Kinetic energy harvesting potential of grazing livestock

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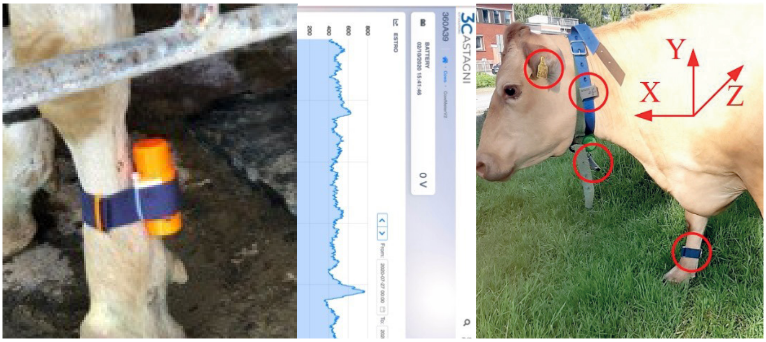
Abstract
The potential of using farm animal kinetic energy for powering wearable precision livestock farming devices has not been researched thus far. Kinetic energy harvesting is a process in which vibration or locomotion is converted by a transducer into electrical energy. This process could potentially enable autonomous livestock wearables. In this paper an approach for measuring and analyzing farm animal locomotion is detailed. By using triaxial accelerometers, free grazing Finncattle locomotion is logged at different cattle body parts and analyzed in MATLAB for future kinetic energy harvesting designs.

Keywords: accelerometer measurements, animal locomotion, kinetic energy harvesting

Introduction
In this paper we present details of locomotion measurements performed on Finncattle during project ENTRAP (CORDIS 2019). These measurements were performed to determine locomotion characteristics, like acceleration amplitudes, directions of excitation, or specific frequencies present in irregular livestock locomotion. This data was then employed to design and prototype a kinetic energy harvesting (KEH) device, as presented in another paper at this conference ('Cow locomotion energy harvester for powering IoT wearables'). KEH devices are designed to convert energy of vibrations or locomotion into electrical energy for enabling low power devices with autonomous power (Siang, J. *et al*., 2018). In the case of a precision livestock farming application, a KEH device would power an animal wearable with electrical energy produced by the animal itself.

The use of accelerometers to characterize animal locomotion specifics has long been employed by animal scientists and ethologists. Most commonly the research has been utilized to determine certain animal health or life cycle events. In this frame accelerometers have been used for lameness detection either from change in activity or gait differentiation, estrus cycle detection and detection of various metabolic disorders (Eckelkamp, E. A. 2019). More specifically cattle (Pastell, M. *et al.* 2009, Rahman, A. *et al.* 2018), sheep (Barwick, J. *et al.* 2018) and geese (Spink, A. *et al.*) locomotion has been previously measured and characterized by tri-axial accelerometers. Usually, data sampling frequencies bordering the Nyquist frequency of animal locomotion have been used. These are inadequate to log a complete locomotion characteristic like a step or ear flap or to capture the exact number of high acceleration events during grazing. Here we propose a very robust measurement apparatus and innovative, simple and easy to use attachments based on 3-D printed casings or commercially available adhesive tapes capable of withstanding several hours of free grazing activity while logging data.



a) b) c)

Figure 1: a) Axivity AX3/6, b) 3D printed sensor casings, c) Sensor locations and axes

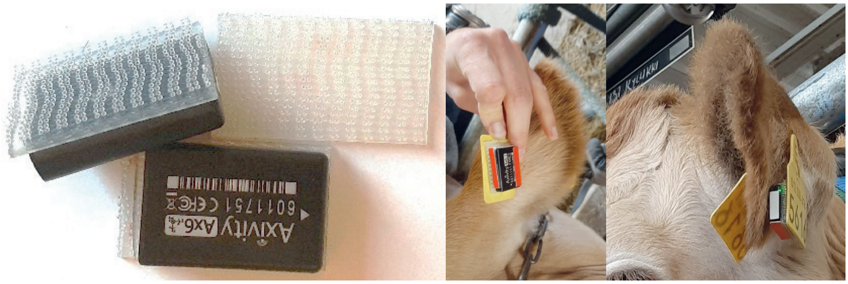
Material and methods

This section will describe in detail the design of the experiment and the measurement apparatus employed during experiments. In the end, the tools for PSD data analysis will be presented.

Measurement apparatus and set-up

For the purpose of experiments presented here, two AX3 triaxial acceleration loggers and one AX6 triaxial accelerometer/gyroscope logger were chosen (manufactured by Axivity, Figure 1, a). These devices are small (23x32.5x8.9 mm) and lightweight, weighing 0.011 kg (important considering ear measurements). They can also be easily configured and synchronized via a USB hub and the AX3/AX6 OMGUI Configuration and Analysis Tool. Both sensors are specified with measurement resolutions of up to 16-bit, configurable accelerometer ranges - ±2/4/8/16 g, and sampling frequencies in the range of 12.5 Hz – 1600/3200 Hz (AX6/AX3) (Axivity 2015). Logging time depends on the configuration but is specified at 14 days configured to a 100 Hz sampling frequency. The sensors themselves do not provide a suitable means of attachment. To equip the animals with the sensors, suitable casings had to be manufactured which could then be used with standard collars and pedometer leg straps (through specifically designed slots) (Figure 1, b). Casings were at first 3D printed with PLA filament on a Prusa I3 MK3 3D fused deposition modelling printer in the FabLab facility of Tampere University. After the PLA cases broke or dismantled due to screws coming loose during grazing, they were replaced with stronger PETG filament printed cases which were also semi-transparent allowing the sensor LEDs to be checked for operation. Also, antivibration nuts were used to secure the casings and these modifications proved to increase robustness.

For the first set of the experiments the following locations were chosen for acceleration measurements: front leg (lateral outer side of the metacarpal just above the fetlock), collar (left side of the neck) and pendant (a casing fitted to freely hang from the marking weight akin to a bell pendulum) (Figure 1, c). Casings were designed to be robust and contoured for animal comfort (especially the front leg position). In the second set of experiments both ears were equipped with the sensors and again the collar sensor was used for control (Figure 2, b & c). Self-adhesive 3M SJ3560 Dual Lock reclosable fasteners were used to attach the sensors to the ears. First part of the Dual Lock was cut to size and glued to the back side of the ear tags (which were scrubbed clean with alcohol to achieve high level of adhesiveness). Second part of the Dual Lock was glued to the Axivity sensors themselves (Figure 2, a). In the initial set of cow experiments the devices were then mounted to the animals with a collar (equipped with two sensors, neck and pendant) and a leg strap. In the second set of experiments both ear sensors were simply mounted with Dual Lock's easy click snapping mechanism (release with peeling motion) while a collar was used again for the neck measurement like in the initial experiments. The collars and leg straps have been fitted with a regular degree of tightness, collar thus being quite loose and the leg strap being a snug comfortable fit while the Dual Lock fasteners inherently provide a snug fit to the ear tag.



a) b) c)

Figure 2: a) Sensors fitted with Dual Lock, b) Sensor on right ear, c) Sensor on left ear

Measurement experiments

Eight free grazing cow locomotion measurements have been performed in August and September of 2020 at a dairy farm, Ahlman (Ahlmanin koulun saatio, Tampere, Finland). Five consecutive experiments were performed as a part of the 'Set 1' (collar, pendant and leg) with a four-year-old Eastern Finncattle cow Neilikka, while in the 'Set 2' (collar and both ears) three consecutive measurements were completed with a five-year-old Western Finncattle cow Miilu. Even though three experiments were compromised with faulty casings each data set resulted with more than 1 h of active grazing time with all sensors present on the animal. Experiment logs for measurement Set 1 & 2 are listed in Table 1.

Signal analysis

The data sets comprising of sampling time and acceleration level in units of gravity were recorded in Axivity's binary format which were all retrieved from the sensors upon experiment completion with the Open Movement OMGUI Tool installed on a laptop. The data sets were then directly imported into MATLAB matrices with Open Movement's recommended import function CWA_readFile.m (Open Movement, 2022). All data was passed through a low-pass filter included in the MATLAB's Signal Analyzer App with the passband frequency set to 20 Hz to filter out the high frequency measurement noise. To remove the effects of sensor positioning with respect to the direction of gravity and its influence on the values, mean values of acceleration were calculated and subtracted for each axis. For ease of identifying overall levels of energy present at each measurement location, the resultant magnitude was first calculated as

$$|\vec{a}| = \sqrt{a_X^2 + a_Y^2 + a_Z^2} \quad (1)$$

Table 1: Experimental logs per day of measurement in August and September 2022.

Set 1					
	Exp. 1	**Exp. 2**	**Exp. 3**	**Exp. 4**	**Exp. 5**
Date	11.08.	12.08.	13.08	14.08	15.08.
Subject	Neilikka	Neilikka	Neilikka	Neilikka	Miilu
Length	5 h	4 h	6.5 h	5.5 h	5 h
Collar	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800Hz / 8 g
Pendant	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 16 g	800 Hz / 16 g
Leg	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g	800 Hz / 8 g
Casing fault	–	pendant	pendant	–	collar

Set 2			
	Exp. 1	**Exp. 2**	**Exp. 3**
Date	11.09.	14.09.	15.09.
Subject	Miilu	Miilu	Miilu
Length	6.5 h	6 h	4.5 h
Collar	400 Hz / 8 g	200 Hz / 8 g	400 Hz / 8 g
Right Ear	400 Hz / 8 g	200 Hz / 8 g	800 Hz / 8 g
Left Ear	400 Hz / 8 g	400 Hz / 8 g	800 Hz / 8 g
Casing fault	–	–	–

Power spectral density of the data sets

To assess the levels of available energy and obtain frequency information of the recorded locomotion, power spectral density (PSD) estimations were used. Using a PSD estimation allows for quick identification of characteristic process frequencies and the levels of energy associated with each frequency emerging from random locomotion. To obtain a PSD, at first MATLAB's fast fourier transform algorithm is used to compute a discrete fourier transform (DFT) of the signal, defined as where the $x[n]$ is the sampled signal, N is the signal length, K is the number of points in the frequency domain (usually $K = N$), $f_k = kf_s / K$ is the normalized frequency where f_s is

$$X(f_k) = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/K} \quad (2)$$

the sampling frequency of the recorded signal. For signals acquired at frequencies two times greater than the maximum frequency of the signal, the Nyquist frequency, the PSD can be estimated with a DFT (Pierre J. and Kubichek R. F. 2002) and easily computed in MATLAB as

The following approach was used to obtain the results: 1) inspection of time series, 2) PSD estimation of $|\vec{a}|$ for a single day record, 3) isolate 1 h of active grazing data,

$$P(f_k) = \frac{2}{f_s N} |X(f_k)|^2 \quad (3)$$

4) PSD estimate of $|\vec{a}|$ during 1 h, 5) PSD estimate for each separate axis during 1 h to obtain directional data. Each PSD was smoothed with a Savitzky-Golay finite impulse response smoothing 3rd order filter and a frame length of 101 samples.

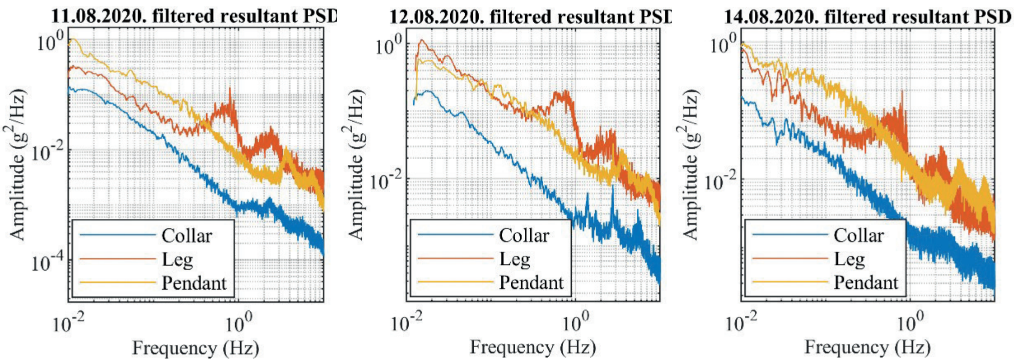
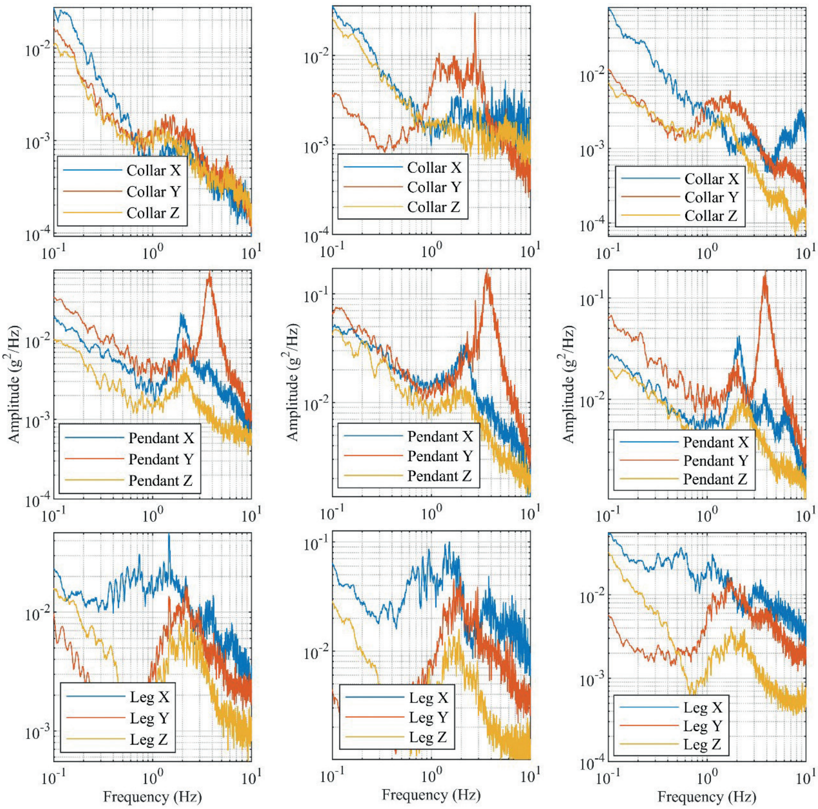


Figure 3: PSDs of the resultant magnitude of acceleration from Set 1 – complete day logs

Table 2: Characteristic cattle locomotion frequencies, Hz

Position	$f_{\|\vec{a}\|}$	f_X	f_Y	f_Z
Collar	2.5	1.5	1.5	1.5
Pendant	3.6 / 7.2	2	2 / 3.7	2
Leg	0.8 / 2.5	1.7	1.7	1.7
Right ear	3.3 / 5.5	2.7	5	2.7
Left ear	3.3 / 5.5	2.7	5	2.7



a) b) c)

Figure 4: PSDs estimated from individual axis records from selected 1 h of active grazing time in Set 1 - a) 11.08., b) 12.08. and c) 14.08

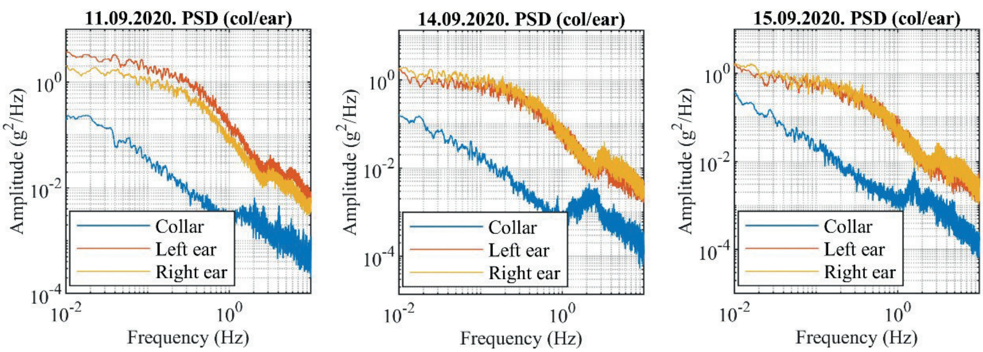
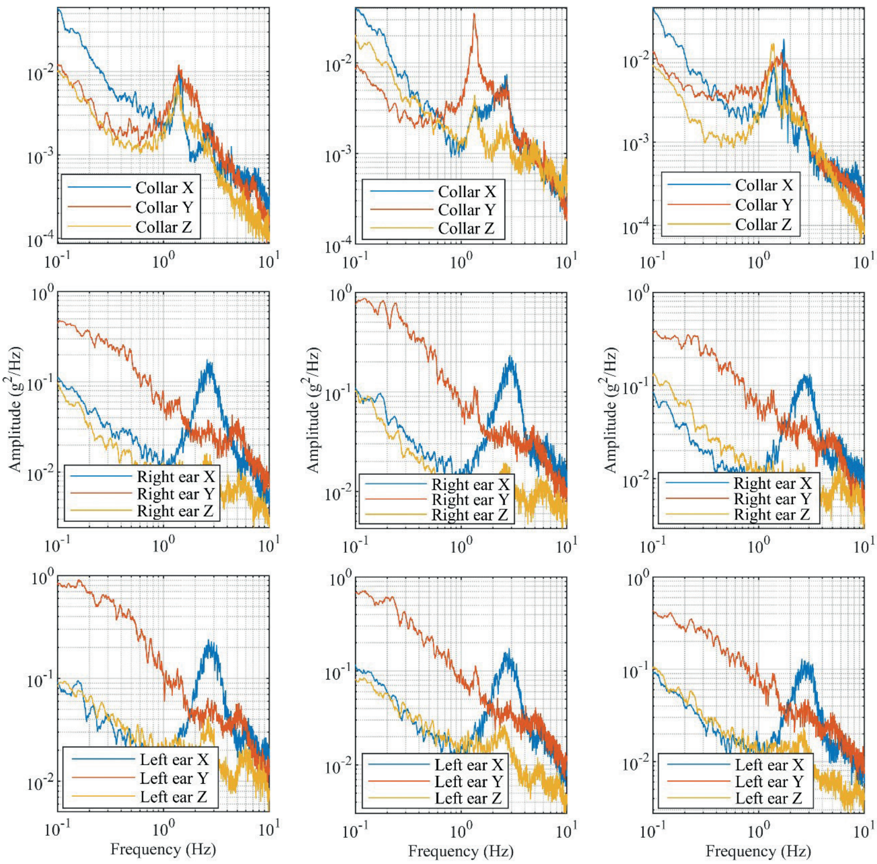


Figure 5: PSDs of the resultant magnitude of acceleration from Set 2 - complete day logs



a) b) c)

Figure 6: PSDs estimated from individual axis records from selected 1 h of active grazing time in Set 1 – a) 11.08., b) 12.08. and c) 14.08

Results and Discussion

In both Figure 3, (three days of Set 1) and Figure 5, (three days of Set 2) whole day resultant $|\vec{a}|$ was used for PSD estimations (idling included). Both figures show the largest power density amplitudes, in units of squared gravitational constant (g2) per frequency (Hz), present at low frequencies and aperiodic, random events (below 1 Hz) decreasing with frequency. The collar logs resulted with the lowest average amplitudes in both sets. In Set 1 (Figure 3), the first identifiable low frequency of leg motion with the largest amplitude occurs at ~0.8 Hz (first peak on orange curves close to 1 Hz). This can be interpreted from the time series as the response of walking motion. Walking motion is transferred also to the collar, the effect of which can be seen in the ~2.5 Hz peak both in the collar and leg (more pronounced in the orange curves - leg, less but still present in blue curves - collar). The pendant has a higher frequency response, ~3.6 Hz / ~7.2 Hz (two peaks in the yellow and orange curves closer to the right side). In Set 2 (Figure 5), both ear sensors display two frequencies, ~3.3 Hz and ~5.5 Hz (first and second peak seen from the overlapping yellow and orange curves to the right side). Results from the collar are identical as in Set 1. When using acceleration magnitude $|\vec{a}|$ as the basis of a PSD estimate, the directional information is lost. To preserve this information and gain insight for potential KEH device locations, individual estimates were performed for each axis during 1 h of grazing. Figure 4 displays individual axis PSD estimates during three days of Set 1. The most easily noticeable peak in all of three days, with the highest power density is the pendant's vertical Y axis at ~3.7 Hz (first high orange curve peak) and the pendant's X forward motion axis at ~2 Hz (first peak in the blue curve). Leg locomotion peaks in X, Y and Z at ~1.7 Hz, while the leg's forward X motion shows higher average power density (blue leg curve). The collar response is again coupling closely with leg locomotion at ~1.5 Hz (identifiable in Figure 4 b). Individual cow step durations were measured from the time series data, lasting 700-800 ms in average (cause of the identified leg frequency). Same principle of analysis has been applied to data from Set 2 (Figure 6), where the forward ear flapping motion peaks (the X axis, blue curves) are instantly noticeable in the right and left ear displaying the largest amplitude at ~2.7 Hz. Second component of the flapping motion is the lateral Z axis (yellow curves) peaking at the same frequency. Second interesting occurrence in the ear harmonics is the prominent peak of ~5 Hz in the vertical Y axis direction of locomotion (orange curve peak close to the right side of individual ear graphs) which could be attributed to free vibration ear response.

Conclusions

This paper proposes a method for measuring animal locomotion considering design practices for KEH devices and standard PLF wearables. The goal of the research was to identify positions and directions on a cow's body which would be suitable for conversion of kinetic into electrical energy either by strong impacts or by tuning the harvester to operate at a specific animal locomotion frequency. Measurement locations - leg, collar, pendant and ear - were chosen considering the frequent forms of PLF wearables (ear tags, leg straps, collars or bells). Power spectral density estimations have been performed from which it could be seen which body parts provide stronger excitations. In general, all PSD plots show that the largest power densities occur aperiodically due to random animal motion or at low frequencies. Specific frequencies have been identified related to walking, pendant swinging, or ear flapping (Table 2). Leg, pendant and ear motion have been identified to have the largest power densities at specific axial directions while the collar position displays the lowest average power densities. Some locations for animal KEH are more feasible than others. Legs and ears, with higher power density, cannot handle bulky devices which hinder movement, while the collar with smaller average power densities can be equipped with a larger device with a heavier moving mass. Designing a low frequency KEH device is not a simple task due to an increase in sizes of the moving masses. Nonlinear and impact energy harvesting mechanisms will have to be considered as well as higher frequency components of the here identified basic frequencies to decrease size and weight. In the future this data will be used to calculate theoretically obtainable KEH powers using a finite element model of a 1D electromagnetic KEH device. The presented measurement data, although acquired with KEH in mind, is objectively quantified with 3D accelerometers and frequency analysis methods and can used to bring further insight into research of animal locomotion. The conclusions will also be important in developing a new class of farm animal kinetic energy harvesting devices.

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