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# Evaluation of the tri-axial accelerometer to identify and predict parturition-related activities of Debouillet ewes in an intensive setting

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ABSTRACT

Identifying and monitoring parturition of individual animals may help producers increase attentiveness, enabling early detection of dystocia during parturition. Parturition events are marked by subtle behavioral changes often difficult to detect by observation alone. The aim of this study was to determine the ability of tri-axial accelerometer data to accurately identify and predict parturition-related behavior of mature ewes in a pen setting. Tri-axial accelerometers recording at 12.5 Hz were placed on ear tags and attached to 13 Debouillet mature ewes before parturition. Activity was monitored 7 days prior to lambing (d −7); on the day of lambing (d 0); and 7 days post lambing (d +7). Using random forest machine learning, accelerometer data and visual observations were used to predict (i) seven mutually-exclusive behaviors; and (ii) activity (active and inactive behavior) based on five metrics calculated using variation of movements recorded by the accelerometer. The accuracy of seven predicted behaviors from an independent validation set was 66.7 %, and the accuracy for activity was 87.2 %. In addition to predicted behavior and activity, metrics calculated from accelerometer data and used for random forest predictions were evaluated 7 d before and after lambing and 12 h before and after lambing on six of the 13 ewes where the actual time of lambing was observed. No differences were detected in the seven predicted behaviors either before or after lambing. Four of five accelerometer metrics ($P \leq 0.002$) were higher during the 7 d after lambing than the 7 d before lambing. Values for three of the five metrics were highest ($P < 0.01$) on the day of lambing. All five accelerometer metrics varied during the 12 h pre- and 12 h post parturition ($P \leq 0.004$). All accelerometer metrics increased ($P \leq 0.008$) 1–2 h before parturition compared to 3–4 h before parturition. In this current study, calculated direct sensor metrics served as a better indicator of lambing than predicted behaviors, processed through complex machine learning algorithms. Commercial use of accelerometers by producers may allow for detection of prolonged labor indicating potential dystocia during parturition, which may reduce lamb mortality and increase production efficiency. These results suggest that real time accelerometers could remotely monitor ewes and potentially provide managers an indication that the dam may lamb soon.

## 1. Introduction

Parturition is a critical time for livestock operations that requires increased supervision to improve animal welfare and decrease offspring mortality (Cornou and Kristensen, 2014). Prey animals such as sheep, have the ability to obscure discomfort and fail to show apparent changes in behavior (Underwood, 2002). Known behavior patterns may assist in identification of changes in the physical health status of animals (Frost et al., 1997). Increased monitoring at the earliest stages of parturition may allow for identification and intervention by the producer (Bellows et al., 1988; Frost et al., 1997; Dobos et al., 2014), which has been shown to result in greater lamb survival in cases of dystocia (Holmøy et al., 2012).

Microelectromechanical system (MEMS) accelerometers are data logging devices capable of detecting slight changes in activity by gathering acceleration signals that are generated in two forms, measuring static accelerations of gravity ($-9.8 \text{ m s}^{-2}$) and dynamic accelerations of movement (Watanabe et al., 2008). Accelerometers may serve as an alternative to labor intensive human observation of livestock (Barwick et al., 2018). Sensor technologies could potentially provide managers with early warning tool in distinguishing abnormalities (Bikker et al., 2014).

Parturition can be characterized into three stages: 1) dilation of the cervix; 2) expulsion of the fetus(es); and 3) expulsion of the placenta.

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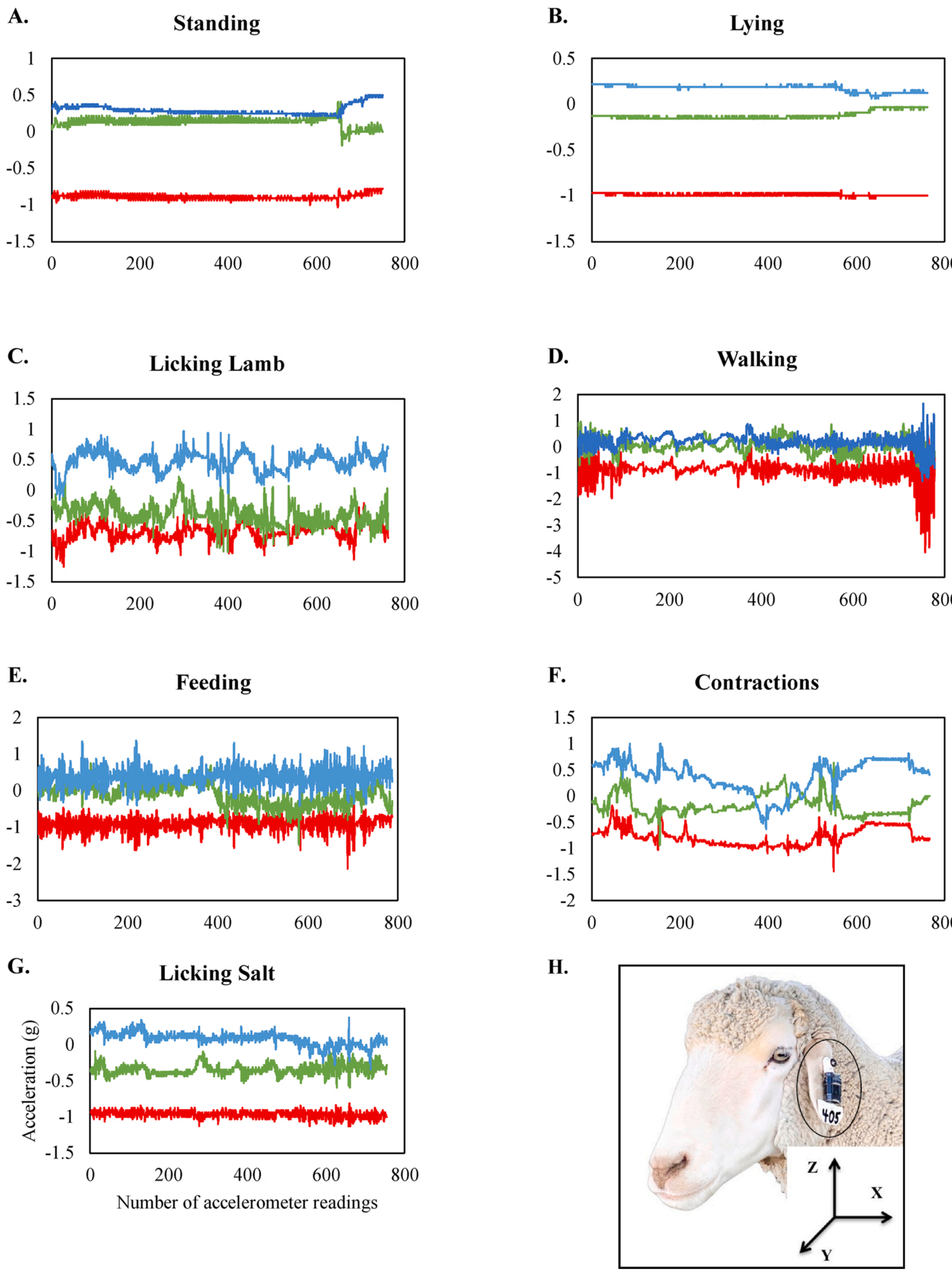


**Fig. 1.** **(A-G)** Examples of tri-axial accelerometer signals of one ewe over 60 s (750 accelerometer readings at 12.5 Hz) for the seven mutually-exclusive behaviors. The X-axis is indicated by the blue line, Y-axis by the green line, and Z-axis by the red line. **(H)** Location and orientation of the tri-axial accelerometer attached to an ear tag as shown on sheep. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

Stage one may be demonstrated through discomfort and constant lying to standing bouts with isolation from the flock. It may last up to 12 h before to lambing and concludes with the rupture of the chorio-allantoic sac. At onset of parturition, livestock increase the amount of standing bouts when compared to pre and post-parturition (Huzzey et al., 2005). Stage two results in visible contractions and abdominal straining of the dam. The ejection of the lamb usually takes 30−45 min. The end of this stage is signified by licking of the lamb. Stage three is the expulsion of the placenta which happens within four hours post-parturition.

Prolonged labor during parturition may increase risk of dystocia and could be avoided with proper identification and intervention (Bellows et al., 1988). Most lamb mortality events occur within the first three days of the lamb's life, with nearly half of all pre-weaning deaths happening on the day of lambing (Dwyer, 2008). The most common causes of lamb mortality are dystocia (20 %) and birth injury (47 %) (Hatcher et al., 2011). Dystocia remains a significant problem for sheep production, as it may lead to injuries and potentially death of the lamb (Cloete et al., 1993; Nowak and Poindron, 2006). Increased attention should be given to primiparous ewes, as they may exhibit lamb refusal and reject suckling of the lamb (Lévy et al., 1995). Primiparous ewes lack motherly experience and tend to have more instances of prolonged labor which may result in higher lamb mortality (Nowak and Poindron, 2006; Dwyer, 2008).

Accelerometers can provide a wide range of fine-scale information on animal behavior and physiology, exceeding human observation abilities which is typically limited to a short period of time and only a fraction of the animals daily activities (Brown et al., 2013). Elusive changes in behavior may indicate health status of livestock (Frost et al., 1997). Changes in activity are not readily observed through physical observation, and technological advancements may allow for the ability to remotely monitor livestock and notify management (Bailey et al., 2018). Remote monitoring systems may detect patterns of activity related to parturition, including highly active behaviors like continuous lying and standing, licking of the lamb, and pushing associated with active contractions. Sensor technologies could detect pivotal changes in behavior associated with health and welfare of livestock (Walton et al., 2018) while relying on little human input, consequently increasing production efficiency (Kuźnicka and Gburzyński, 2017). The aim of this current study was to determine the ability of a tri-axial accelerometer to accurately identify and predict parturition-related activities of mature ewes in a pen setting. We hypothesized that accelerometers will accurately detect changes in activity and/or ewe movement patterns prior to and during parturition, which might be useful for prediction of parturition events.

## 2. Materials and methods

### 2.1. Site and animals

All procedures were approved by the New Mexico State University Institutional Animal Care and Use Committee (2019-007).

This study was conducted on the campus of New Mexico State University in Las Cruces, New Mexico, USA at the West Sheep Unit research facility. Thirteen pregnant Debouillet ewes averaging 3 years (± 0.3) were housed in a single pen (18.3×9.1 m) and monitored from 13 March until 13 April 2019. Ewes were confirmed pregnant by evaluation of progesterone concentration via radioimmunoassay. Each ewe was fed 1.6 kg of an alfalfa-corn ration in the morning (08:00 h) with *ad libitum* access to water, mineral, and salt.

### 2.2. Accelerometers

A tri-axial Axivity AX3 MEMS accelerometer (Axivity Ltd, Newcastle, UK) was attached to an Allflex ear tag (Allflex USA Inc., DFW, TX, USA) with shrink wrap tubing, which was then conventionally attached to the pinna of either the left or right ear of the ewe prior to parturition. Accelerometers were charged prior to deployment to last a duration minimum of 30 days (study duration). Accelerometers were configured to collect acceleration signals at a sample rate of 12.5 Hz measuring longitudinal movements of the horizontal X-axis (left and right), longitudinal Y-axis (forward and backward), and vertical Z-axis (up and down) demonstrated in Fig. 1H. The dimensions of each accelerometer were 23 × 32.5 × 7.6 mm and weighed 11 g.

Accelerometer movements were subsequently stored on the NAND Memory within the device. Accelerometers were removed post-study to retrieve data via USB connection to the OmGui Axivity computer software. The OmGui program downloads data from the accelerometer, allows for manipulation for desired study period, and stores raw data as a. CWA file, not compatible with Microsoft Excel (Microsoft Corporation, Redmond, WA, USA).

### 2.3. Data collected

Data were retrieved using the Axivity proprietary software, OmGui, and condensed into 10 s epochs using Anaconda Python (Anaconda, Inc., Austin, TX, USA) programming.

### 2.4. Behavioral annotation

Sheep behaviors were recorded 24 h a day by four Reolink Argus 2 video cameras (Reolink, Hong Kong, China) placed in each corner of the pen. Ewes were marked on their sides using Paintstik markers for visual identification and monitored during the 30 day study. Cameras were weatherproof security cameras capable of capturing footage in both dark and daylight with built in motion sensors to activate recording. Cameras were retrieved every 3–4 days to recharge batteries and download videos to computer via USB connection then placed back in pen after retrieval of data. Post-study, video recordings were analyzed and annotated.

**Table 1**
Calculated features from the raw X, Y, and Z-axis values. Maximum, mean, minimum, and range were calculated for each axis. Equations discussed in (Fogarty et al., 2020c; Tobin et al., 2020).

| Feature | Equation |
|---|---|
| Maximum (Max) | The maximum acceleration value of x,y,z axes within each epoch |
| Mean (A) | $A = \frac{1}{T}\sum_{t=1}^{T} x(t)$ |
| Minimum (Min) | The minimum acceleration value of x,y,z axes within each epoch |
| Movement Intensity (MI) | $MI = \frac{1}{T}\sum_{t=1}^{T}\sqrt{(Ax^2) + (Ay^2) + (Az^2)(t)}$ |
| Range (R) | $R = max - min$ |
| Standard Deviation (SD) | $SD = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x(t) - \overline{x})^2}$ |
| Signal Magnitude Area (SMA) | $SMA = \frac{1}{T}(\sum_{t=1}^{\mathbf{T}}\lvert\mathbf{Ax(t)}\rvert + \sum_{t=1}^{\mathbf{T}}\lvert\mathbf{Ay(t)}\rvert + \sum_{t=1}^{\mathbf{T}}\lvert\mathbf{Az(t)}\rvert)$ |

Video recordings were analyzed seven days prior to parturition (d - 7) until the day of lambing (d 0). Each dam was observed individually to determine a specific activity displayed. The behaviors most prominent throughout the study were: standing, lying, walking, feeding, licking salt, licking of the lamb, and active contractions. Feeding was defined as the ewe consuming feed from the bunk, chewing with head up or down while standing or moving. Licking salt was the movement of head up and down, licking salt block. Licking lamb was the large movement of head up and down while licking the lamb after parturition. Contractions were classified as such when the ewe was on its side with movement of head due to straining during the process of parturition. Each ewe had to perform one of the seven behaviors for at least sixty consecutive seconds for it to be annotated as such. If the ewe changed between one behavior and another or if the observer was unsure, the annotation was not used. This 1 min epoch minimum for annotation helped ensure that the accelerometer readings could be tied to a specific behavior and increase validation accuracy. At onset of parturition, behavioral events were recorded, including: continuous lying to standing bouts, contractions, and licking of the lamb. Time stamps of the annotated behaviors were manually synchronized and integrated with the time stamps of the accelerometer data in Microsoft Excel to merge the data into one file for statistical analysis.

### 2.5. Observation and validation data sets

Accelerometer data and associated behaviors were partitioned randomly by ewe into two groups to create the training and validation data sets. Seventy percent of the data from each of the 13 ewes was used to develop (train) the model; thirty percent of the data was used to validate the model predictions.

### 2.6. Development of activity classification algorithm

The mean, maximum, minimum, range and standard deviation were calculated for each 10 s epoch from each of the accelerometer axes (x, y, z). In addition, the mean and standard deviation of movement intensity and signal magnitude area (Table 1) were calculated for each 10 s epoch. The 10 s epoch was selected for this study to help ensure the accelerometer data during the epoch reflected one behavior (Fogarty et al., 2020c). The 10 s epochs were then averaged into 1-minute intervals that were time matched with the annotated behavior data, which were based on 1 min intervals. A total of 3288 and 1420 behavior observations were used in the training and validation, respectively. Table 2 provides the number of behavioral observations used for training and validation.

**Table 2**
Confusion matrix of classification of: Model I the seven mutually-exclusive behaviors; Model II active and inactive behaviors; from the random forest model using the validation data set. Feeding, licking lamb, licking salt, contractions, and walking were classified as active. Laying and standing were classified as inactive. The numbers in bold indicate the percent of accurate classification behaviors by comparing both observed and predicted behaviors Model I and the percent of accurately classified activity Model II. Overall accuracy of each model: (I) 66.7 %; (II) 87.2 %.

| ObservedBehavior (%) | Predicted Behavior (%) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Behavior | | | | | | | | |
| *Model I* | Feeding | Laying | Licking Lamb | Licking Salt | Contractions | Standing | Walking | Validation[a] | Training[b] |
| Feeding | **75.6** | 5.7 | 4.1 | 0.5 | 0 | 2.6 | 11.4 | 193 | 502 |
| Laying | 4.9 | **83.6** | 0.3 | 0 | 0.3 | 8.7 | 2.1 | 654 | 1445 |
| Licking Lamb | 46.3 | 3.0 | **35.8** | 0 | 0 | 10.4 | 4.5 | 67 | 145 |
| Licking Salt | 6.5 | 27.4 | 0 | **29.0** | 0 | 30.6 | 6.5 | 62 | 150 |
| Contractions | 14.3 | 23.8 | 9.5 | 0 | **23.8** | 0 | 28.6 | 21 | 64 |
| Standing | 5.2 | 32.8 | 0.3 | 0 | 1.4 | **56.2** | 4.1 | 290 | 709 |
| Walking | 39.1 | 15.0 | 3.0 | 1.5 | 0 | 8.3 | **33.1** | 133 | 266 |
| | | | | | | | | 1420 | 3288 |
| | Activity | | | | | | | | |
| *Model II* | Active | Inactive | | | | | | | |
| Active | **79.9** | 20.1 | | | | | | 492 | |
| Inactive | 8.9 | **91.1** | | | | | | 928 | |
| | | | | | | | | 1420 | |

[a] Total number of observations from the 13 ewes that were fitted with accelerometers used in validation.
[b] Total number of observations from the 13 ewes that were fitted with accelerometers used in training the random forests model.

Random forest machine learning was used to predict behaviors using metrics calculated from the 1-minute epochs and the annotated behaviors. The parameters for PROC HPFOREST (Nord and Keeley, 2016) of SAS (SAS Institute Inc., NC, USA) used in the analyses were: 1) six for the maximum variables to try, 2) 20 for the maximum number of trees, 3) 0.1 for the prune threshold, 4) 30 for the number of category bins, 5) five for the minimum category size, and 6) 100 for the number of interval bins. Gini was used as the split criterion.

Using the validation data set, predicted behaviors were determined using PROC HPSCORED (SAS Institute, Inc.) and the random forest final model. The performance of the algorithm was evaluated by calculating the sensitivity, specificity, precision, and recall (Alvarenga et al., 2016; Barwick et al., 2018). Confusion matrices were used to evaluate the accuracy of the model and predicted behaviors (Table 2).

Accelerometer metrics and predicted behavior from the random forests model (both training and validation data) were averaged into 1 h periods by ewe for subsequent repeated measures analyses using SAS Proc Mixed (Littell et al., 2006). The hour periods including the hour lambing occurred (h 0) and the 12 h before lambing (h −12 to −1) and the 12 h following lambing (h + 1 to +12). The response variables included the five most informative accelerometer metrics used in random forests for predicting behaviors: the range of the X-axis, the standard deviation from the X-axis, the range of the Y-axis, the minimum SMA and the minimum of the X-axis. Response variables also included predicted behavior from the random forests model: percent active, percent lying, percent standing, percent walking and percent feeding. The fixed effect was hour of lambing (−12 to +12), and the subject was ewe. The covariance structures evaluated were compound symmetry, autoregressive order 1 and unstructured (Littell et al., 2006), and the structure used of the three was based on the lowest Akaike Information Criterion (AIC). Pre-planned orthogonal contrasts were also used to evaluate differences between the 2 h before lambing (−1 and −2 h) and the 3–4 h before lambing (−3 and −4 h).

Accelerometer metrics and predicted behavior from the random forests model and (both training and validation data) were also averaged into 1 day periods (24 h, 00:00 to 23:59 h) for subsequent repeated measures analyses using SAS Proc Mixed (Littell et al., 2006). This analysis included the day of lambing (day 0), the 7 d before lambing (days −7 to −1), and the 7 d after lambing (days +1 to +7). The response variables were the same as for the hour analysis above. The fixed effect was day of lambing (−7 to +7), and the subject was ewe. Similar to the hour analysis above the covariance structure with lowest AIC was selected. Pre-planned orthogonal contrasts were used to evaluate differences before (days −7 to −1) and after lambing (days +1 to +7). Pre-planned orthogonal contrasts were also used to evaluate differences between the day of lambing (day 0) and the two days prior to lambing (days −2 and −1).

### 2.7. Radioimmunoassay

The progesterone ($P_4$) assay (MP Biomedical) utilized polypropylene tubes coated with an antibody against $P_4$ and $^{125}I$-$P_4$ as the tracer. A stock standard solution was prepared by suspending $P_4$ (Sigma) at 10 ng/mL in assay buffer and pipetted into the antibody-coated tubes in amounts to provide a standard curve of 0, 0.1, 0.2, 0.4, 0.8, 1.6, and 3.2 ng of $P_4$ per tube. Serum samples were assayed at a 100 u L, and all tubes were normalized to 0.5 mL using assay buffer and assayed in duplicate. Each tube subsequently received 1.0 mL MP Biomedical $P_4$-tracer, after which tubes were vortexed and incubated at room temperature for 24-h. Tubes were decanted and counted for 1 min. The specific binding was 82 %. Detection limit (95 % of maximum binding) of the assay was 0.1 ng/mL. Serum progesterone values were used to determine pregnancy and allowed for selection of ewes for the study. Progesterone values greater than 2.5 ng/mL were considered pregnant as described by (Schneider and Hallford, 1996).

## 3. Results

### 3.1. Ewe and lambing data

Initially 13 ewes were used in this study, with the first birth occurring on the first day of accelerometer deployment (15 March 2019) and the last birth 16 days later (31 March 2019). Of the 13 ewes, data from six were analyzed, as exact lambing times were successfully determined from video analysis. The earliest birth occurred within hours of accelerometer deployment and was excluded from analysis. The exact hour of lambing were not determined for five of the thirteen ewes. One ewe was removed from study because of a prolapsed uterus, shortly following parturition.

### 3.2. Prediction of animal behavior using accelerometer metrics

The five most important accelerometer variables for predicting activity (active and inactive) and behaviors were X-axis range, X-axis

**Table 3**
Precision, recall and specificity for predicted behaviors from the random forest using the validation data obtained the 13 ewes fitted with accelerometers. Behavioral observations used in validation are shown in Table 3.

| Behavior | Precision (%) | Recall (%) | Specificity (%) |
|---|---|---|---|
| Feeding | 0.76 | 0.52 | 0.74 |
| Lying | 0.84 | 0.78 | 0.58 |
| Licking lamb | 0.36 | 0.59 | 0.28 |
| Licking salt | 0.29 | 0.86 | 0.06 |
| Contractions | 0.24 | 0.45 | 0.27 |
| Standing | 0.56 | 0.62 | 0.44 |
| Walking | 0.33 | 0.42 | 0.41 |

standard deviation, Y-axis range, signal magnitude area minimum, and X-axis minimum. The gini values ranged from 0.107 to 0.025 for these five predictors of the seven behaviors. For activity (active or inactive) the gini values for these five most important variables varied from 0.111 to 0.023.

Table 2 highlights the confusion matrix classification for the seven mutually-exclusive behaviors utilized in the random forest model. Lying (83.6 %) and feeding (75.6 %) had the highest level of agreement between observed and predicted individual behaviors. The initial model had difficulty predicting the behaviors for walking (33.1 %), licking salt (29.0 %), contractions (23.8 %) and licking of the lamb (35.8 %). The second model was more successful in predicting activity. When ewes were inactive (standing or lying) the model predictions agreed with observations 91.2 % of the time. When ewes were active, the model successfully predicted that sheep were active 79.9 % of the time.

### 3.3. Classification algorithm performance evaluation

The overall accuracy, sensitivity, precision, and specificity of predictions of active and inactive behaviors from the random forest models approached or exceeded 80.0 % (Table 2). The random forests model was not as successful predicting specific behaviors (Table 3). The precision of predictions of lamb licking, salt licking, contractions, and walking was less than 50.0 %. Recall rates for predictions of walking and contractions was less than 50.0 %. The specificity was less than 50.0 % for all behaviors except lying and feeding. The overall accuracy of the random forests model for predicting the seven behaviors was 66.7 %.

Differences in the precision, recall and sensitivity among the seven predicted behaviors may be partially explained by the comparisons of the signals recorded by the accelerometers. Fig. 1 shows examples of accelerometer signals from each behavior. The acceleration signals from the standing (Fig. 1A) and lying (Fig. 1B) behaviors were similar with minimal amplitude on all three axes. Licking salt and licking of the lamb behaviors had different levels of amplitude during the 60 s example, which differed from feeding (Fig. 1E), which had consistent and

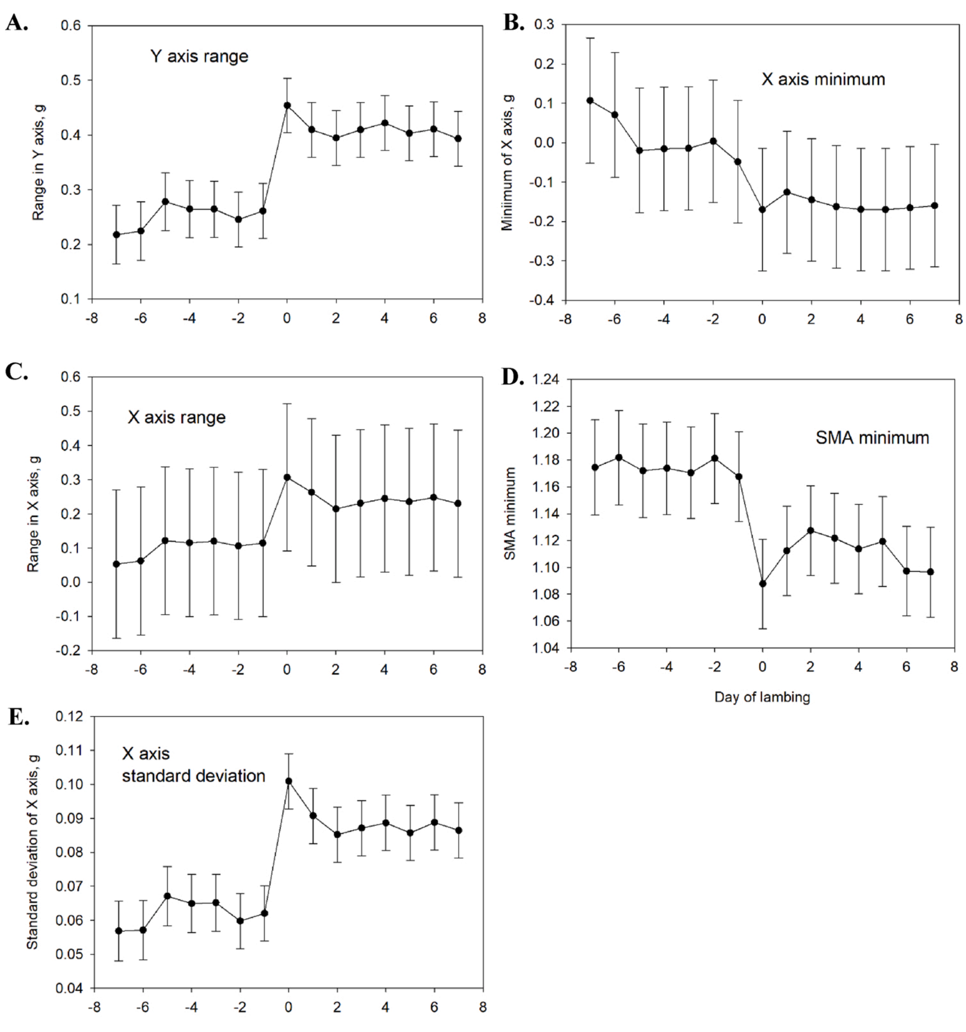


**Fig. 2.** Mean (+/- SE) of the five most important metrics: A.) Y-axis range; B.) X-axis minimum; C.) X-axis range; D.) signal magnitude area minimum; E.) X-axis standard deviation; derived directly from accelerometer over a 15 d period, with day 0 indicating the day of lambing. Data is from the six ewes that were fitted with accelerometers and observed by cameras at lambing. Error bars represent standard errors.

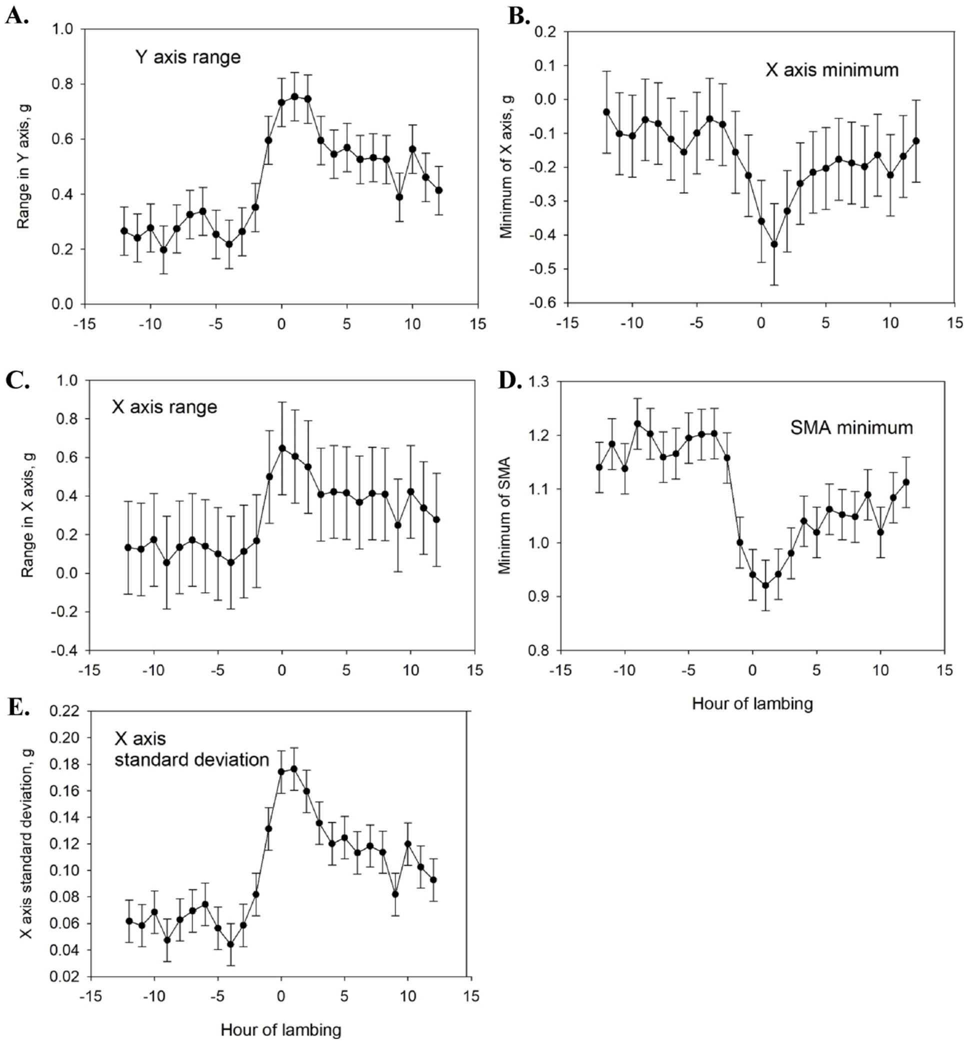


**Fig. 3.** Mean (+/- SE) of the five most important metrics: A.) Y-axis range; B.) X-axis minimum; C.) X-axis range; D.) signal magnitude area minimum; E.) X-axis standard deviation; derived directly from accelerometer attached to six ewes over a 24 h period, with hour 0 indicating the time of expulsion of the fetus. Error bars represent standard errors.

relatively large amplitude on all three axes. Acceleration signals of contractions had a unique pattern with infrequent peaks followed by low levels of activity.

### *3.4. Accelerometer metrics and predicted behavior before, during, and following parturition*

The Y-axis range varied ($P < 0.001$) among days (Fig. 2A), was higher on the day of lambing and had values higher ($P = 0.001$) after lambing than before lambing. No differences in the X-axis minimum (Fig. 2B) were detected among days ($P = 0.14$). The X-axis range varied ($P < 0.001$) among days (−7 to +7) was greatest on the day of lambing (Fig. 2C) and was greater ($P = 0.03$) after lambing than before lambing. The minimum of SMA varied ($P = 0.002$) among days, and values were lower ($P = 0.03$) after lambing than before lambing (Fig. 2D). The standard deviation of the X-axis also varied ($P < 0.001$) among days. The X-axis standard deviation was greatest on the day of lambing (day 0) (Fig. 2E), with the values following lambing being greater than before to lambing ($P = 0.001$).

The predicted percent of active behavior varied ($P < 0.001$) among days (-7 to +7), but no differences were detected before and after lambing. No differences ($P = 0.11$) for activity were detected between the day of lambing and the two days before lambing. Time spent lying varied ($P < 0.001$) among days, but no differences were detected before and after lambing ($P = 0.60$) and the day of lambing versus the two days before lambing ($P = 0.27$). No differences were detected for the time spent standing among days ($P = 0.99$). Time spent feeding varied among days ($P < 0.001$), but no differences were detected before and after lambing ($P = 0.33$) or between the day of lambing and the two days before lambing ($P = 0.17$). No differences in time spent walking were detected among days ($P = 0.11$).

The Y-axis range was greater ($P = 0.001$) after lambing than before lambing (Fig. 3A), varied during the 12 h before and after lambing ($P = 0.002$) and was also greater ($P = 0.002$) 1–2 h before lambing than 3–4 h before lambing. The X-axis minimum varied ($P < 0.001$) during the 12 h before and after lambing (Fig. 3B), was greater ($P < 0.001$) after lambing than before lambing and was higher ($P = 0.008$) 1–2 h before lambing than 3–4 h before lambing. The X-axis range varied ($P = 0.004$) during the 12 h before and after lambing (Fig. 3C), with no differences ($P = 0.12$) detected before and after lambing. However, the X-axis range was higher ($P = 0.004$) 1–2 h before lambing than 3 and 4 h before lambing. The SMA minimum varied ($P = 0.001$) during the 12 h before and after lambing (Fig. 3D), was lower ($P < 0.001$) after lambing than before lambing, and lower ($P < 0.001$) 1–2 h before than 3–4 h before lambing. The X-axis standard deviation varied ($P < 0.001$) between the 12 h preceding and following lambing (Fig. 3E), was greater ($P < 0.001$) after lambing than before lambing, and was higher 1–2 h before lambing than 3–4 h before lambing.

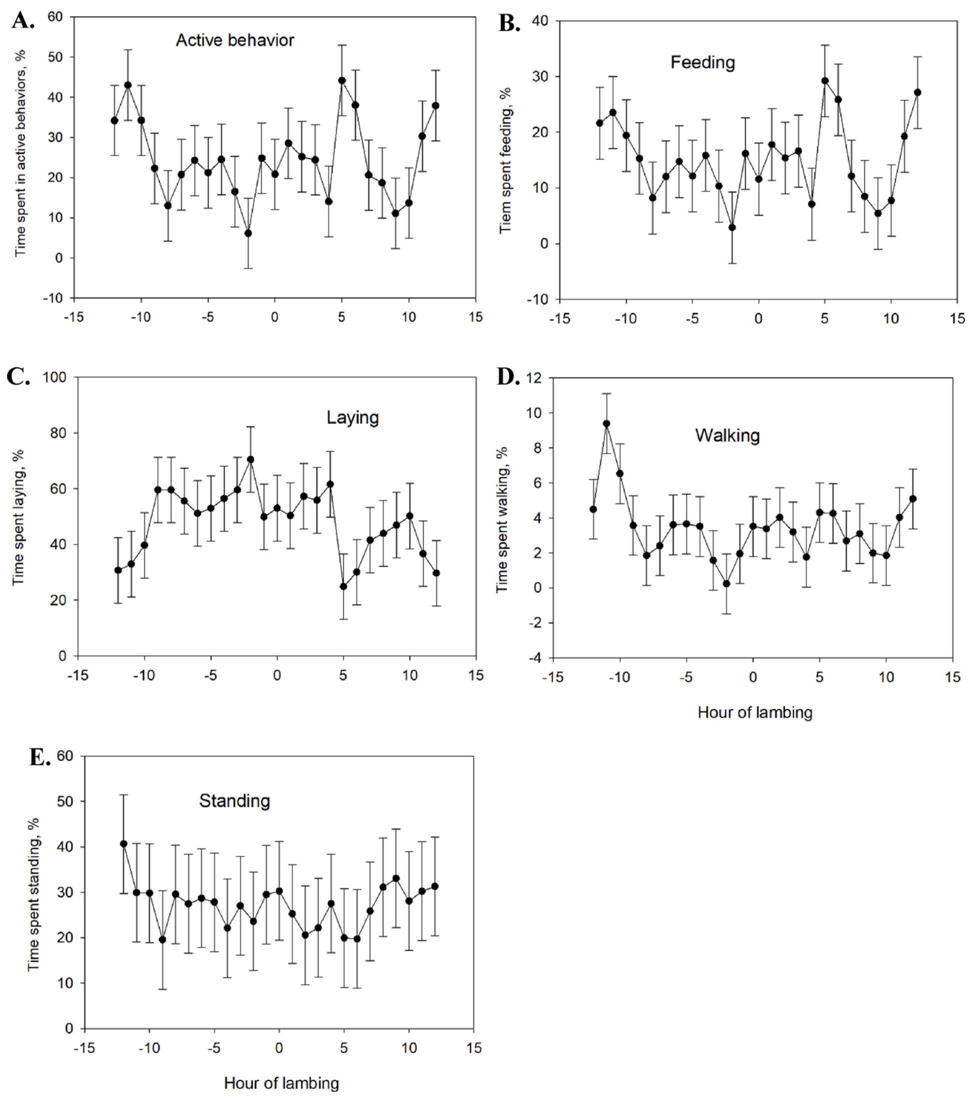


**Fig. 4.** Mean (+/- SE) proportion of time spent performing A.) active behaviors; B.) feeding; C.) lying; D.) walking; E.) standing; over a 24 h period, with hour 0 indicating the time of expulsion of the fetus.

No differences were detected ($P = 0.06$) in the percent active behavior during the 12 h preceding and following lambing (Fig. 4A). The predicted time ewes spent feeding varied ($P = 0.04$) during the 12 h before and after lambing (Fig. 4B), but no differences in predicted feeding time were detected before and after lambing ($P = 0.70$) and between 1–2 h before lambing and 3–4 h before lambing ($P = 0.55$). The predicted time ewes spent lying varied ($P = 0.05$) during the 12 h preceding and following lambing (Fig. 4C), but no differences were detected in the time spent lying before and after lambing ($P = 0.37$) or between 1–2 h before lambing compared to 3–4 h before lambing ($P = 0.82$). No differences ($P = 0.33$) were found for predicted time spent walking (Fig. 4D) and predicted time spent standing ($P = 0.26$) during the 12 h before and after lambing (Fig. 4E).

## 4. Discussion

The ability of an ear-tag positioned tri-axial accelerometer to accurately detect changes in activity associated with parturition events, was evaluated using 10 s epochs for the calculation of accelerometer metrics in this study. The 10 s epoch was selected as the most suitable due to the length and complexity of the parturition period. Recent studies have evaluated varying lengths of epochs to determine which is the most accurate for certain activities (Alvarenga et al., 2016; Walton et al., 2018; Fogarty et al., 2020c). Alvarenga et al. (2016) discovered the 3 s epoch performed poorly for predicting common behaviors. However, shorter epochs could be more useful in predicting sub-behaviors such as chewing and small movements of the head. Walton et al. (2018) compared short period lengths of 3, 5, and 7 s, ultimately selecting the 7 s epoch. These authors also reported that longer epochs would be better suited for more complex behaviors. In this current study, the behaviors with the highest percent of accuracy were feeding (75.6 %) and lying (83.6 %). Alvarenga et al. (2016) accurately predicted grazing (89.8 %), running (100.0 %), and walking (100.0 %) using a 10 s epoch. Data herein did not include running, due to the limitation of space in a pen setting. Also, predictions of walking in our study were low (33.1 %) and were often misclassified as feeding. The initial model had a relatively low overall accuracy (66.7 %) for predicting specific behaviors. An additional model was created to predict behaviors as either active or inactive, similar to those described in Cornou and Kristensen (2014) and McLennan et al. (2015). McLennan et al. (2015) classified activity scores first as six behaviors then as low, medium, and high activity. This study found that the accuracy of the medium activity was low compared to the low and high levels. Subsequently McLennan et al. (2015) categorized activity as active and inactive which improved accuracy. Similarly, classifying activity into two levels (active and inactive) rather than multiple categories increased accuracy in our study.

Previous studies have monitored sheep in a pasture setting, which could potentially challenge results from studies in a confined operation, attributable to ewes performing more behaviors such as grazing and walking on pasture (Alvarenga et al., 2016; Walton et al., 2018). Time spent walking in our study was low, due to limited amount of space in a pen setting and the requirement for a continuous bout of 60 s for behavioral annotation. Studies have monitored parturition using GNSS tracking, which lacks the capability of the accelerometer to detect subtle behavioral changes (Dobos et al., 2014; Fogarty et al., 2020b, c). Fogarty et al. (2020b) discovered GNSS tracking used independently is not adequate in detecting the onset of parturition, but were able to determine activity change on a daily scale.

Similarly, Fogarty et al. (2020b) identified parturition patterns that may be used to inform a model to predict the onset of lambing, when compared to a 'normal' baseline pattern. Our results demonstrate an increase in activity 2 h prior to lambing, which may be due to restlessness of the ewe and onset of abdominal straining. Results reported by (Fogarty et al., 2020a) are similar, as restlessness peaked between h −1 to h + 2. Huzzey et al. (2005) found an 80 % increase in number of standing bouts during parturition, in relation to restless and discomfort due to calving. Pre-partum ewes frequently change position, begin pawing the ground, and increase activity through abdominal straining associated with active contractions (Owens et al., 1985). Immediately following the expulsion of the fetus, the dam begins to groom the lamb, which may be why the dam maintains high activity slightly after parturition. Contrary to our results, others have reported a decrease in sow activity at the hour when farrowing begins, and peak of activity is observed at h −9, before farrowing (Bohnenkamp et al., 2013; Cornou and Kristensen, 2014).

Fogarty et al. (2020a) successfully used changes in predicted behaviors from accelerometer readings to estimate the time of lambing. In our study, metrics calculated directly from the accelerometer such as the range in the X-axis change were more related to the time of lambing than predicted behaviors. Calculations made directly from the sensor reduces the amount of computation, which may be helpful in a future algorithm for potential real time data output and analysis. In this current study, accelerometer signals varied among ewes which was accounted for in the subject term of the repeated measures, but was not accounted for by predicted behaviors derived from random forest modelling. The accelerometer signals deviated from normal patterns about 2 h before lambing. Such deviations could be identified using simple algorithms. Tobin et al. (2020) demonstrated the potential for using a 4-day moving average to detect changes in normal behavioral patterns that occur on the onset of bovine ephemeral fever in beef heifers. This approach allowed comparisons of an individual animal against its previous behaviors rather than against means calculated from the herd.

To be useful for managers in detecting lambing, accelerometers on ear tags should provide data or data summaries in real time or near real time (Bailey et al., 2018). To facilitate data transfer from the tag to a reader or the internet, the data will likely need to be summarized to minimize battery usage for transmissions. Data processing and summarization is a new field termed as edge computing (Habib ur Rehman et al., 2016; Habib ur Rehman et al., 2017). The results from this study suggest that future research projects should consider edge computing when developing sensor technologies to remotely monitor livestock welfare issues such as lambing.

## 5. Conclusion

Our study has demonstrated the ability of the tri-axial accelerometer to detect changes in individual animal activity related to parturition events on both an hourly and daily scale. The initial model developed had difficulty discriminating specific behaviors. However, using active and inactive behaviors only increased model accuracy. Metrics calculated directly from accelerometer axes provided a better indication of lambing than predicted behaviors processed through complex machine learning algorithms. Our results suggest that real time accelerometers could remotely monitor pregnant ewes and potentially be used in a commercial setting, providing managers with an indication that the dam may lamb soon.

## Declaration of Competing Interest

The authors report no declarations of interest.

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