Gait Anomaly Detection in Dairy Cattle

Juan Haladjian
Technical University Munich
Munich, Germany
haladjia@in.tum.de

Zardosht Hodaie
Technical University Munich
Munich, Germany
hodaie@in.tum.de

Stefan Nüske
Ludwig Maximilian University
Munich, Germany
stefan.nueske@lmu.de

Bernd Brügge
Technical University Munich
Munich, Germany
bruegge@in.tum.de

ABSTRACT
Cow lameness is a common welfare issue in the dairy industry that causes severe health and life quality issues to cows, including pain and a reduction in their life expectancy. The earlier a lame cow is detected, the earlier and more effectively it can be treated. A change in the gait of the cow is the earliest symptom of lameness. Currently, lame cows are detected by visual inspection performed by herdsmen, which is subjective and time consuming. We present an approach to automatically detect anomalies in the walking pattern of a cow as a possible indicator of lameness. The detection is done by a wearable motion sensor attached to a cow's hind left leg. Our approach builds an individual model of the usual walking pattern of a cow during the first minutes of use and detects deviations from this model afterwards. Results from a controlled experiment we conducted indicate that our approach can detect deviations in cows' gait with an accuracy of 91.1%. This information can be used by veterinarians to keep track of changes in the walking pattern of cows and to decide whether to treat a specific cow.

ACM Classification Keywords
H.5.2 Information interfaces and presentation: Miscellaneous

Author Keywords
lameness, cow, wearable, animal, anomaly detection, gait analysis

INTRODUCTION
Lameness is a manifestation of painful disorders that result in an impaired movement or deviation from normal gait or posture [18]. In dairy cattle, the main causes of lameness are lesions in the claws which cause bacterial infections and swelling in cows' hooves and legs. Lameness causes severe pain and is associated with health issues such as the loss of fertility. Furthermore, lameness causes serious welfare and economic problems in the dairy industry. Some of the costs associated with lameness are the need for veterinary treatment and a reduction in milk production and cow's reproductive performance. At advanced stages of the disease, a lame cow might die or have to be sacrificed by humans. Lameness is a common issue in dairy cows, with some stables having up to 72% lame cows. [18].

The earlier a lame cow is identified, the earlier the causes of the disorder can be treated. Currently, lame cows are identified by visual inspection of their walking pattern, which is done by herdsmen. However, automation and the rapid growth in livestock production have led to more cattle and less employees per herd. As a consequence, herdsmen have less time to monitor the health condition of their cows.

Automated systems for cow milking, feeding and cleaning are already being used in commercial herds. Neckbands with integrated motion sensors are being used in commercial herds to predict whether a cow is undergoing oestrus (i.e. the period of sexual fertility in a female mammal). These neckbands are used by veterinarians to determine the proper time to inseminate a cow. In contrast, systems to detect lameness are rarely used in commercial herds, despite the variety of solutions proposed by the scientific community.

Approaches for automated lameness detection include those based on computer vision and pressure sensing. These approaches require expensive equipment and are limited to measuring a few steps per cow, which might not be enough to accurately detect lameness. Motion sensors have also been studied to detect lameness. Most of these approaches keep track of a cow's physical activity (lying down, standing and walking) [11, 10]. However, changes in physical activity due to lameness occur at more advanced stages of the disorder. The first observable symptom of lameness is a change in a cow's usual walking pattern (i.e. gait).

We present an approach to detect deviations in cows' usual walking pattern using a wearable motion sensor. Assuming the cow is healthy and walks normally at the time the sensor is attached to it, our approach creates a model of the usual walk-

ACI'17, November 21–23, 2017, Milton Keynes, United Kingdom

ACM ISBN 978-1-4503-5364-9/17/11...$15.00

DOI: https://doi.org/10.1145/3152130.3152135

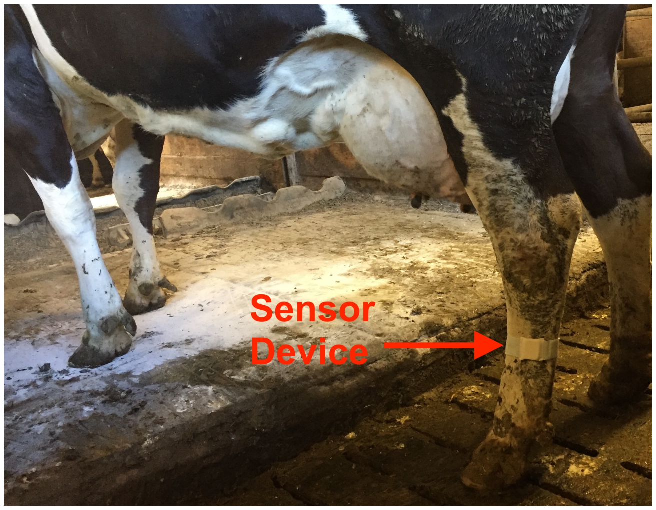

Figure 1. Motion sensor attached to a cow's hind left leg.

ing pattern for each individual cow during the first minutes of use and detects deviations from that pattern later on. The cows that have been detected as having a deviation in their usual walking pattern can be investigated by veterinarians later on. Our approach requires a single motion sensor attached to cows' hind left leg. The motion sensor is shown in Figure 1.

The rest of the paper is structured as follows. The *Related Work* Section provides a comprehensive overview of other automated lameness detection systems and highlights how our approach relates to them. In the *Approach* Section, we describe the hardware we designed, the signal acquired by our device while a cow is in motion and how our algorithm works. In particular, we present a wearable motion sensor and a set of algorithmic steps to train the model and classify cow steps into *normal* or *abnormal*. The *Controlled Experiment* Section presents the results of a controlled experiment we conducted in order to validate our approach.

RELATED WORK

Most modern stables collect data from cows' daily activity such as the amount of milk cows yield and how much food they are fed. Different studies have suggested using this data to predict lameness [7, 5]. However, changes in milk yield and feeding behavior due to lameness might manifest days after changes in gait. Detecting a lame cow based on its gait would make it possible to stop further development of the disorder. This would allow veterinarians to treat the cause of the disorder earlier, relieving it from pain and restoring its normal function.

Approaches for lameness detection based on gait analysis include those based on computer vision, weight sensing and motion sensing. Computer vision approaches extract lameness-related parameters from video, such as the arching of a cow's back [15], the amount of overlapping between a cow's consecutive steps [16] and the angle at which a cow's fetlock joint makes contact with the ground during a step [14].

Weight sensing approaches measure the weight a cow places on each limb while standing on force plates [12] or walking over a force-sensitive mattress [8]. Based on this data, information about cows' walking and standing behavior is calculated, such as the length and duration of a stride [8], the amount of kicks a cow performs while standing [12] and the weight distribution under single hooves [6].

Computer vision and weight sensing approaches require expensive devices and are limited to measuring a few steps per cow. These approaches face additional challenges such as the fact that cows near the measuring area might disrupt the measurements [18] and the need for additional technologies to identify the cow being measured.

Motion-based lameness detection approaches rely on motion sensors that are attached to cows' legs and/or neck. Most motion-based lameness detection approaches measure parameters related to cows' daily physical activity, such as the amount of time cows spend lying, standing and walking [17, 2], the number of steps cows perform per day [10] and the time of the days when cows start and stop walking [19]. These approaches do not analyze gait per se, but predict lameness based on cows' daily activity.

Two studies have investigated cow gait for lameness detection based on motion data. Pastell et al. [13] applied wavelet analysis to accelerometer data and found that there is less symmetry in the acceleration of hind legs in lame cows than in healthy cows. Chapinal et al. [3] found that the variance of acceleration of front and hind legs could be used to predict gait scores. These studies compared lame cows with non-lame cows in order to discover differences in their gait.

The approaches mentioned so far are based on the models that do not consider the differences in the physical behavior and tolerance to pain of each individual cow. However, Alsaaod et al. [2] found that the variation of physical activity among cows is significantly larger than the variation of physical activity caused by lameness. This suggests that lameness should be regarded as a per-cow basis rather than comparing a cow's motion to a baseline established from other cows.

Our approach compares the gait of a cow to a baseline established by the cow itself during the first minutes of use. The approach is based in anomaly detection, a technique commonly used to detect bank fraud and intrusion in computer networks. We chose to detect anomalies in gait because of two main reasons. First, a deviation from the normal gait is the first indicator of a possible lameness. Second, this approach takes into consideration the uniqueness of each cow's gait [2].

APPROACH

In this section, we describe our approach for anomaly detection in a cow's gait, including the sensor device that senses motion data and the anomaly detection approach. Our anomaly detection approach consists of two phases: the training phase and the detection phase. The training phase builds a model of the usual gait of a single cow. The detection phase classifies the gait of a cow into *normal* or *abnormal* based on a comparison of its current gait with a model created based on the gait of that particular cow during the first minutes of use of our wearable device. The training phase is done in four steps:

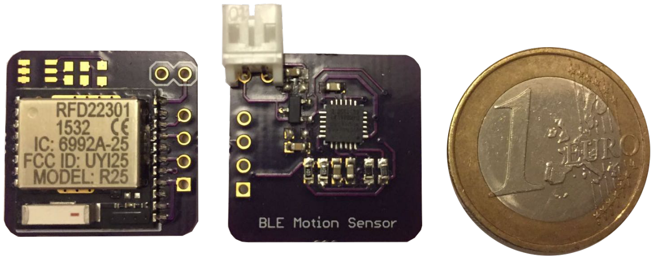

Figure 2. The front (left) and back (right) side of the sensor device.

data preprocessing, step segmentation, feature extraction and model training.

Sensor Device

We designed a sensor device containing an ARM Cortex-M0 microcontroller, a 6-axis Inertial Measurement Unit (IMU) and a Bluetooth Low Energy (BLE) module. We aimed for a low cost, low energy consumption and small footprint design. The ARM Cortex-M0 microcontroller operates at 16 MHz and is characterized by its low-power consumption rate and small footprint. The MPU-6050 from Invensense measures acceleration and rotation and performs sensor fusion directly on the chip. This allows for an energy-efficient and accurate computation of the device's orientation. The orientation of the hoof is relevant for lameness detection because lame cows often step at a particular angle in order to avoid pain [14]. As a communication module, we decided on BLE due to it's low-power consumption feature. We designed the circuit as a two-layer board placing the motion sensor on the front side and the microcontroller and BLE module on the back side. The dimensions of the circuit board are 21 x 21 x 2.5 mm. Figure 2 shows the front and back sides of the circuit board. The device functions at 3.3 v and is powered by a 400 mAh battery.

Preprocessing

The sensor device measures linear acceleration and rotation at 100 Hz along 3 axes (x,y,z). The device is oriented such that the y-axis represents vertical accelerations, the x-axis is parallel to the cow (i.e. in its walking direction) and the z-axis is lateral (i.e. left and right) to a cow. Figure 3 illustrates the correlation between walking strides and accelerometer signals along x- and y-axes.

The preprocessing step divides the incoming acceleration and rotation signals into chunks (windows) - units that are further processed and classified as 'normal' or 'abnormal' in the following steps. The choice of the window size has an impact on the accuracy of the anomaly detection as well as on the hardware requirements. The larger the size of a window, the more information that can potentially be extracted from it. However, the need to process larger windows of data leads to larger memory footprints, more computations and higher energy consumption rates.

We chose a chunk size of 3000 samples (30 seconds) by following a greedy heuristic approach using the average accuracy of our anomaly detection approach as metric for optimization. This parameter can be decreased to lower the requirements to the hardware device or increased for higher accuracy of the anomaly detection.

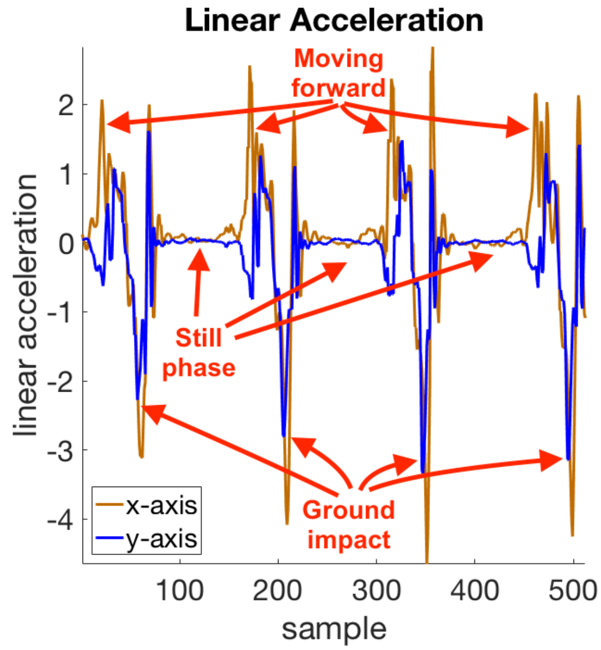

Figure 3. Linear acceleration along x- and y-axes during four strides. Forward movements during a stride cause a positive acceleration along the x-axis. Impacts with the ground can be seen as peaks in the acceleration along the y-axis. Furthermore, the periods while the hoof is in contact with the ground (still phases) have almost zero acceleration.

In order to remove noise caused by the accelerometer, we apply a second order Butterworth low-pass filter at 20 Hz to each window. Low-pass filters eliminate high frequencies in a signal making it smoother. After applying the filter, we compute the magnitude of each linear acceleration vector. This produces a total of 7 data sets: linear acceleration and rotation along three axes and magnitude of linear acceleration.

Step Segmentation

The purpose of the step segmentation is to detect the beginning and ending of a step. We segment the steps based on the peaks produced during the stride. We chose to do the step segmentation based on the linear acceleration along the y-axis because the highest peaks in the signal during a cow's stride are caused by the impact of its hoof with the ground. The step segmentation is done in the following three steps:

1. Every step has two upper peaks. We detect the highest peak with a peak detection algorithm. We ignore peaks that are less than 60 samples away from a previously detected peak. This also filters out periods when cows did not walk.
2. Every step is preceded by periods of small variance in acceleration. We find these periods by searching for the 9-sample window with smallest variance in acceleration among the 70 samples before and after the detected peak. We call the center of these windows *initial step segments*.
3. Between two initial step segments, additional samples are included that might not belong to a step. Therefore, we trim

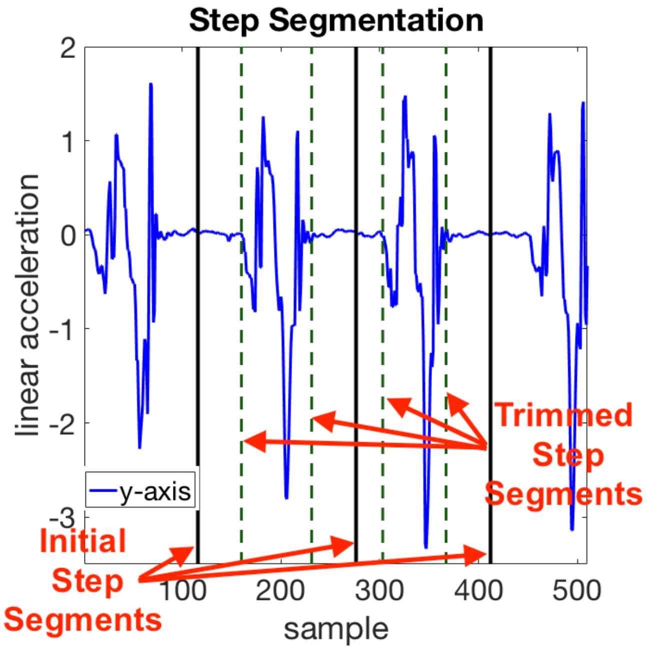

Figure 4. Initial and trimmed segments detected with our step segmentation algorithm applied to linear acceleration along the y-axis.

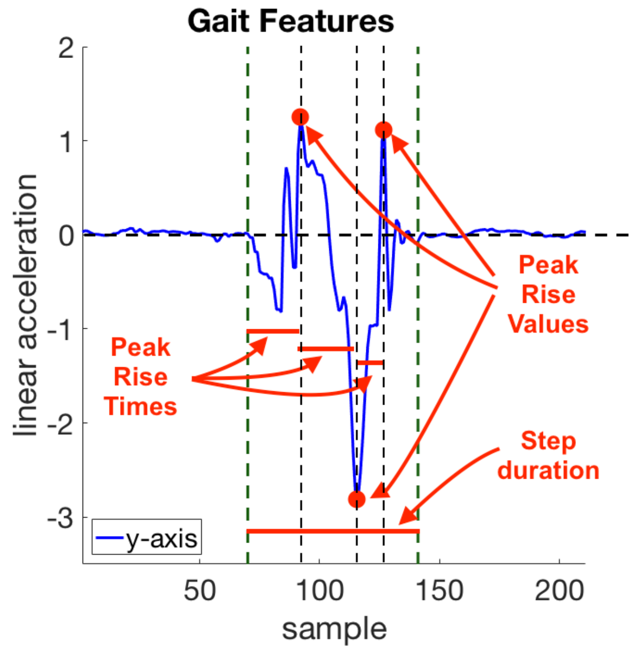

Figure 5. Gait features: peak rise values, peak rise times and step duration. These seven features are computed for all three accelerometer axes. This figure illustrates the computation of these features on the linear acceleration along the y-axis.

the step by shifting the initial step segments towards the peak detected in step 1. The initial step segments are shifted until the standard deviation of a 6-sample window centered at the shifted step segment is larger than 0.2.

Figure 4 shows the linear acceleration along the y-axis of four consecutive steps with annotations pointing at initial and trimmed step segments.

Feature Extraction

For each step segmented, we compute a set of gait and statistical features. Gait features are measurements specific of a step. Every step is characterized by three peaks: two upper peaks and one lower peak. We first detect all three peaks. If any of the peaks could not be found, we ignore the step. This might happen if the cow shortly lifted a leg or got bumped by another cow. For all three peaks, we compute its rise value and time. The rise times are computed as the difference in samples to the previous peak. The rise time of the first peak is computed as the difference in samples to the first sample in the trimmed step segment. In addition, the total duration of the step is added to the feature set. Figure 5 illustrates how the gait features are computed based on the three peaks of a single step.

Statistical features are measures to extract information from data sets. We extract the following statistical features: mean, median, standard deviation, Zero Crossing Rate (ZCR), Peak-to-Peak amplitude (P2P), Root Mean Square (RMS) and Average Acceleration Variation (AAV) for every step. ZCR is a measure of the amount of times a signal crosses the zero value. A high ZCR might indicate a highly intense or periodic activity. P2P is the difference between the maximum and minimum acceleration value in a step and provides information about the intensity of a step. RMS is the square root of the mean of the values in a step squared. This measurement provides information about the amount of acceleration and variation in a step. AAV is calculated as the sum of the absolute differences between consecutive samples in a step normalized by the number of samples. AAV provides an indication of how sudden changes in acceleration happen within a step. These measurements are commonly used for activity recognition applications and have been recently used for fall-detection and gait analysis in humans [4, 1].

The list of gait and statistical features are enumerated in table 1. Gait features are computed on linear acceleration and statistical features are computed on linear acceleration, rotation and magnitude of acceleration. ZCR is only computed on the linear acceleration. This gives us a total of 21 gait features and 45 statistical features per step. A window might contain several steps. We average the features extracted from the same window. A vector containing the 66 averaged features is called *gait observation*.

Model Training

Our anomaly detection approach is based on a one-class Support Vector Machine (SVM) classifier. Binary SVM classifiers calculate a boundary that maximizes the distance between observations (i.e. samples) of two different classes. Our one-class SVM classifier finds a boundary around observations of the *normal* class and classifies new observations based on their distance to this boundary. The classifier is trained automatically based on the gait of a cow acquired during the first minutes of use.

Table 1. Gait and statistical features used by our approach. Features labeled as *accel* are computed on all three axes of the linear acceleration and features labeled as *all* are computed on every axis of the linear acceleration, rotation and on the magnitude vector of the linear acceleration.

	Feature	Signal	#
Gait features	rise values	accel	9
	rise times	accel	9
	step duration	accel	3
Statistical features	mean	all	7
	median	all	7
	STD	all	7
	ZCR	accel	3
	P2P	all	7
	RMS	all	7
	AAV	all	7
Total			66

The boundary of our classifier is defined such that a fraction *outlier fraction* of the observations in the training set is classified as *abnormal*. The *outlier fraction* is used to define how 'compact' the boundary around *normal* gait observations is. The smaller the *outlier fraction*, the higher the specificity of the model (i.e. the less false alarms the model produces). On the other hand, a small *outlier fraction* reduces the sensitivity of the model (i.e. more prone to missing *abnormal* gait observations).

Anomaly Detection

New gait observations are classified as *normal* or *abnormal* according to their distance to the boundary of the *normal* observation set. Gait observations are classified as *abnormal* if and only if their distance to the boundary of *normal* gait observations is smaller than the *abnormality threshold*. The performance of the classifier is determined by the *outlier fraction* and *abnormality threshold* parameters.

CONTROLLED EXPERIMENT

This section describes a controlled experiment we designed following an animal-centered research methodology and applying ACI ethical guidelines.

Animal-centered Design

Previous work in automatic lameness recognition studied the gait of lame cows by forcing cows with different degrees of lameness to walk while their motion was being recorded. However, forcing an animal in pain to walk would be unacceptable for an animal-centered research approach and would violate several ethical principles accepted in ACI [9].

We have developed an approach to detect deviations from usual gait in cows. One way to evaluate our approach would be to attach our sensor device to several cows and wait until their gait changes (e.g. due to lameness or pregnancy). However, this could take several months, which makes this approach impractical for research purposes.

Another alternative we considered was to let cows walk under normal conditions and have experts determine whether any of the steps or sequences of steps were different from its usual gait. However, this study would require correlating every step of a cow in a video recording to the motion signal and would be prone to the subjective definition of 'abnormal' step.

Instead, our evaluation method is inspired by other research on anomaly detection, in which the detection of seldom occurring events were evaluated by simulating those events [4, 1]. For example, Cola et al. [4] evaluated their approach to detect anomalies in human gait by letting subjects walk with strap bands around their knee.

In order to cause a change in the walking pattern of cows, we decided to attach a plastic block to one of their hind hooves. Veterinarians usually attach such plastic blocks to cow hooves in order to relieve pain and allow an injured claw to heal. Attaching a plastic block to a hind hoof causes a similar change in walking pattern as lameness: in both cases, cows shift their weight towards the opposite hind limb. We attached blocks to the hind hooves because hind limbs are the ones most commonly affected by lameness. Figure 6 shows a plastic block attached to the outer claw of a left hind hoof.

Our procedure consisted of the following steps:

1. We let cows walk normally during a period of less than 10 minutes. We repeated this procedure on three different days in order to reduce fatigue and stress caused to the animal subject.

2. We attached a plastic block to one hind-hoove and let the cow walk with it.

3. We attached a plastic block to the opposite hoove and let the animal walk with it.

We consider this approach to be the most appropriate for an animal-centered research among the other approaches we considered because it does not involve pain and requires a considerable shorter intervention to cows' daily activity. The intervention to cows' daily activities lasted approximately 40 minutes: 10 minutes for the attachment of the sensor and recording of normal walking (this was repeated on three different occasions) and 30 minutes for the attachment of the plastic blocks.

Ethical Considerations

Our research required cows to take part in an experiment. In order to ensure an ethically appropriate involvement of the cows in our experiment, we designed our experiment based on the ethical guidelines proposed by Mancini [9]. We addressed these principles as follows:

1. *Respecting and caring for every participant without discrimination.* The participants of this experiment were cows of different ages and breeds. We did not harm any of the them or make any discrimination as for the selection of participants or treatment they received during the experiment.

2. *Garnering participants mediated and contingent consent.* We conducted this experiment together with two professional veterinaries who are the legal representatives of the cows that participated in the experiment. Both veterinaries know the needs and welfare requirements of these cows and

Figure 6. Plastic block attached to the outer claw of a cow's left hind hoof.

gave us their consent to conduct the experiment. Furthermore, they accompanied us and supported us throughout the entire experiment to ensure these requirements were met.

3. *Doing research that is relevant to participants and consistent with their welfare.* The results of our research suggest it is possible to automatically detect a condition that is painful for cows and highly detrimental to their health (e.g. might lead to death if not treated early enough). Our research has the potential to benefit the individual cows that participated in the experiment, as well as other cows. This research was conducted in the natural environment of the participating cows, an indoor stable located in the outskirts of Munich, Germany.

4. *Avoiding research procedures that may be harmful to participants.* According to the veterinaries that supported us throughout this study, attaching a sensor device and plastic block to cows and encouraging them to walk for less than 10 minutes did not cause any lasting harm to these cows. Veterinaries trimmed cows before attaching the plastic block to ensure the block was placed and fit properly to the claw. Trimming claws is a procedure undertaken to maintain a healthy hoof condition and prevent injury and disease. In addition, we limited the walking sessions to a maximum of 10 minutes per day and continued the data recording on a different day in order to reduce the level of fatigue caused to the cows.

5. *Assessing research proposals and obtaining expert support.* The cow interventions performed in this study were done by professional veterinarians and were approved by the ethics committee of the Ludwig Maximilian University in Munich, Germany to ensure no harm was done to the cows.

Data Collection

We recorded the motion of 10 cows while walking. Cows were chosen to maximize the diversity of age, weight and breed. Table 2 displays demographic information about each cow.

Cow	Age (Years)	Weight (Kg)	Breed (GH% / FV%)
1	5	910	31,25 / 68,75
2	5	680	68,75 / 31,25
3	5	720	43,75 / 56,25
4	7	560	87,5 / 12,5
5	6	700	31,25 / 68,75
6	4	780	62,5 / 37,5
7	3	680	0 / 100
8	5	640	100 / 0
9	4	610	0 / 100
10	3	700	0 / 100

Table 2. Information about the cows that took part in the controlled experiment. GH = German Holstein, FV = Fleckvieh.

Figure 7. A member of our team walks behind a subject cow during the controlled experiment.

We conducted three runs per cow. During the first run, cows walked normally. During the other two runs, cows walked with a plastic block attached to the outer claw of either their left or right hind hoof. We refer to gait observations produced by the first run as *normal* and to gait observations produced by the other two runs as *abnormal* gait observations. Each run lasted approximately 7 minutes.

We designed the experiment to resemble the conditions in which our approach would be used. We let cows walk in their usual environment rather than isolated walkways specially designed for the experiment. Furthermore, we included motion data of periods when cows stopped walking, turned and got bumped by other cows. Cows walked on two different types of ground: rubber and concrete. Figure 7 shows a cow walking during the experiment.

Data Analysis

We measured the performance of our approach according to the following metrics:

- Accuracy: The ability of our approach to classify gait observations correctly. It answers the question: what percent

Cow	Accuracy	Specificity	Sensitivity
1	95,8%	96,3%	83,3%
2	94,6%	95,1%	78,6%
3	81,9%	82,0%	78,6%
4	96,4%	97,2%	66,7%
5	97,3%	97,6%	80,0%
6	81,3%	81,7%	70,6%
7	95,4%	96,6%	62,5%
8	92,6%	93,0%	77,8%
9	87,2%	87,6%	73,1%
10	88,2%	88,7%	70,6%

Table 3. Accuracy, specificity and sensitivity of our approach at detecting *abnormal* gait observations.

of the classified gait observations (classified as *normal* or *abnormal*) is correct? Accuracy is calculated as: *number correctly classified instances / number total instances*.

- Specificity: The ability of our approach to identify *normal* gait observations. It answers the question: when a cow walks normally, what percent of its gait observations does our approach classify as *normal*? This is also referred to as true negative rate and computed as: *number instances detected as normal / number normal instances*.
- Sensitivity: The ability of our approach to identify *abnormal* gait observations. It answers the question: when a cow walks abnormally, what percent of its gait observations does our approach classify as *abnormal*? This is also referred to as "true positive rate" and computed as: *number instances detected as abnormal / number abnormal instances*.

The aforementioned measurements were computed by means of the leave-one-out cross-validation technique. First, we trained the SVM model with N-1 *normal* gait observations, where N is the total number of *normal* gait observations for a specific cow. Second, we used the model to classify the *normal* gait observation that was not used to train the model and every *abnormal* gait observation. We repeated this procedure N times; each time we left out a different *normal* gait observation. We averaged the accuracies, specificities and sensitivities obtained by the trained models in each repetition.

Results
Table 3 shows the accuracy, specificity and sensitivity of our approach for each cow involved in the experiment. Parameters used were: *outlier fraction* $= 0.15$ and *lameness threshold* $= -0.6$. We selected these values to maximize the sensitivity and specificity achieved by our approach for every cow based on the data collected during the controlled experiment.

Our approach classified gait instances with an average accuracy of 91.1% among all the cows (specificity = 91.6% and sensitivity = 74.2%). According to these results, our approach classifies 8.4% of the gait observations of a cow walking normally as *abnormal*. In contrast, when cows do indeed walk abnormally, our approach classifies 74.2% of their gait observations as *abnormal*. These results suggest our approach detects a deviation from a cow's usual walking pattern after this deviation occurs.

CONCLUSION
We presented and validated a new approach to detect deviation in cows' usual gait. In contrast to other gait monitoring approaches, our approach does not require expensive equipment or a specific setup and can be used in stables as well as outdoors. Furthermore, our approach considers the differences in gait of each cow by comparing the walking pattern of a cow to a baseline established for that particular cow during the first minutes of use of our device.

The results of the controlled experiment we conducted suggest that our approach would detect deviations from usual gait with an accuracy of 91.1%. A system based on the approach we propose could be used by veterinarians to gain information about the health condition of the cows in a herd. In particular, veterinarians might decide to examine a cow if the number of detected *lame* gait observations has exceeded considerably the usual amount for that particular cow. Our approach generates new gait observations every 15 seconds while cows walk.

We argue that the deviation from normal gait caused by lameness is more radical than the change in gait caused by the plastic block which we used to evaluate our approach. This is because cows suffering lameness will try to avoid pain by bearing as little weight as possible in the affected hoof. As a consequence, lame cows perform considerably shorter strides or stop using one limb all together. This causes an asymmetry in the gait, which is observable visually. In contrast, the change caused by the plastic block is more subtle. We were not able to assess visually whether a cow was using a plastic block or not by looking at its gait. As a consequence, we believe our approach might be more accurate at detecting deviations in gait caused by lameness than those caused by a plastic block. In the future, our approach will have to be validated in a longer-term field study.

In this work, we did not study the power consumption rate of our wearable device. However, a low power consumption rate that enables the device to function for several months is important in order to deploy our approach in a stable for longer periods of time. We will be able to reduce the power consumption of our wearable device considerably by different means. First, we will study the trade-off between accuracy of the computations and energy consumption when reducing the sampling frequency. Second, we will select a subset of the features we proposed in this paper. With less features, less computations will have to be executed by the wearable device, which will come at the cost of a loss in accuracy. Furthermore, we will study other unsupervised machine learning algorithms for anomaly detection that might require less computations.

ACKNOWLEDGMENTS
We would like to thank Dan Siewiorek for reviewing this paper, Ayca Ermis for helping collect the data used in this study and Nina Rittweg and the staff from the Lehr- und Versuchsgut Oberschleissheim from the Ludwig Maximilian University for supporting and guiding this project.

REFERENCES

1. Stefano Abbate, Marco Avvenuti, Francesco Bonatesta, Guglielmo Cola, Paolo Corsini, and Alessio Vecchio. 2012. A smartphone-based fall detection system. *Pervasive and Mobile Computing* 8, 6 (2012), 883–899.
2. Maher Alsaaod, Christoph Römer, Jens Kleinmanns, Kathrin Hendriksen, Sandra Rose-Meierhöfer, Lutz Plümer, and Wolfgang Büscher. 2012. Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. *Applied Animal Behaviour Science* 142, 3 (2012), 134–141.
3. Nuria Chapinal, Anne Marie de Passille, Matti Pastell, Laura Hänninen, Lene Munksgaard, and Jeff Rushen. 2011. Measurement of acceleration while walking as an automated method for gait assessment in dairy cattle. *Journal of dairy science* 94, 6 (2011), 2895–2901.
4. Guglielmo Cola, Marco Avvenuti, Alessio Vecchio, Guang-Zhong Yang, and Benny Lo. 2015. An on-node processing approach for anomaly detection in gait. *IEEE Sensors Journal* 15, 11 (2015), 6640–6649.
5. R M De Mol, G André, E J B Bleumer, J T N 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. *Journal of dairy science* 96, 6 (2013), 3703–3712.
6. P P J der Tol, J H M Metz, E N Noordhuizen-Stassen, W Back, C R Braam, and W A Weijs. 2002. The pressure distribution under the bovine claw during square standing on a flat substrate. *Journal of dairy science* 85, 6 (2002), 1476–1481.
7. T Van Hertem, E Maltz, A Antler, C E B Romanini, S Viazzi, C Bahr, A Schlageter-Tello, C Lokhorst, D Berckmans, and I Halachmi. 2013. Lameness detection based on multivariate continuous sensing of milk yield, rumination, and neck activity. *Journal of Dairy Science* 96, 7 (2013), 4286–4298.
8. Willem Maertens, Jürgen Vangeyte, Jeroen Baert, Alexandru Jantuan, Koen C Mertens, Sam De Campeneere, Arno Pluk, Geert Opsomer, Stephanie Van Weyenberg, and Annelies Van Nuffel. 2011. Development of a real time cow gait tracking and analysing tool to assess lameness using a pressure sensitive walkway: the GAITWISE system. *Biosystems Engineering* 110, 1 (2011), 29–39.
9. Clara Mancini. 2017. Towards an animal-centred ethics for Animal–Computer Interaction. *International Journal of Human-Computer Studies* 98 (2017), 221–233.
10. Hamutal Mazrier, Shlomit Tal, Eliezer Aizinbud, and Uri Bargai. 2006. A field investigation of the use of the pedometer for the early detection of lameness in cattle. *The Canadian Veterinary Journal* 47, 9 (2006), 883.
11. Lars Relund Nielsen, Asger Roer Pedersen, Mette S Herskin, and Lene Munksgaard. 2010. Quantifying walking and standing behaviour of dairy cows using a moving average based on output from an accelerometer. *Applied Animal Behaviour Science* 127, 1 (2010), 12–19.
12. Matti Pastell and Minna Kujala. 2007. A Probabilistic Neural Network Model for Lameness Detection. *Journal of Dairy Science* 90, 5 (2007), 2283–2292.
13. Matti Pastell, Johannes Tiusanen, Mikko Hakojärvi, and Laura Hänninen. 2009. A wireless accelerometer system with wavelet analysis for assessing lameness in cattle. *Biosystems engineering* 104, 4 (2009), 545–551.
14. Arno Pluk, Claudia Bahr, Ahmad Poursaberi, Willem Maertens, Annelies Van Nuffel, and Daniel Berckmans. 2012. Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques. *Journal of dairy science* 95, 4 (2012), 1738–1748.
15. Ahmad Poursaberi, Claudia Bahr, Arno Pluk, Annelies Van Nuffel, and Daniel Berckmans. 2010. Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques. *Computers and Electronics in Agriculture* 74, 1 (2010), 110–119.
16. Xiangyu Song, Toon Leroy, Erik Vranken, Willem Maertens, Bart Sonck, and Daniel Berckmans. 2008. Automatic detection of lameness in dairy cattle-Vision-based trackway analysis in cow's locomotion. *Computers and electronics in agriculture* 64, 1 (2008), 39–44.
17. Vivi Morkore Thorup, L Munksgaard, P-E Robert, H W Erhard, P T Thomsen, and N C Friggens. 2015. Lameness detection via leg-mounted accelerometers on dairy cows on four commercial farms. *animal* 9, 10 (2015), 1704–1712.
18. Annelies Van Nuffel, Ingrid Zwertvaegher, Liesbet Pluym, Stephanie Van Weyenberg, Vivi M Thorup, Matti Pastell, Bart Sonck, and Wouter Saeys. 2015. Lameness detection in dairy cows: Part 1. How to distinguish between non-lame and lame cows based on differences in locomotion or behavior. *Animals* 5, 3 (2015), 838–860.
19. C Yunta, I Guasch, and A Bach. 2012. Short communication: Lying behavior of lactating dairy cows is influenced by lameness especially around feeding time. *Journal of dairy science* 95, 11 (2012), 6546–6549.