Research Note

EVALUATION OF A COMMERCIAL ACCELEROMETER FOR REMOTE MONITORING OF LYING AND STANDING EVENTS IN DAIRY CALVES IN PUERTO RICO[1,2]

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Behavior monitoring provides important information about the impact of environment (Bonk et al., 2013), food (DeVries et al., 2003; González et al., 2008; Nielsen, 2013; Rayas-Amor et al., 2017) and water intake (Lukas et al., 2008; McDonald et al., 2019), welfare (Müller and Schrader, 2003), health (González et al., 2008; Lukas et al., 2008) and comfort status (Lomb et al., 2018) on dairy cattle. Thus, two methods have been commonly used to evaluate animal behavior for scientific research: direct visual observations and video footage analysis (Nielsen et al., 2010). However, both monitoring systems are time consuming (Ledgerwood et al., 2010; Bonk et al., 2013; Nielsen, 2013) and labor consuming (Ito et al., 2009; Ledgerwood et al., 2010), which limits considerably their feasibility. For these reasons livestock research has incorporated automated tools, such as data loggers, to remotely monitor animal behavior (Ledgerwood et al., 2010; Bonk et al., 2013).

Even though multiple studies have confirmed the effectiveness of using data loggers as indicators for lying events in mature dairy cows (Ito et al., 2009; Ledgerwood et al., 2010; Swartz et al., 2016), to our knowledge there is only one study (Bonk et al., 2013) that has validated these sensors for the study of lying activity in Holstein calves. However, the Bonk et al. (2013) study was performed in Germany, a country with very different environmental conditions than Puerto Rico (temperate vs. tropical weather, respectively). Thus, although their data loggers' validation may be highly useful as a guide when evaluating similar behavior in other countries, their results may not be directly extrapolated to Puerto Rico's environmental conditions.

Since Puerto Rico is located in the tropical region, the chronic nature of its high relative humidity and environmental temperature (Daly et al., 2003; PRCCC, 2013) can lead to heat stress in dairy cattle (West, 2003; Chen et al., 2013). This problem is exacerbated because Holstein cattle, the most common dairy breed on the island (Cortés et al., 2010), are highly adapted to temperate climates (Javed et al., 2004). This is important because heat stress has been reported to significantly affect cattle behavior, including their lying and standing patterns (Schütz et al., 2010; Chen et al., 2013; Polsky and von Keyser-

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lingk, 2017). Given that the results reported by Bonk et al. (2013) may not be representative for animals raised under tropical conditions, this study aimed to evaluate the use of the aforementioned data loggers (i.e., accelerometers) for the remote monitoring and study of lying and standing behavior in Puerto Rican dairy calves.

Five pre-weaned Puerto Rican Holstein heifers (53±20-day-old) from the Agricultural Experiment Station dairy herd at Lajas (Puerto Rico) were evaluated. Calves were individually housed (from birth) in pens with wire mesh floors and galvanized steel side panels located in the calves' barn at the dairy facilities. Ad libitum access to starter feed and water was provided during the study. During data collection each calf was fed approximately three liters of milk at around 0800 h, as part of the normal farm management practices. Each calf pen was 122 cm long and 46 cm wide.

A HOBO pendant G accelerometer (which records the g- force on the x-, y- and z-axis; Onset Computer Corporation, Bourne, MA)[6] was tied to the right hind leg of each calf, making sure that its y-axis was perpendicular to the ground when the calves were standing (Figure 1). Using two plastic cable ties (20.32 cm in length; Commercial Electric, Thailand), these sensors were attached to a previously perforated 3.81 x 30.48 cm flagger leg band (Nasco, Fort Atkinson, WI). To avoid any friction that the sensor may cause on the leg skin, a Vet Wrap bandage (Co-Flex, Andover Healthcare, Salisbury, MA) was placed three times around the sensor and leg band. The data loggers were programmed to collect g- force values on the y-axis at one-second intervals from 0700 to 0836 h in one day. Data loggers were installed on the calves' legs at 0600 h with no sign of associated distress being observed. One technician per calf was assigned to visually collect the specific time periods the calves were lying or standing during sampling. These visually collected lying and standing events were used as the gold standards (or standards for comparison) for the evaluation of the data loggers' recordings as possible indicators of these behaviors.

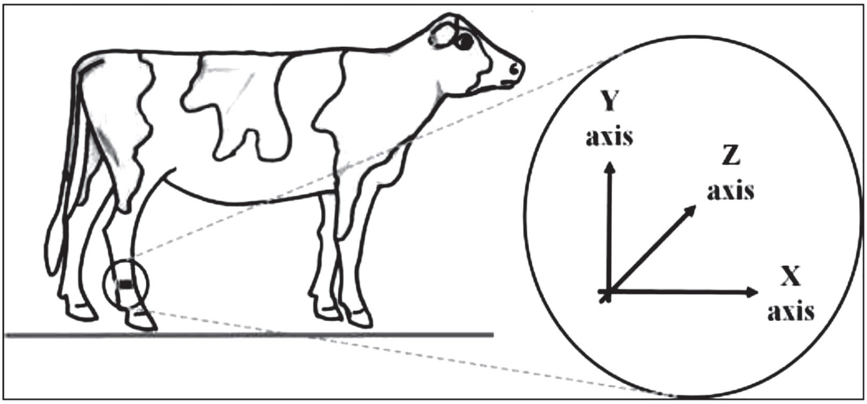

FIGURE 1. Image illustrating the placement of the HOBO Pendant G data logger on the calf's leg. Note that the data logger was placed so the y-axis points towards the calf's thurl, perpendicular to the floor surface.

[6]Company or trade names in this publication are used only to provide specific information. Mention of a company or trade name does not constitute an endorsement by the Agricultural Experiment Station of the University of Puerto Rico, nor is this mention a statement of preference over other equipment or materials.

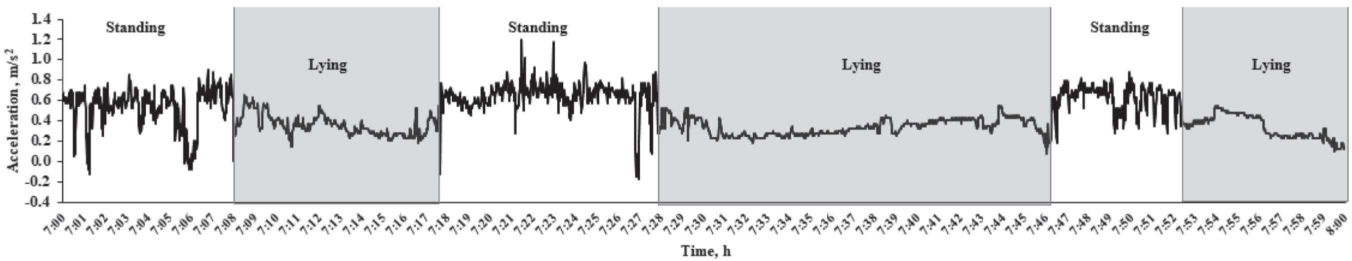

FIGURE 2. Illustration of the y-axis acceleration values recorded from 0700 to 0800 h by the HOBO Pendant G data logger on calf # 2231. The white spaces represent the time spent standing by the calf, while the gray boxes identify the time spent lying.

In order to classify the y-axis acceleration values recorded by the HOBO Pendant G accelerometers as lying or standing events, the overall mean and standard deviation values during the respective visually recorded events were calculated. The transitional movements between the lying and standing events were excluded from the data set. Using the obtained mean and standard deviation for each visually recorded behavior (i.e., lying and standing), a series of respective accelerometer categories were created, including the acceleration values ranging between 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations below and above the mean (Table 1). Using the IF-THEN statement in SAS, a dataset containing columns with all the created categories was made. The FREQ procedure in SAS was used to determine the probability that a visually recorded event was successfully classified by the data logger categories (sensitivity; Bonk et al., 2013), as well as the visual-accelerometer misclassifications and observations not receiving a classification in each category. The visual-accelerometer misclassifications included situations where a visually recorded lying event was classified as standing by the created category (lying-standing misclassification) or when a visually recorded standing event was classified as lying (standing-lying misclassification). Data outside the created ranges failed to be categorized and are referred to as non-classified data. Four more data sets were created for evaluating larger sampling intervals, including 30 seconds, as well as one, two, and five minutes. The IF-THEN statement of SAS was used to temporarily eliminate the undesired data in each new sampling interval.

Tables 2 to 6 present the sensitivities, misclassifications and non-classified values in each evaluated category and sampling interval. At the one-second sampling interval, all evaluated categories presented sensitivity values exceeding 99% (Table 2). However, the smaller the created classification category, the larger the amount of missed data due to non-classified values (from 0.46 to 55% of non-classified values in the 2.6 to 0.4 standard deviation categories, respectively). Thus, the categories that better classified the calves' behavior when sampling every second were 2, 2.2, 2.4, and 2.6 standard deviations below and above the mean. There, the lying and standing events were successfully

TABLE 1.—*Lying and standing categories with their y-axis acceleration values.*

Created Category[1] (Standard Deviations)	Lying		Standing	
	Minimum	Maximum	Minimum	Maximum
0.4	0.06741912	0.17132488	-1.05276992	-0.94686968
0.6	0.04144268	0.19730132	-1.07924498	-0.92039462
0.8	0.01546624	0.22327776	-1.10572004	-0.89391956
1	-0.01051020	0.24925420	-1.13219510	-0.86744450
1.2	-0.03648664	0.27523064	-1.15867016	0.84096944
1.4	-0.06246308	0.30120708	-1.18514522	-0.81449438
1.6	-0.08843952	0.32718352	-1.21162028	-0.78801932
1.8	-0.11441596	0.35315996	-1.23809534	-0.76154426
2	-0.14039240	0.37913640	-1.26457040	-0.73506920
2.2	-0.16636884	-0.40511284	-1.29104546	-0.70859414
2.4	-0.19234528	0.43108928	-1.31752052	-0.68211908
2.6	-0.21832172	0.45706572	-1.34399558	-0.65564402

[1]The overall acceleration mean and standard deviations for the standing (-0.2338588±0.0831065) and lying (0.1820495±0.2282673) events were calculated and used to create a series of respective classification categories ranging between 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations below and above the mean.

TABLE 2.—*Probability that a visually recorded event was successfully classified by the data logger categories (sensitivity) of a commercial data logger as an indicator of lying and standing activity in five pre-weaned Holstein heifers. Data were recorded at 1-second intervals from 0700 to 0836 h (N=23,408) during one morning.*[1]

	Visual Observations: Lying	*Visual Observations:* Standing	*Visual Observations:* Lying	*Visual Observations:* Standing	
Y-Axis[2]	*Data Logger:* Lying %	*Data Logger:* Standing %	*Data Logger:* Standing %	*Data Logger:* Lying %	Frequency Missing
± 0.4 SD	99.95	100.00	0	0.05	12866
± 0.6 SD	99.92	100.00	0	0.08	9636
± 0.8 SD	99.92	100.00	0	0.08	7849
± 1 SD	99.90	100.00	0	0.10	6735
± 1.2 SD	99.92	100.00	0	0.08	3468
± 1.4 SD	99.91	99.99	0.01	0.09	2202
± 1.6 SD	99.91	99.99	0.01	0.09	892
± 1.8 SD	99.90	99.98	0.02	0.10	705
± 2 SD	99.89	99.98	0.02	0.11	287
± 2.2 SD	99.88	99.97	0.03	0.12	139
± 2.4 SD	99.86	99.97	0.03	0.14	122
± 2.6 SD	99.85	99.97	0.03	0.15	109

[1]Only data with a definite visually recorded behavior (lying or standing) were used for the statistical analysis.
[2]The data logger categories were created in the ranges of 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations (SD) below and above the mean.

classified by the data loggers close to 100% of the time, while missing less than 1.24% of the dataset due to non-classifications. However, sampling at 1-second intervals will only allow for six hours of data collection due to the memory limitations of the sensors. As a result, multiple researchers have used larger intervals to study similar behaviors in cattle (Ledgerwood et al., 2010). Thus, the evaluation of greater sampling intervals is required. Sampling times of 30 seconds, one, two, and five minutes allow for data storage capacities of 7.5, 15.1, 30.1, and 75.3 days, respectively.

For the 30-second measuring interval, all categories reported sensitivity values above 99% (Table 3). Nevertheless, the smaller the data logger classification category, the larger the amount of missed data as a result of non-classified values (from 0.38 to 54% of non-classified values for the 2.6 to 0.4 standard deviations below and above the mean categories, respectively). For this reason, the categories that best represented the lying and standing events were also those using 2, 2.2, 2.4 and 2.6 standard deviations below and above the mean. In such categories the data loggers successfully identified the lying and standing events close to 100% of the time, while the misclassified values represented less than 1.15% of the dataset.

In the one-minute sampling interval all the lying and standing events were accurately identified (sensitivities of 100%) for all the evaluated categories (Table 4). Therefore, the determination of the most efficient classifications was focused on the amount of missing data due to non-classified values. Such categories were also the 2, 2.2, 2.4 and 2.6 standard deviations below and above the mean, which only presented less than 1.54% of non-classified data.

As previously mentioned, increasing the sampling interval to two or five minutes will allow for considerably greater sampling periods. However, as stated in Table 5, when data was collected every two minutes, a considerable decrease in the sensitivity of the evaluated classification categories was observed, only ranging between 70 to 91%. Even in the 2, 2.2, 2.4, and 2.6 standard deviations classifications, where only less than 2.6% of the data was lost due to non-classified values, the observed sensitivity ranged between 74 and 87%.

Similar to the sampling interval of two minutes (Table 5), the collection of data every five minutes (Table 6) resulted in a decline in the sensitivity of the evaluated classifications, when compared to the sampling intervals of one second (Table 2), 30 seconds (Table 3), and one minute (Table 4). In the five-minute sampling interval (Table 6), even when the sensitivity of classifying the lying events reached 100% in the 0.4, 0.6, and 0.8 standard deviations below and above the mean categories, the respective misclassifications ranged between 12 and 18%. Moreover, when using such categories, 37 to 55% of the data was lost due to non-classified values. Even in the categories from 1.6 to 2.6 standard deviations below and above the mean, where only less than 2.7% of the data was lost due to non-classifications, the obtained sensitivities only ranged between 84.38 and 93.48%.

The evaluated sensors were able to accurately identify the calves' lying and standing events when the sampling interval was maintained below or equal to one minute (Tables 2, 3, and 4). These findings are in agreement with the lying activity studies carried out by Bonk et al. (2013) in dairy calves, as well as Ito et al. (2009) and Ledgerwood et al. (2010) in dairy cows. Rayas-Amor et al. (2017) reported a similar trend when evaluating grazing activity with the same data loggers in dairy cows. Moreover, even when all the evaluated sampling intervals below or equal to one minute showed sensitivities exceeding 99% (Tables 2, 3, and 4), only the one-minute interval showed sensitivity values of 100%, suggesting this is the most accurate sampling interval. These results are similar to those reported by Bonk et al. (2013), Ito et al. (2009), and Ledgerwood et al. (2010). However, it is important to consider that going from a sampling interval of 30 seconds

TABLE 3.—*Probability that a visually recorded event was successfully classified by the data logger categories (sensitivity) of a commercial data logger as an indicator of lying and standing activity in five pre-weaned Holstein heifers. Data were recorded at 30-second intervals from 0700 to 0836 h (N=780) during one morning.*[1]

	Visual Observations: Lying	*Visual Observations:* Standing	*Visual Observations:* Lying	*Visual Observations:* Standing	
Y-Axis[2]	*Data Logger:* Lying %	*Data Logger:* Standing %	*Data Logger:* Standing%	*Data Logger:* Lying%	Frequency Missing
± 0.4 SD	99.34	100.00	0.00	0.66	425
± 0.6 SD	99.50	100.00	0.00	0.50	321
± 0.8 SD	99.52	100.00	0.00	0.48	264
± 1 SD	99.57	100.00	0.00	0.43	221
± 1.2 SD	99.70	100.00	0.00	0.30	112
± 1.4 SD	99.73	100.00	0.00	0.27	69
± 1.6 SD	99.76	100.00	0.00	0.24	24
± 1.8 SD	99.76	99.70	0.30	0.24	19
± 2 SD	99.77	99.70	0.30	0.23	9
± 2.2 SD	99.77	99.71	0.29	0.23	4
± 2.4 SD	99.77	99.71	0.29	0.23	3
± 2.6 SD	99.77	99.71	0.29	0.23	3

[1]Only data with a definite visually recorded behavior (lying or standing) were used for the statistical analysis. [2]The data logger categories were created in the ranges of 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations (SD) below and above the mean.

TABLE 4.—*Probability that a visually recorded event was successfully classified by the data logger categories (sensitivity) of a commercial data logger as an indicator of lying and standing activity in five pre-weaned Holstein heifers. Data were recorded at 60-second intervals from 0700 to 0836 h (N=390) during one morning.*[1]

	Visual Observations: Lying	*Visual Observations:* Standing	*Visual Observations:* Lying	*Visual Observations:* Standing	
Y-Axis[2]	*Data Logger:* Lying%	*Data Logger:* Standing%	*Data Logger:* Standing%	*Data Logger:* Lying%	Frequency Missing
± 0.4 SD	100.00	100.00	0.00	0.00	211
± 0.6 SD	100.00	100.00	0.00	0.00	158
± 0.8 SD	100.00	100.00	0.00	0.00	133
± 1 SD	100.00	100.00	0.00	0.00	112
± 1.2 SD	100.00	100.00	0.00	0.00	55
± 1.4 SD	100.00	100.00	0.00	0.00	34
± 1.6 SD	100.00	100.00	0.00	0.00	14
± 1.8 SD	100.00	100.00	0.00	0.00	12
± 2 SD	100.00	100.00	0.00	0.00	6
± 2.2 SD	100.00	100.00	0.00	0.00	3
± 2.4 SD	100.00	100.00	0.00	0.00	2
± 2.6 SD	100.00	100.00	0.00	0.00	2

[1]Only data with a definite visually recorded behavior (lying or standing) were used for the statistical analysis. [2]The data logger categories were created in the ranges of 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations (SD) below and above the mean.

TABLE 5.—*Probability that a visually recorded event was successfully classified by the data logger categories (sensitivity) of a commercial data logger as an indicator of lying and standing activity in five pre-weaned Holstein heifers. Data were recorded at 2-minute intervals from 0700 to 0836 h (N=195) during one morning.*[1]

	Visual Observations: Lying	*Visual Observations:* Standing	*Visual Observations:* Lying	*Visual Observations:* Standing	
Y-Axis[2]	*Data Logger:* Lying%	*Data Logger:* Standing%	*Data Logger:* Standing%	*Data Logger:* Lying%	Frequency Missing
± 0.4 SD	90.70	70.00	30.00	9.30	102
± 0.6 SD	89.09	72.58	27.42	10.91	78
± 0.8 SD	89.47	75.36	24.64	10.53	69
± 1 SD	88.89	76.39	23.61	11.11	60
± 1.2 SD	86.52	76.71	23.29	13.48	33
± 1.4 SD	86.73	75.00	25.00	13.27	21
± 1.6 SD	86.11	75.00	25.00	13.89	11
± 1.8 SD	86.24	75.00	25.00	13.76	10
± 2 SD	86.73	74.03	25.97	13.27	5
± 2.2 SD	86.84	74.03	25.97	13.16	4
± 2.4 SD	86.84	74.03	25.97	13.16	4
± 2.6 SD	86.09	74.03	25.97	13.91	3

[1]Only data with a definite visually recorded behavior (lying or standing) were used for the statistical analysis. [2]The data logger categories were created in the ranges of 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations (SD) below and above the mean.

TABLE 6.—*Probability that a visually recorded event was successfully classified by the data logger categories (sensitivity) of a commercial data logger as an indicator of lying and standing activity in five pre-weaned Holstein heifers. Data were recorded at 5-minute intervals from 0700 to 0836 h (N=78) during one morning.*[1]

	Visual Observations: Lying	*Visual Observations:* Standing	*Visual Observations:* Lying	*Visual Observations:* Standing	
Y-Axis[2]	*Data Logger:* Lying%	*Data Logger:* Standing%	*Data Logger:* Standing%	*Data Logger:* Lying%	Frequency Missing
± 0.4 SD	100.00	85.00	15.00	0.00	43
± 0.6 SD	100.00	88.00	12.00	0.00	33
± 0.8 SD	100.00	82.14	17.86	0.00	29
± 1 SD	95.83	83.87	16.13	4.17	23
± 1.2 SD	94.12	84.38	15.63	5.88	12
± 1.4 SD	92.50	84.38	15.63	7.50	6
± 1.6 SD	93.18	84.38	15.63	6.82	2
± 1.8 SD	93.18	84.38	15.63	6.82	2
± 2 SD	93.48	84.38	15.63	6.52	0
± 2.2 SD	93.48	84.38	15.63	6.52	0
± 2.4 SD	93.48	84.38	15.63	6.52	0
± 2.6 SD	93.48	84.38	15.63	6.52	0

[1]Only data with a definite visually recorded behavior (lying or standing) were used for the statistical analysis. [2]The data logger categories were created in the ranges of 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, 2, 2.2, 2.4 or 2.6 standard deviations (SD) below and above the mean.

to 60 seconds (Tables 3 and 4) will result in the loss of a considerable amount of behavior recordings (including misclassified data), subsequently giving a false idea of greater sensitivity. Similarly, the limitation of the sampling intervals of two and five minutes, which obtained considerably lower sensitivity values (Tables 5 and 6), may be the loss of important behavior data due to the increased sampling interval. In fact, Ito et al. (2009) suggested that the greater the data collection frequency (smaller sampling interval), the greater the accuracy in behavior identification.

The present study validated the use of accelerometers as viable tools for the assessment of lying and standing behavior in dairy calves raised in the tropics (Puerto Rico). The evaluated sensors were able to successfully identify the lying and standing events when the sampling interval was maintained ≤ one minute, and the classification category included the acceleration values between 2 to 2.6 standard deviations below and above the mean. Inside these values, the ideal sampling interval will depend on the required duration of the study, since more frequent sampling implies a shorter memory life of the sensor. Future studies should be directed towards evaluating the feasibility of these sensors as indicators of other behaviors in cattle raised in the tropics.

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