval number 16-6611AA). The experiment was conducted over a 1-d period in July 2018 at the CSU Agriculture Research, Development and Education Center (ARDEC; Fort Collins, CO).

Cattle, Housing and Test Area

Eight commercial, 2-yr old crossbred and purebred bulls (n = 4, Red Angus; n = 4, Stabilizers; n = 8), were utilized for the study. Bulls were part of a commercial feed trial and had an initial mean BW of 588.54 kg (± 70.92 kg). Bulls were group-penned in 2 outdoor lots with roughly 30 animals per pen. Approximately ¼ of the pens were shaded with concrete flooring in feeding areas. Concrete flooring, and other various synthetic flooring types, have been reported as a contributing factor to abnormal developments in an animal’s musculoskeletal structure when animals are housed on it.

Animal Selection and Testing

Two trained observers identified individual bulls based on visual observation criteria. Researchers and observers defined criteria prior to the start of the experiment. From each pen, 2 animals were deemed structurally sound and paired with 2 visually unsound animals. Animals were evaluated at a walking gait during selection and grouped as either sound or unsound. Once selected, animals were guided to a holding pen prior to entering the facilities for testing.

An embedded-optical-base system (EOBS) platform was utilized with an optical point sensor provided by Ag Tech Optics, LLC (ATO; Bryan, TX). The platform recorded signal and kinematic readings for each bull's pass. Readings were acquired for 3 complete gait passes (CGP) over the EOBS platform. Only 3 CGP were used due to observed bulls' agitated demeanor influencing consistency and quality of passes over the EOBS platform. Bulls were guided down an alleyway into a squeeze chute where they were weighed, measured and identified. Bulls were identified by manually reading their ear tags while in the chute. In addition, length (i.e., point of shoulder to hip) and weight measurements were recorded for future data analysis. Once initial measurements were obtained, bulls were released from the chute. An extended alleyway, formed by metal paneling, connected to the chute allowed animals to exit in a straight path towards a holding pen. Cattle exited the chute onto a 2-inch thick sheet of rubber matting (1.829 m (width) x 1.829 m (length)) that lined the floor of the alleyway. Rubber mats were used to provide stability, traction and even flooring for animals so as to eliminate deviations in gait. Once animals crossed the initial rubber matting they stepped on the EOBS platform. After passing over the system, animals crossed a secondary rubber mat and exited the alleyway. Aerial and sideview videos were captured as animals crossed over the EOBS platform. Cameras were oriented perpendicular and parallel to the sensing section to allow for an unobstructed view of hoof contacts. Acquisition of each video was manually controlled during each animals' pass over the EOBS platform. Initial data measured was time duration (T) for complete gait passes (CGP) over the EOBS from first hoof contact (i.e., when a hoof impacted the platform) to last break-over (i.e., when the last hoof lifted from the platform). Additionally, max and min signal amplitude peaks (ΔS_{avg}^{mn} and ΔS_{avg}^{mx}) from impacts and break-overs were recorded. Signal outputs (S_O) as a whole were comprised of the stance phase (i.e., when a hoof was in contact with the platform prior being lifted) and swing phase (i.e., when a limb was in movement from the platform to its next impact) during CGP over the EOBS.

Data Acquisition and Processing

Three complete gait passes (CGP) over the EOBS platform were collected for all 8 bulls. Signal characteristics for peak amplitude curves were measured. Bull signal readings were obtained during a 3-hr sampling period for 1 d. Signal readings were recorded at a sampling rate of ~100 average samples per second (s). Optical readings included complete gait pass (CGP) time duration (T) and signal amplitudes (ΔS). Additionally, bull structure, gait characteristics (i.e., hoof contact and break-over observations) and stepping behavior while passing over the EOBS platform were assessed. Two standard camera systems were used to record bull passes over the EOBS platform. Videos were synchronized with the signal readings. Video data was recorded at a frame rate of 30 fps with an image resolution of 1280 pixels (w) x 720 pixels (h). Final video dataset contained a total of 6 videos from 8 bulls. Video data allowed for observation of any animal overlapping, stopping or abnormal behavior, while providing visual features for cross-validation with signal readings.

Statistical Analysis

Qualitative video and signal analyses were used to observe initial signal fluctuations of an animal's pass over the EOBS. Observations on the EOBS's performance and ability to record signal deviations from animals with structural abnormalities was recorded for each pass (Figure 7.1). Total complete gait pass (CGP) time duration (i.e., range from first signal fluctuation to last; T), signal max and min peak differences (ΔS_{avg}^{mn} and ΔS_{avg}^{mx}) and average signal amplitude (ΔS_{avg}) were used to describe an animal's contact with the EOBS platform. A repeated linear mixed-model was created to take into consideration the effects of T and the difference between min and max signal fluctuations. The model (7.1) was fitted and expressed as

$$Y_j = a + T_i + D_k + H_j + e_j \tag{7.1}$$

where, Y_j represents average signal amplitude (ΔS_{avg}) observed in animal j; a is the intercept; T_i represents the fixed effect of time duration i (T_{log}; log transformed); D_k represents the fixed effect of signal max and min peak differences k; H_j is the repeated measures term for j^{th} bull; e_j is the residual term. Bull was used as random effect due to animals having multiple passes over the sensor. A Shapiro-Wilk test was used to validate the assumption of normality. A conservative Kruskal-Wallis test was used to determine distribution differences between bulls based on residuals from the linear mixed model (7.1). Equal variance and independence between samples is not assumed by the Kruskal-Wallis test making it valid for small-sampled repeated measures. The Kruskal-Wallis test is limited in power but does not require the assumption of normality. Data analysis was performed using R [26,27] and a p-value of ≤ 0.05 was considered significant.

RESULTS AND DISCUSSIONS

Bulls exhibited a total average complete gait pass (CGP) time duration (T_{avg}) of 2.105 ± 1.288 (mean ± SD; seconds (s)), a total average signal amplitude (ΔS^{ttl}_{avg}) of 0.642 ± 0.002 (mean ± SD), a total max signal average (ΔS^{mx}_{avg}) of 0.721 ± 0.050 (mean ± SD), and a total min signal average (ΔS^{mn}_{avg}) of 0.571 ± 0.045 (mean ± SD). Based on fixed effects for the model (7.1), both T_{log} ($P < 0.05$; $0.0029 \pm 7.406e^{-4}$) and max-min signal difference ($P = 0.033$; $0.00824 \pm 3.575e^{-3}$) were found to be significant though the p-value was small for time (T_{log}).

Further analysis resulted in no difference in the distribution of residuals for bulls to be found ($H = 8.1502$; $P = 0.3195$; df = 7; Figure 7.2). Though there was no significant difference in the residual differences, bulls exhibited observable variation in passes over the EOBS platform

[26] R Core Team. 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. URL https://www.R-project.org. (Version 3.5.0 - "Joy in Playing")
[27] RStudio Team. 2018. RStudio: Integrated Development for R. RStudio, Inc. Boston, MA. URL http://www.rstudio.com. (Version 1.1.453)

(Figure 7.3). Through qualitative analysis, bull 40 was found to have a greater variation between rounds while bull 21 and 15 exhibited no noticeable variation between passes over the EOBS platform (Figures 7.4 and 7.5). However, small sample sizes represent issues in reporting whether significant and non-significant differences exist due to lacking power. Lastly, during analysis of readings and video data for bull's deemed sound, some bulls were found to be unsound. Upon further analysis, bull 21 was considered structurally sound while bulls 41, 331 and 242 were questionable in musculoskeletal structure.

Conclusions

In conclusion, the small field study allowed for both qualitative and quantitative analysis to be performed, yet quantitative statistical results were questionable. During visual inspection of signal readings, bulls were considered to be variable in structural abnormalities which did affect locomotion. From this standpoint, signal attributes utilized within the study may lack appropriateness in describing observed differences. Robustness and generality of data may be enhanced with additional animal effects. Variables utilized to determine deviations of structurally sound and unsound animals require reassessment as signal deviations in sound bulls were found. Accurate testing of the signal with robust analysis of the attributes associated with gait might help to provide focused observation. Continuous measurement of animals as they move across the EOBS platform may additionally help visualize a more valuable statistical differentiation between animals. Analyzing solely based on signal characteristics was impractical for implementation during the study but provided a starting point for understanding the functioning of the novel sensor. Although the study lacked statistical robustness for developing further statistical insight into the bull signals, it suggests that the area needs further exploration as to the interrelationship between features and corresponding animal traits.

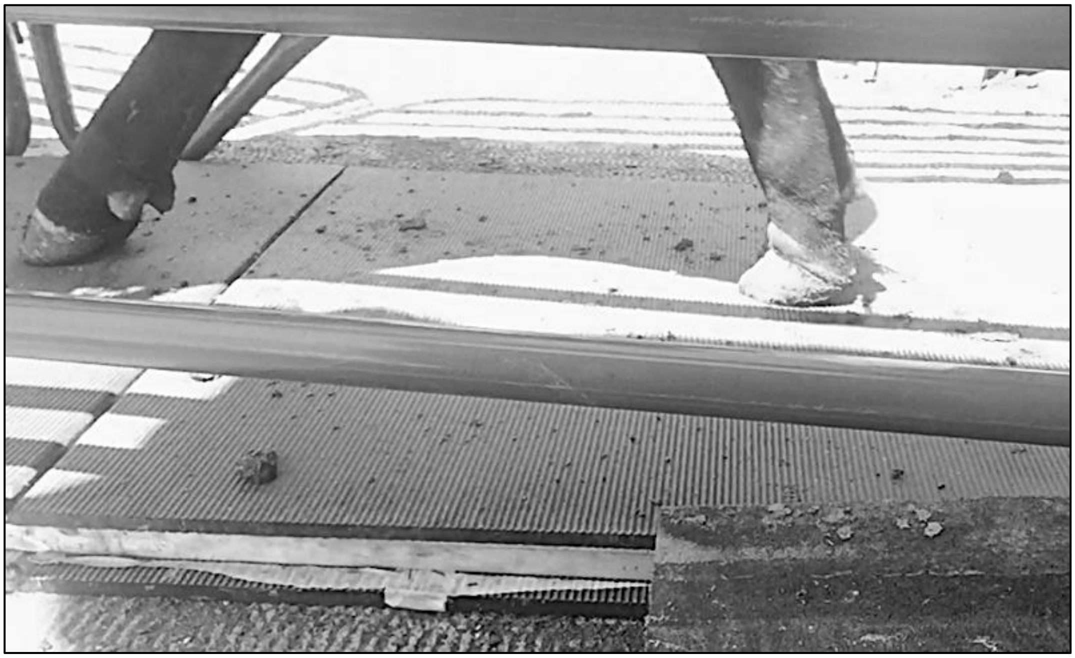

Figure 7.1 Image of bull passing over the embedded-optical-base system (EOBS) platform.

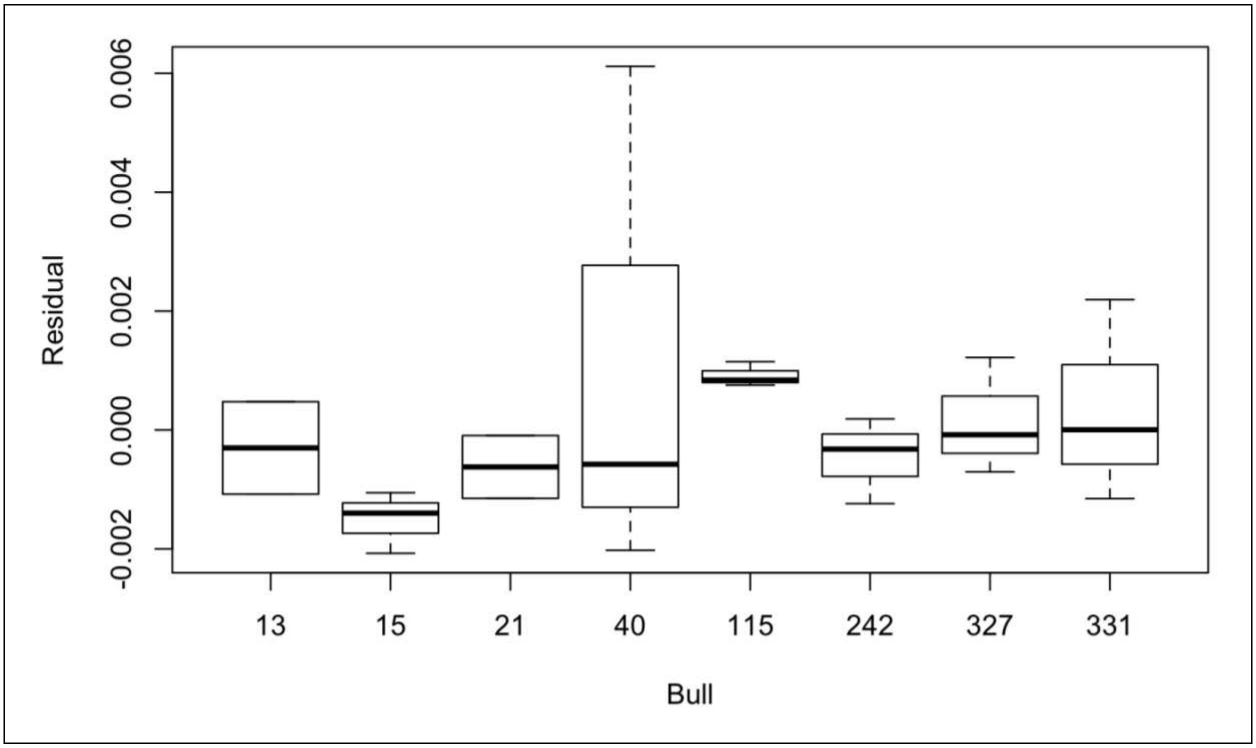

Figure 7.2 Box and whisker plot of residual mean distributions for 3 passes per bull for 1 d. Bull 40 exhibited greatest deviation in passes. Bulls 21 and 13 exhibited no deviation in passes and were used for final comparison between sound and unsound musculoskeletal structure. It is noted that bulls 21 and 13 were both missing a third pass due to animals' signals lacking difference between passes. Signal interruptions with multiple animals on the platform may influence readings causing the third pass for the 2 bulls to be dropped. Though lacking in a third pass they were still used for qualitative analysis and comparison. Residual values range from -0.002 to 0.006 and were derived from linear mixed model.

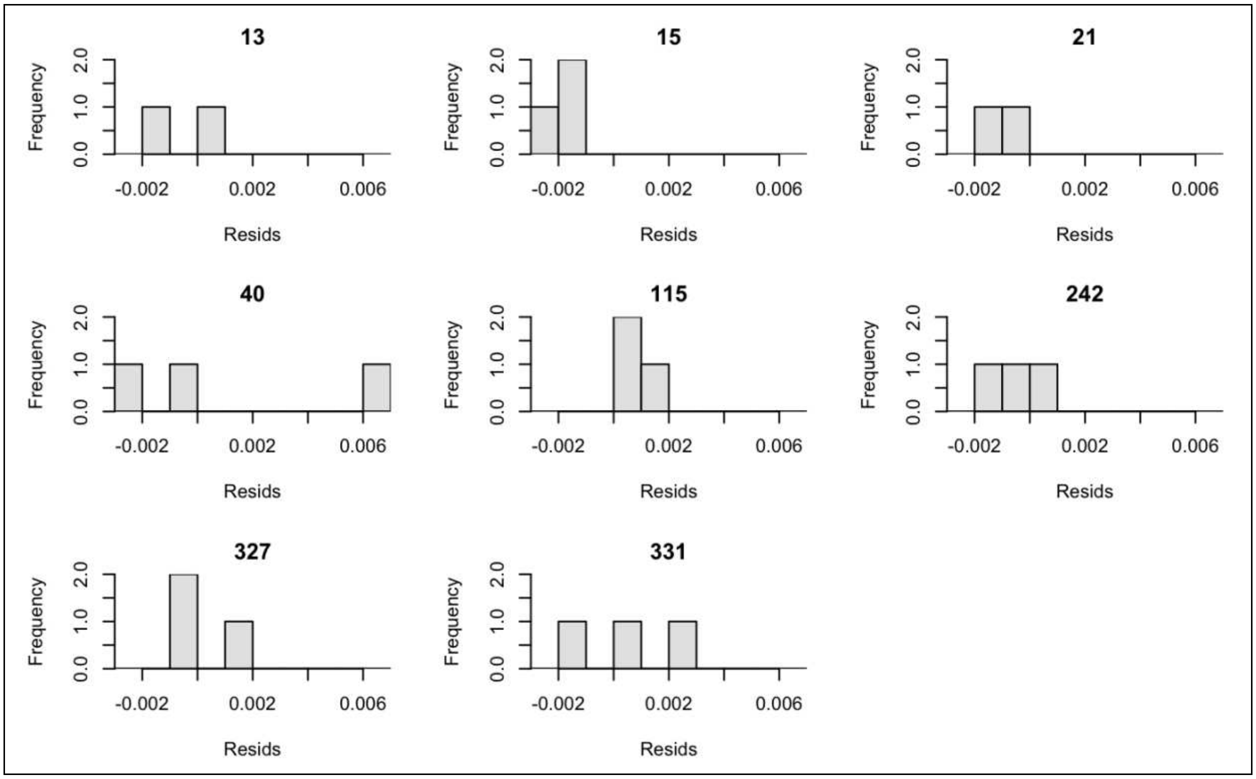

Figure 7.3 Histograms of residual mean distributions for 3 passes per bull for 1 d. Bulls 21 and 13 lacked a true third pass over the embedded-optical-base system (EOBS) due to lacking time differentiation from bull 21's pass to bull 13's pass over the EOBS. Bull 40 exhibited the largest distribution in residuals while bull's 15, 115 and 327 each had 2 passes within the same residual range.

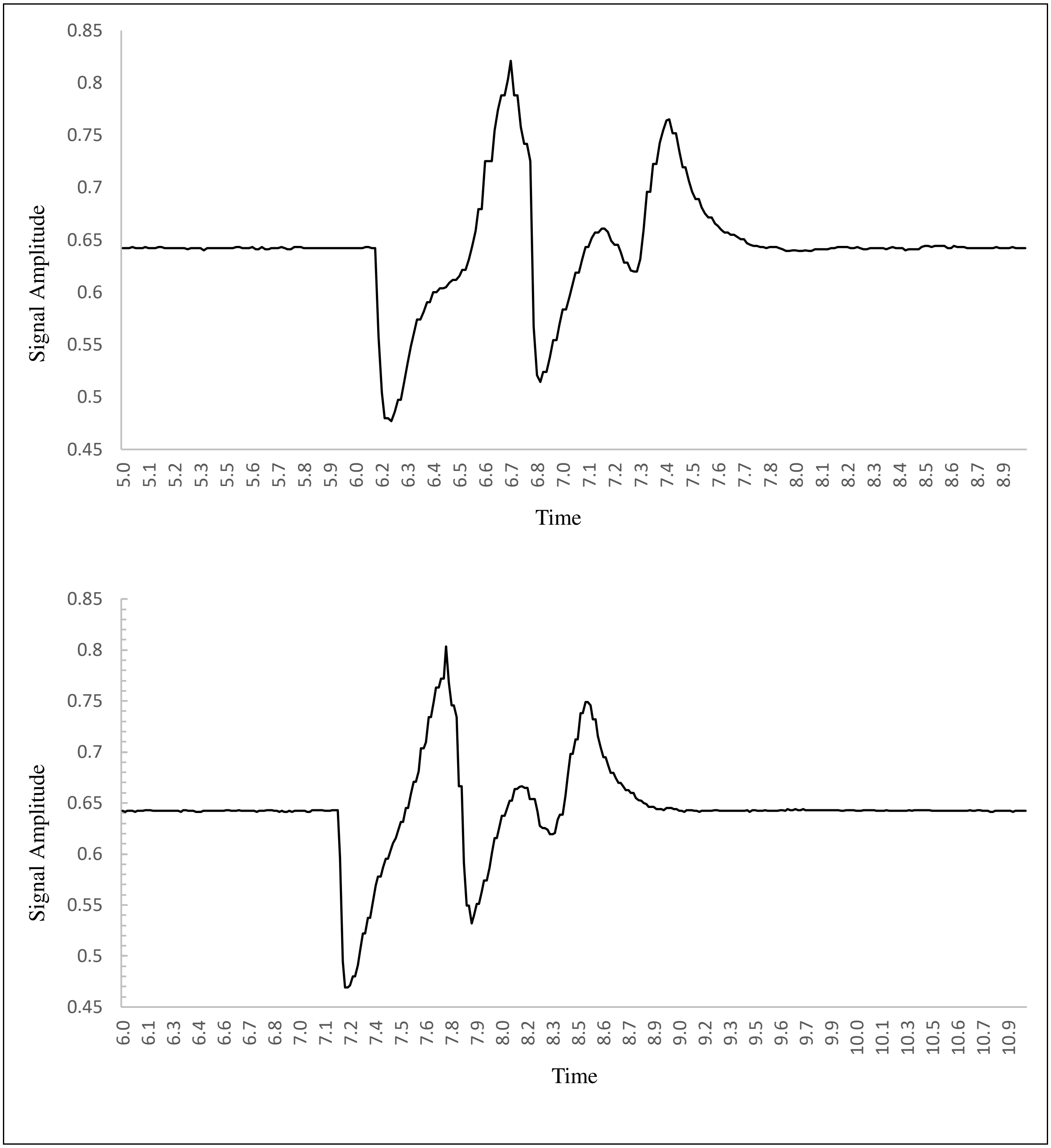

Figure 7.4 Two complete gait passes (CGPs) over the embedded-optical-base system (EOBS) for bull 21. Signal fluctuation patterns represent a sound (i.e., presenting no signal irregularities from structural abnormalities or unsoundness) animal's EOBS readings. X-axis is time in seconds (s) and y-axis is signal amplitude in arbitrary units (au).

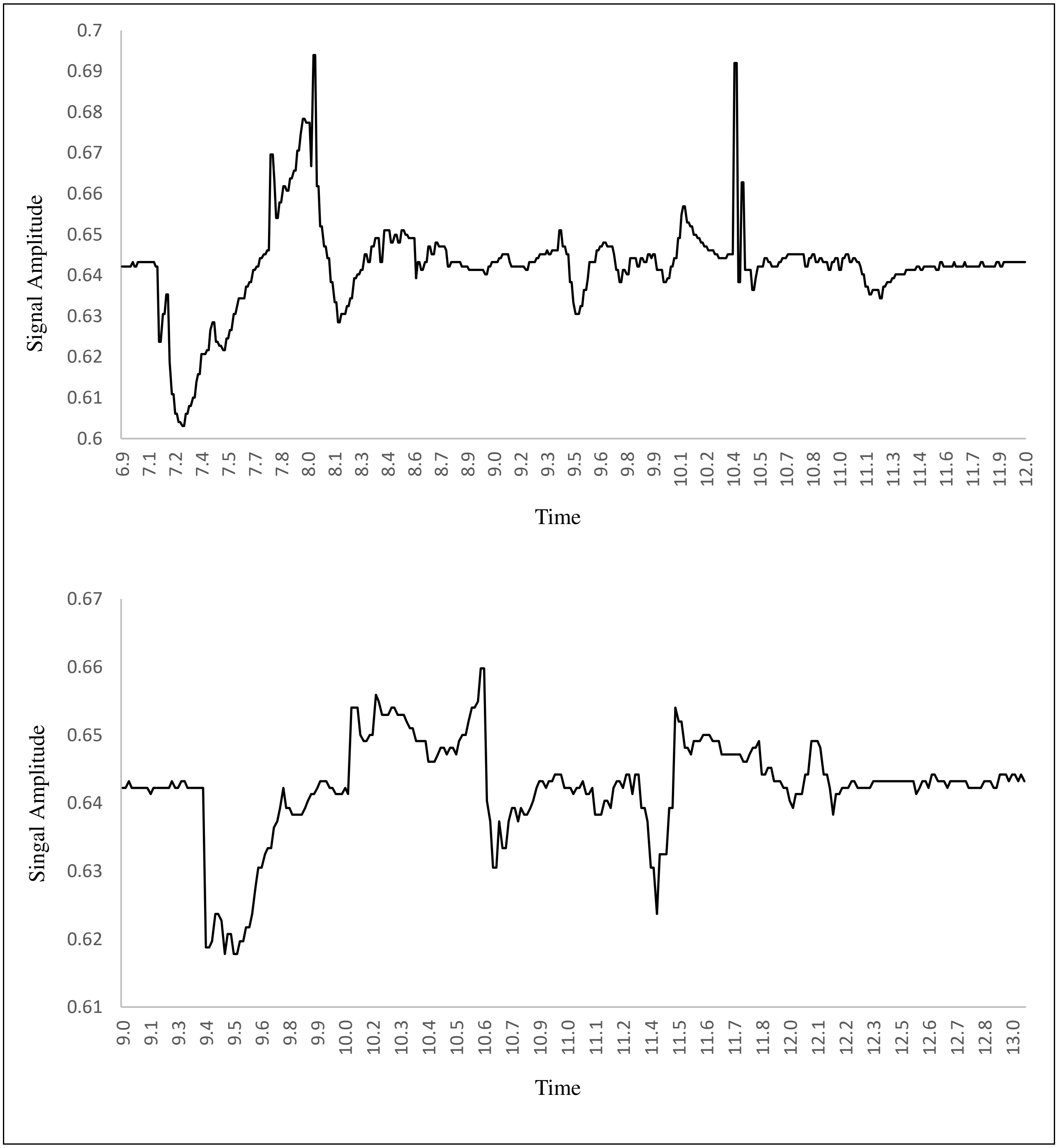

Figure 7.5 Two complete gait passes (CGPs) over the embedded-optical-base system (EOBS) for bull 13. Signal fluctuation patterns represent an unsound (i.e., presenting signal irregularities from a structural abnormality; severely post-legged) animal's EOBS readings. X-axis is time in seconds (s) and y-axis is signal amplitude in arbitrary units (au).

References

1. Clayton, H. M., H. C. Schamhardt, M. A. Willemen, J. L. Lanovaz, and G. R. Colborne. 2000. Kinematics and ground reaction forces in horses with superficial digital flexor tendinitis. Am. J. Vet. Res. 61:191-196.

2. Griffin, D., L. Perino, and D. Hudson. 1993. G93-1159 *feedlot lameness*. Historical Materials from University of Nebraska-Lincoln Extension. digitalcommons.unl.edu /extensionhist/196 (Accessed 10 July 2018.)

3. Leach, K. A., H. R. Whay, C. M. Maggs, Z. E. Barker, E. S. Paul, A. K. Bell, and D. C. J. Main. 2010. Working towards a reduction in cattle lameness: 1. Understanding barriers to lameness control on dairy farms. Res. Vet. Sci. 89:311-317. doi: 10.1016/j.rvsc.2010. 02.014.

4. Merkens, H. W., and H. C. Schamhardt, 1988. Evaluation of equine locomotion during degrees of experimentally induced lameness. II: Distribution of ground reaction force patterns of the concurrently loaded limbs. Equine Vet. J. Suppl. 6:107-112.

5. Rajkondawar, P. G., U. Tasch, A. M. Lefcourt, B. Erez, R. M. Dyer, and M. A. Varner. 2002. A system for identifying lameness in dairy cattle. Appl. Eng. Agric. 18:87. doi: 10.13031/2013.7707.

6. Scott, G. B. 1989. Changes in limb loading with lameness for a number of Friesian cattle, Br. Vet. J. 145:28-38. doi: 10.1016/0007-1935(89)90005-5.

7. Skjøth, F., V. M. Thorup, O. F. do Nascimento, K. L. Ingvartsen, M. D. Rasmussen, and M. Voigt. 2013. Computerized identification and classification of stance phases as made by front or hind feet of walking cows based on 3-dimensional ground reaction forces. Comput. Electron. Agric. 90:7-13. doi: 10.1016/j.compag.2012.10.002.

8. Telezhenko, E. 2009. Measurement of spatial gait parameters from footprints of dairy cows. Anim. 3:1746-1753. doi: 10.1017/S1751731109990644.

9. Terrell, S. P., C. D. Reinhardt, C. K. Larson, C. I. Vahl, and D. U. Thomson. 2017. Incidence of lameness and association of cause and severity of lameness on the outcome for cattle on six commercial beef feedlots. J. Am. Vet. Med. Assoc. 250:437-445. doi: 10.2460/javma.250.4.437.

10. Van De Gucht, T., W. Saeys, J. Van Meensel, A. Van Nuffel, J. Vangeyte, and L. Lauwers. 2018. Farm-specific economic value of automatic lameness detection systems in dairy cattle: From concepts to operational simulations. J. Dairy Sci. 101:637-648. doi: 10.3168/jds.2017-12867.

11. Wells, S. J., A. M. Trent, W. E. Marsh, and R. A. Robinson. 1993. Prevalence and severity of lameness in lactating dairy cows in a sample of Minnesota and Wisconsin herds. J. Am. Vet. Med. Assoc. 202:78-82.

12. Whay, H. R., D. C. J. Main, L. E. Green, and A. J. F. Webster. 2003. Assessment of the welfare of dairy cattle using animal-based measurements: Direct observations and investigation of farm records. Vet. Rec. 153:197-202. doi: 10.1136/vr.153.7.197.

Chapter Eight

Summary and conclusions

Gait can be influenced by diseases and disorders of the hoof or limb from physiological, biological and environmental risk factors capable of causing significant livestock loss. Early diagnosis and treatment are economically crucial for animal welfare, recovery and prevention of loss. Presently, subjective visual inspection is the most accepted form currently used for detecting problems such as lameness. However, rapid detection is challenging when relying on human observers without the aid of objective measurement tools. New advances in technology will allow for rapid changes in how producers perform gait analysis by providing new detection methods that are viable both onsite or remotely.

Sensor-oriented technologies provide an automated method of gait analysis for determining animal health and well-being. Various sensors can be applied to collect animal biometrics; however, their commercial viability has been irregular or limited by cost and function. Determining a technology's readiness by researching its functionality and application is necessary prior to successful commercial implementation. Preliminary studies to determine a technology's readiness provide technical and applicable information required prior to producers incorporating the tool into daily operations. As such, reported studies provided initial analysis for a new optical sensing method to advance monitoring and analyzing of gait biometrics.

Four research studies assessed the use of an embedded-optical-base system (EOBS) (provided by Ag Tech Optics LLC (ATO)) and its functionality in real-time measuring cattle and horse biomechanical patterns. Gait biometrics were collected by using a metal platform containing 1 EOBS. Animals passed over the EOBS platform resulting in signal fluctuations caused by hoof impact. Signal (e.g., amplitude) and kinematic (e.g., estimated speed and velocity) readings were recorded during each pass over the EOBS platform.

First proof-of-concept field study revealed that the EOBS's optical-point sensor successfully detected animal contact in the form of signal fluctuations (i.e., baseline deviations). Additionally, animal hoof contact with the EOBS resulted in time signatures (i.e., markers) during the collected time-series. A visual correlation between signal amplitude per fluctuation and platform grid (i.e., row and column) was discovered. A secondary field study showed that animals exhibited detectable signal groupings. Gait groupings, based on time signatures, were repeatable for animal passes over the EOBS platform. Animal passes were identified as standard or unique. In addition, the EOBS exhibited robustness in handling a large set of animal impacts while recording distinct and sensitive information over a longer testing period. A third control study provided insight into true signal readings that did not contain error or noise. Signal fluctuations were relatable to first hoof contacts and break-overs on the EOBS platform. Animal first hoof contact and last break-over were detectable with significant difference between the 2. A strong correlation for signal amplitude per fluctuation from animal contact with the EOBS and with platform grid (row and column) was found. Hoof contact closest to the EOBS sensor location was stronger than hoof contacts further away from the sensor. Both signals were usable with correction factors applied. Lastly, a final field study revealed that uniform and non-uniform patterns of signal fluctuations from animal contact with the EOBS were detectable and could be associated with structurally sound and unsound animals, respectively.

Research additionally was designed to investigate the overall functionality and operability of the EOBS. The EOBS detected periodic and aperiodic fore- and hind limb hoof contact during a set time interval. This was determined by assessing signal readings during animal passes over the EOBS platform. Proprietary detection thresholds of the EOBS for animal contact were determined between studies by analyzing collected signals, defining signal boundaries and then re-calibrating the system. Cross-validation of signal readings and video data allowed for identifying uniform and non-uniform hoof contact patterns at various gaits that could be used for gait analysis. Overall, the research built a knowledge database on the EOBS's initial workings in detecting biomechanical measurements between and within animals both in controlled and field studies.

Overall, preliminary investigative research addressed whether the EOBS optical-point sensor could be utilized as a gait analysis tool. The sensor showed exceptional detectability of animal contact and associated gait biometrics. Though sample sizes lacked robust numbers to draw significant conclusions, the combined studies exhibited significant repeatability of signal readings indicating a quality detection rate. With this, strong similarity of signals obtained for animals suggested the EOBS optical-point sensor is able to assess variable gait biometrics when combined with other technologies (cameras and video systems) for true analysis. It also provides an objective measurement tool to cross-validate existing technologies that were constructed on visual assessment standards. Additionally, research revealed that distribution of signal amplitudes may offer potential evaluation of hoof pressure when in contact with the EOBS's sensing surface. However, estimation of variability from different sources is needed to determine necessary number of passes for a given animal prior to determining true unique distinctions per individual animals. Lastly, more research is needed to determine the specificity, sensitivity and accuracy of the EOBS's signal outputs for their future use in automated lameness detection.

Through new innovative research such as the investigative studies achieved in collaboration with Ag Tech Optics LLC (ATO), Colorado State University (CSU) researchers hope to provide viable technology options for the livestock industry. In conclusion, the developed system provides quantifiable grounds for further investigation of the EOBS's optical-point sensor and its use as an efficient objective-based method in assessing gait biometrics for lameness detection in livestock.

Appendices

Appendix I: R packages

1. Bartoń, K. 2018. MuMIn: Multi-model inference. R package version 1.42.1. https://cran.r-project.org/package=MuMIn.

2. Bates, D., M. Maechler, B. Bolker, and S. Walker. 2015. Fitting linear mixed-effects models using lme4. Journal of Statistical Software. 67(1):1-48. doi: 10.18637/jss.v067.i01. https://cran.r-project.org/package=lme4.

3. Gross, J., and U. Ligges. 2015. nortest: Tests for normality. R package version 1.0-4. https://cran.r-project.org/package=nortest.

4. Long, J. A. 2018. jtools: Analysis and presentation of social scientific data. R package version 1.0.0. https://cran.r-project.org/package=jtools.

5. Lenth, R. V. 2016. Least-squares means: The R package lsmeans. Journal of Statistical Software. 69(1):1-33. doi:10.18637/jss.v069.i01. URL https://cran.r-project.org/package=lsmeans [28].

[28] Note: *The lsmeans package is being archived. The emmeans package is an available replacement that can be downloaded at https://cran.r-project.org/package=emmeans.*

List of Abbreviations

ΔS	Signal Amplitude Difference
ΔS_{avg}	Average Signal Difference
ΔS_{avg}^{HL}	Average Max and Min Sampling Signal Amplitude
ΔS_{C}^{HL}	Max and Min Sampling Count per Fluctuation
ΔS_{avg}^{mx}	Total Average Max Signal
ΔS_{avg}^{mn}	Total Average Min Signal
ΔS_{TS}	Signal Amplitude based on True First Hoof Contact
ΔS_{avg}^{ttl}	Total Average Signal Amplitude
ΔS_{TL}	Signal Amplitude based on True Last Break-Over
ΔT_{avg}	Average Impact Time Differences
au	Arbitrary Units
A_R	Standard Run Classification
A_W	Standard Walk Classification
BL	Left Hind Limb
BR	Right Hind Limb
B_{WR}	Unique/Other Classification
CGG	Complete Gait Grouping
CGP	Complete Gait Pass
FR	Right Forelimb
FL	Left Forelimb
IT	Impact Time
IT_{avg}	Average Impact Time
LT_{avg}	Average Break-Over Time
P_C	Platform Column
P_R	Platform Row
S_O	Signal Output
SR	Sampling Rate
ST_{avg}	Average Hoof Contact Time
T	Overall Animal Time per CGP over EOBS
T_{avg}	Average Complete Gait Pass Time per Animal
T_{avg}^{ttl}	Total Average Time
T_{log}	Time Duration (Log Transformed)
v	Velocity (Estimated; $\sim v$)
$\sim v_{avg}$	Estimated Total Average Velocity
V	Voltage