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Tjotta accelerometer monitored lambing dataset

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Abstract: Early detection of lambing is essential for improving animal welfare and farm management, as it enables timely intervention and reduces complications. Wearable inertial sensors have been applied to sheep monitoring, with frequent transitions between standing and lying identified as key behavioral indicators of lambing. However, unlike in larger livestock, no accelerometry-based system currently provides real-time detection for small ruminants, and existing studies remain limited to preliminary approaches.

This study monitored 61 ewes using accelerometers sampling at 20 Hz, while lambing was simultaneously recorded on video to establish precise birth times for 113 events. Video analysis also documented litter size and the need for assistance. Data were organized per ewe, supplemented with information such as birth year, previous lambing records, and ultrasound results. A video of one birth was included to illustrate behavior during the process. The dataset provides a valuable foundation for developing algorithms capable of classifying birth-related behaviors, thereby supporting future automated lambing detection systems.

Background & Summary

Managing hundreds of animals makes it challenging for the farmers to identify welfare issues early, particularly in systems that are already facing an aging and dwindling workforce [1]. Additionally, small ruminants tend to flock together and may not reveal signs of weakness until their condition has turned serious [2,3]. This situation poses not only an animal welfare problem, but early detection also holds an economic benefit, saving good breeding animals instead of culling and suffering loss [32].

Being able to detect deviations from normal behavior at an early stage and providing adequate management and treatment is especially important during lambing and kidding [2]. Among the most serious and important welfare issues identified by stakeholders within the small ruminant production in Europe, we find [4] dystocia and poor maternal

behavior [5]. The Norwegian White Sheep breed [4] is particularly known for delivering multiple lambs per pregnancy, and as the number of lambs increases, so does the risk of complications [6].

In Norway, lambing typically occur once per year, in spring [1]. However, nearly eight percent of all lambs born do not survive to leave the barn for pasture [7]. The workload during lambing is intense, particularly as the number of expected ewes increases. Many farmers hire additional help, a necessity which can put further strain on the economic aspects of production.

In Portugal, despite the differences in the sheep breeds raised compared to Norway, there are many similarities regarding lambing practices: the rate of losses during lambing is remarkably similar between the two countries [8], and flock management is carefully organized so that lambing occurs just once a year [1,9]. Sheep farming in Portugal is often integrated with dairy production [10], which requires producers to synchronize the reproductive cycle. This synchronization is strategically planned to align the post-lambing period with times of greatest food abundance, ensuring optimal conditions for both ewes and lambs [11]. In Portugal, the demand for sheep meat reaches its highest levels during Carnival and Easter [12]. To align with this seasonal trend, farmers plan lambing schedules so that lambs are ready for market during these festive occasions [9]. This strategic timing not only enhances production profitability but also supports the country's rich cultural and culinary traditions [13].

Providing timely assistance for lambing cases requires continuous monitoring of the animals, a very costly process if implemented by humans [3]. With the current technology development within precision livestock farming, the need for closer inspection and early detection of health or welfare issues could be assisted by sensor technology [14,15]. From a recent review it was clear that several techniques for automatic detection and warning of parturition events have been tested and developed [16]. Nevertheless, such parturition detector products have not yet been made available for small ruminants [16].

Wearable inertial sensors offer a convenient [17], non-invasive method for continuously monitoring sheep behavior in real time. They can automatically detect specific movement patterns associated with the onset of lambing [17,18], reducing the need for constant human supervision. This technology enables timely intervention, improving animal welfare and lamb survival rates. Furthermore, they can use multiple algorithms to monitor multiple patterns that identify other behaviors, thus allowing the same sensor to be used in different scenarios such as activity monitoring [5,19] and behavior classification [20–22].

The present paper aims to share a dataset from an experiment testing a wearable inertial sensor for detection and prediction of parturition in sheep. In addition to the data collected by the accelerometers, the paper includes information about the animals, as well as notes made by the keepers about the lambing event, which can help data scientists to annotate the data in the way they find most convenient.

Methods

The experiment was conducted in an approved facility for animal research (171 NIBIO), located at the Norwegian Institute for Bioeconomy Research station at Tjøtta (Lat 65º 49' 41.153''; Lon 12º 25' 29.075'') in Nordland County, Norway.

Animals and housing

At the Tjøtta farm, pregnant ewes expecting twins were selected from the original herd of production sheep. The majority of the ewes were of the Norwegian White breed (55), with a few Spael (5) and one Pelt sheep included. All sheep were raised primarily for meat production. They were housed indoors for most of the winter season and were clipped twice a year (November and March) in accordance with standard practices and national regulations regarding sheep health and welfare.

To assess the number of lambs expected and estimate relative time of parturition (early or late), all ewes underwent ultrasound scanning at an early stage of their pregnancy.

In preparation of the experiment, ewes were gently moved from their regular home pens to a designated experimental unit [23] equipped with video surveillance and in-dividual pens, at least one week before their expected parturition date. Each ewe was fitted with neck collars containing an accelerometer measuring x, y and z components of acceleration and the temperature, weighing 180 grams (see Figure 1).

Figure 1 - Illustration of a Norwegian White Sheep wearing a collar equipped with an accelerometer sensor to detect parturition events

The pens were equipped with slatted floors made of composite material as illustrated in Figure 1, and they included feed mangers that automatic recorded feed intake and feeding bouts [23]. Water was provided ad libitum from buckets, and each ewe received 200 grams of standard concentrate feed daily. When early signs of parturition were detected by the staff, mats with litter were added on the slatted pen floors to make it more comfortable for the lambs at birth. To minimize disturbance to the ewes, only the original farm staff, representing familiar faces, were involved in the lambing process. Obstetric aid was offered to ewes if needed, and this evaluation was left to the farmer to decide in each case. The researchers and technicians only helped with instrumentation, surveillance and feeding. Animals were fed ad libitum roughage from large bales of silage (around 30% DM). Feed and water were replenished in the morning (8-9 am) and afternoon (2-3 pm) hours.

The experimental barn consisted of 24 individual pens, so initially, only this number of ewes were moved to the unit. After lambing, the ewes and their lambs were allowed two full days of bonding before being moved back to their home pens. They were then replaced with new expecting ewes. This exchange routine made it possible for the collection of data from a total of 61 parturition events where 113 lambs were born. The experiment lasted for a month, with the first lambing detected on April 23rd and the last on May 24th 2024.

Data collection

The data recording was conducted from 22nd April to 27th May using a collar [24] fitted to sheep's neck. The collars were configured using a mobile phone application. Collar orientation was aided by an arrow-shaped marking, and the collars operated at a frequency of 20Hz. In addition to the collar, the monitoring platform illustrated Figure 2, includes a gateway positioned at the center of the barn's ceiling. This gateway aggregated data from the collar sensors and forwarded it to the cloud via an Ethernet cable. The setup also included a series of video cameras, each of them continuously filming two cages. The internal clock of all data recording platforms was temporally synchronized through Network Time Protocol (NTP).

The collars are initially configured via a mobile app that activates them via a Near Field Communication (NFC) switch and then configured through Bluetooth Low Energy (BLE). The communication between the collar and the gateway implements a temporal synchronization mechanism that allows the creation of a timestamp associated with each monitoring record. Additionally, it allows the transfer of data collected by the collars and aggregated by the livestock facility gateway.
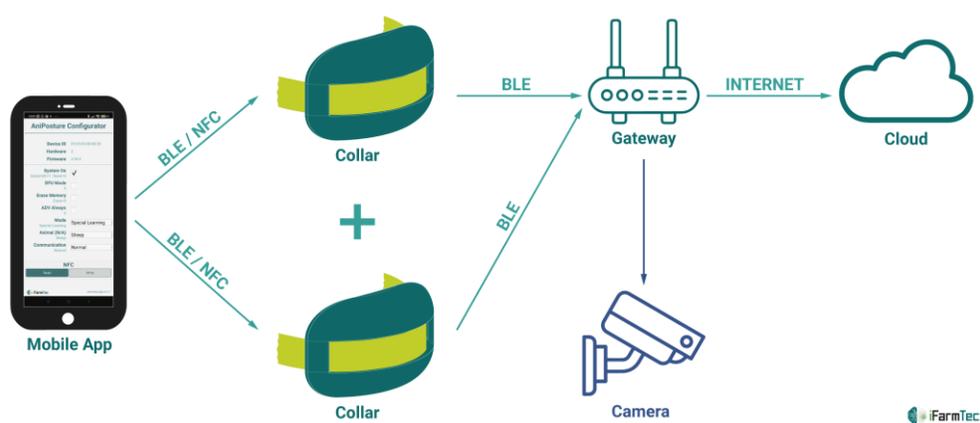

Figure 2 - Illustration of the ewe monitoring platform, representing the data flow from the collars worn by the ewes and the video surveillance system in place to offer a ground truth validation dataset for the lambing period [24].

The cameras are connected via cable to a Mobotix multiplexer unit [25] that coordinates the digital video from all these cameras. The unit can add filters and motion detection solutions to record only changes to the picture and save storage room. The video files are saved on an internal hard drive and are downloaded from there to a portable drive for further analysis or long-term storage. The Mobotix MVR (MOVE Network Video Record) machine also have settings for continuous recordings or specified recordings in time-lapse settings. During this experiment with the lambing sensors the recordings were set to continuous, and the video files were stored and saved daily on a portable hard drive to make sure no video was missing.

The subsequent analysis of the images collected allowed the annotation of the data collected by the collars. This included additional information such as the time of birth, and whether the birth occurred naturally or whether it involved some type of nursing intervention. Figure 3 illustrates video system management interface.

Figure 3 - Snapshot of the video surveillance system used for validating the ground truth dataset during the lambing period

Lambing video visualization

Unlike animal handling, the supervision process was conducted remotely by re-viewing video footage and consulting notes made by the animal handling staff. Each animal in the experiment had a dedicated note sheet placed next to its cage. The notes provided by the animal handling staff (Figure 4) are summarized in Annex Table 1. These notes included information about the time, the number of offspring born, and separate information related to the process. To validate this information and minimize errors, the data were cross referenced with the information obtained from the video recordings illustrated in Figure 3.
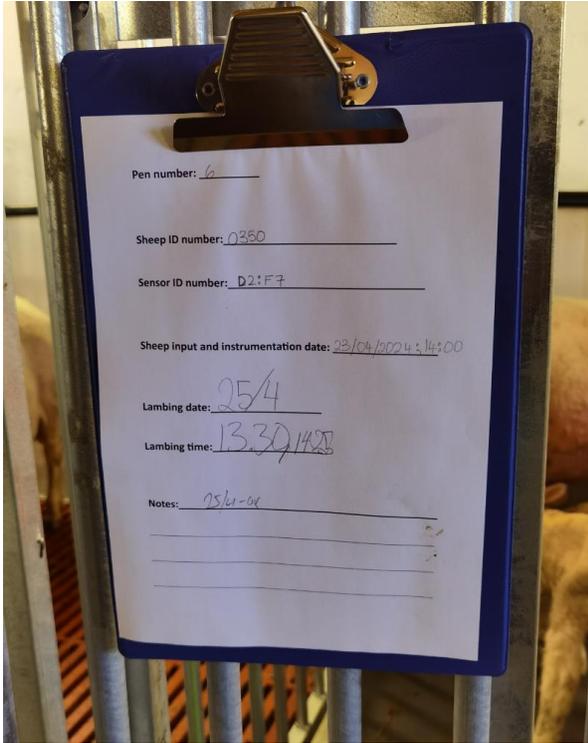
Figure 4 - Example of notebook notes taken by handling staff

Ewe information annotations

Annex Table 2 adds a set of details about the animals that can be used to complement the existing monitoring data in the dataset. Among the fields in the table are the animal's identification tag number, the year of birth of the animal, the parity number that defines the number of births the ewe has had, the number of offspring lambed in the last 3 years, as well as the number of offspring in the 2024 season, the time and date of birth of the first offspring. Finally, the table includes a column of diverse information related to birth, where various facts such as the breed or destination of the animals were noted.

Data records

Dataset Summary

The original dataset [26] contains 50870520 records collected between 23ʳᵈ April and 27ᵗʰ May 2024. Table 1 describes data structure gathered by the collars.

Table 1 - Structure of data sent by collars, including a UTC time stamp, the components of acceleration (x, y, and z) and the temperature.

Timestamp (ms)	Acc_X (mg)	Acc_Y (mg)	Acc_Z (mg)	Temperature (C)
1715268840000	236	260	-972	17.3
1715268840050	236	248	-960	17.3
1715268840100	240	268	-972	17.3
1715268840150	236	256	-948	17.3
1715268840200	248	260	-952	17.3

Because the collars were used on a rotating basis between ewes, and were removed from an animal after ewe lambing to be used by a new lambing ewe, the data gathered from a collar were cut to include individual sheep monitored data. the duration of the dataset for individual observations varies, with the longest being 4 days (2533243433 rows) and the shortest taking 18 hours (2313134 rows) collection. Additionally, the data from each lambing event were organized into files whose name included the ear tag id and the collar identification (Mac Address). Annex Table 3 lists the files that include the dataset as well the number of records in each file.

The data were subsequently filtered to remove incomplete records as well as outliers, resulting in a total number of 973070128 records.

Technical Validation

Figure 5 shows the distribution of data in terms of x, y, and z components from the accelerometer of the ewe 10199 monitored in cage 15 by the collar C0077C8DC4D3 and that lambed on 10ᵗʰ May 2024.
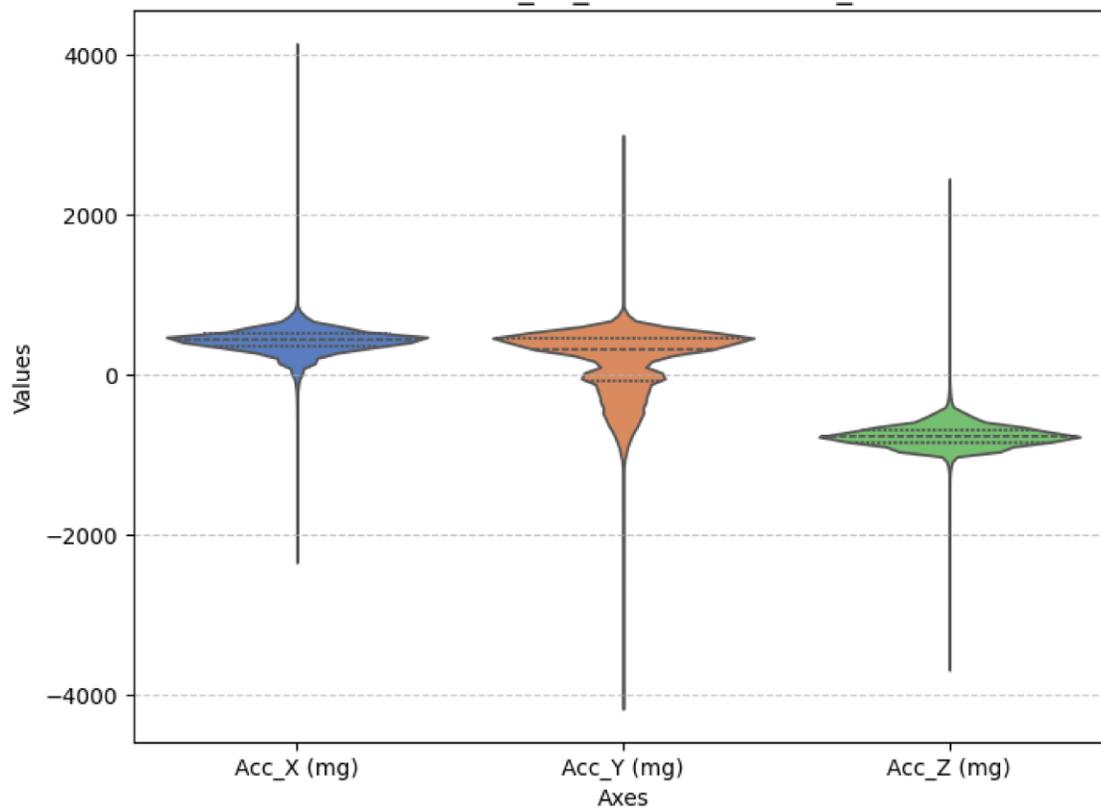
Figure 5 - Value distribution recorded at 20 Hz from a tri-axis accelerometer on a collar worn by an ewe during parturition for Animal_10199_C0077C8DC4D3.csv.

Figure 6 shows the histogram of the acceleration distribution from ewe 10199 monitored by the collar C0077C8DC4D3 and that lambed on 10th May 2024.
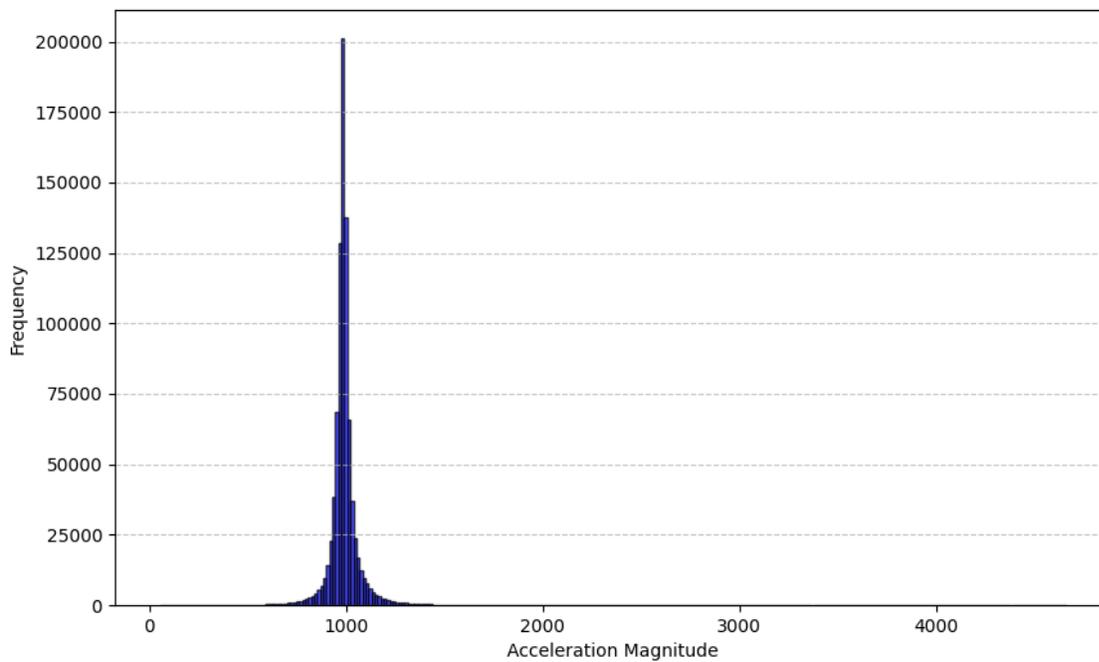
Figure 6 - Histogram distribution of accelerations recorded at 20 Hz from a collar worn by an ewe during parturition for Animal_10199_C0077C8DC4D3.csv.

For illustrative purposes, Figure 7 also shows the evolution of the activity measured by the accelerometer for the same sheep.
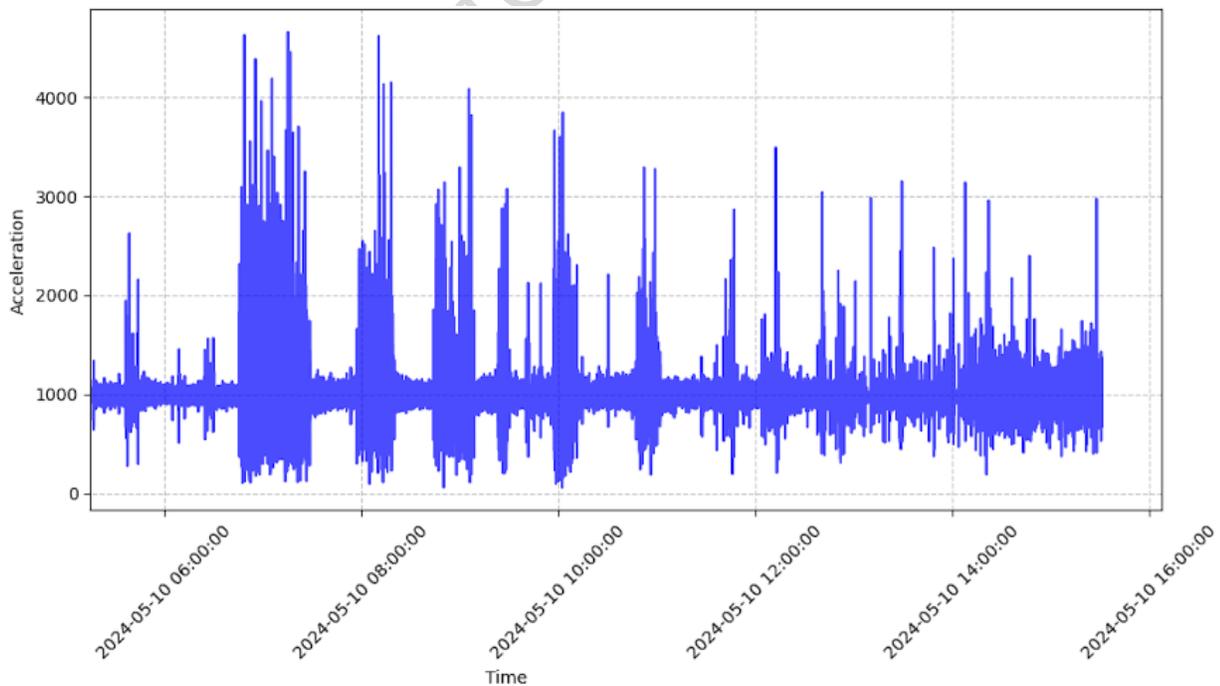
Figure 7 - Activity evolution recorded at 20 Hz shown over a time scale worn by an ewe approaching parturition for Animal_10199_C0077C8DC4D3.csv.

Usage Notes

This dataset is unique in that it was collected within a barn environment. While such a setting allows for controlled experimental conditions, it cannot capture the full complexity of natural sheep behavior. Key ecological elements such as unrestricted grazing, wide-range movement, predator avoidance are absent. The recorded behaviors therefore likely reflect adaptations to confinement, including altered feeding schedules and restricted spatial activity. Although valuable for agricultural and behavioral research under managed conditions, the dataset does not represent the complete behavioral repertoire observed in free-ranging, pasture-based systems. Moreover, the behavioral expression in this dataset is also shaped by both the breed studied and the specific characteristics of the barn environment, including its climate, diet, and management regime. These factors limit the generalizability of the findings to other breeds or regions that differ in husbandry practices, vegetation, or topography.

A minor issue arose from the occasional misplacement of accelerometer collars, some of which were attached in reverse orientation. This error can be corrected algorithmically by inverting the acceleration vectors during the affected time intervals. Table 1 documents the periods of collar placement, removal, and correction. The adjustment involves a straightforward computational inversion of the data corresponding to the intervals when collars were reversed.

The dataset also exhibits a pronounced class imbalance, with Class 0 representing roughly one-tenth the duration of the remaining classes. This imbalance poses a significant challenge for model development, as it biases learning algorithms toward majority classes (1–11 and –1) and limits their ability to identify patterns associated with the minority class. To mitigate this effect, strategies such as oversampling of Class 0, under sampling of dominant classes, or synthetic data generation (for example, using SMOTE) should be applied prior to model training.

Intrinsic biological variation—particularly differences in age and body mass—further influences movement dynamics. Older or heavier animals typically exhibit lower acceleration magnitudes and slower, more stable motion than younger or lighter individuals. Such variability can confound models seeking to distinguish behavioral states. Normalizing acceleration relative to each animal's physical capacity would reduce this bias, yielding a more uniform feature space that reflects behavioral rather than morphological or age-related differences.

During data cleaning, incomplete records were removed. No outliers were excluded, and no interpolation was used to reconstruct missing data, preserving the dataset's original statistical structure.

Data Availability

Data is available for download at figshare repository under the address https://doi.org/10.6084/m9.figshare.28815974.v1.

10.6084/m9.figshare.28815974

Code availability

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