

Validation of mercury tip-switch and accelerometer activity sensors for identifying resting and active behavior in bears

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Abstract: Activity sensors are often included in wildlife transmitters and can provide information on the behavior and activity patterns of animals remotely. However, interpreting activity-sensor data relative to animal behavior can be difficult if animals cannot be continuously observed. In this study, we examined the performance of a mercury tip-switch and a tri-axial accelerometer housed in collars to determine whether sensor data can be accurately classified as resting and active behaviors and whether data are comparable for the 2 sensor types. Five captive bears (3 polar [*Ursus maritimus*] and 2 brown [*U. arctos horribilis*]) were fitted with a collar specially designed to internally house the sensors. The bears' behaviors were recorded, classified, and then compared with sensor readings. A separate tri-axial accelerometer that sampled continuously at a higher frequency and provided raw acceleration values from 3 axes was also mounted on the collar to compare with the lower resolution sensors. Both accelerometers more accurately identified resting and active behaviors at time intervals ranging from 1 minute to 1 hour ($\geq 91.1\%$ accuracy) compared with the mercury tip-switch (range = 75.5–86.3%). However, mercury tip-switch accuracy improved when sampled at longer intervals (e.g., 30–60 min). Data from the lower resolution accelerometer, but not the mercury tip-switch, accurately predicted the percentage of time spent resting during an hour. Although the number of bears available for this study was small, our results suggest that these activity sensors can remotely identify resting versus active behaviors across most time intervals. We recommend that investigators consider both study objectives and the variation in accuracy of classifying resting and active behaviors reported here when determining sampling interval.

Key words: activity sensors, biotelemetry, brown bear, collars, polar bear, satellite transmitters, *Ursus arctos horribilis*, *Ursus maritimus*

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Biotelemetry, the remote monitoring of physiological and behavioral variables, provides insight into the ecology and behavior of wildlife species (Cooke et al. 2004) by reducing the potential disturbance associated with direct observation and increasing the capacity to infer behavior of species that are difficult to observe. Activity sensors are useful tools for

remotely monitoring levels of activity (Garshelis and Pelton 1980, Georgii 1981, Smith 1986, Larivière et al. 1994, Kaczensky et al. 2006) and have the potential to reveal animal behaviors ranging from general categories of “active” (e.g., walking, running, feeding) to “inactive” (Moen et al. 1996, Coulombe et al. 2006, Gervasi et al. 2006, Yamazaki et al. 2008, Gottardi et al. 2010) to more specific discriminations such as walking, diving, drinking, hunting, and foraging or

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grazing (Green and Bear 1990, Watanabe et al. 2005; Shepard et al. 2008, Löttker et al. 2009, Wilson et al. 2013). Insights into behavior provided by activity data have been used to assess the energy expenditure of animals (Halsey et al. 2009, Gleiss et al. 2011, Elliott et al. 2013, Shepard et al. 2013). Remotely monitoring ursid activity can provide an indication of the potential impact of seasonal changes, food availability, and conspecific or human interactions on bear behavior (Garshelis and Pelton 1980, Larivière et al. 1994, MacHutchon et al. 1998, Munro et al. 2006, Schwartz et al. 2010).

Although activity sensors have been deployed on bears for decades, these data have been underutilized because of the difficulty of validating sensor readings with the behavior of free-ranging bears. Activity data were historically collected by mercury tip-switch sensors in which head movement of a bear is recorded uni-directionally (one axis) in binary mode (Messier et al. 1992). Accelerometers capable of dual- or tri-axial motion detection have largely replaced mercury tip-switches. Dual-axis accelerometers typically measure movement in horizontal axes, whereas tri-axial accelerometers add an additional vertical axis for 360° motion sensing. Activity sensor data have typically been collected and recorded at time intervals of 30–60 minutes to accommodate limitations of on-board storage or to accommodate transmission limitations when using satellites. Two- or 3-axis accelerometers that store raw data are now available and can collect data at much higher frequencies than could previous activity sensors. However, the large volume of raw acceleration data generated by modern accelerometers can typically only be stored on-board, with limited data transmitted via satellite; this requires recapture of the bear in many cases to retrieve all of the data.

Here, we evaluate whether 2 commonly deployed sensors—the mercury tip-switch (Garshelis et al. 1982, Gillingham and Bunnell 1985, Messier et al. 1992, Te Wong et al. 2004, Ratnayeke et al. 2007, Schwartz et al. 2010) and accelerometer (Fischbach et al. 2007, Durner et al. 2009, Fortin et al. 2013), both of which provide a single measure of activity—can be used to discriminate resting (i.e., laying, sitting, or standing) from active behaviors (e.g., walking, running, swimming, feeding) in brown (*Ursus arctos horribilis*) and polar bears (*U. maritimus*). This binomial classification could be used to understand how the activity patterns of bears are affected by food shortages or human activities. Both of these

sensor types have been deployed on several species of ursids and in many populations. We also investigated whether a standardization procedure could be developed that would allow the 2 types of sensor data to be combined in a single data set. Historically, many investigators deployed mercury tip-switch sensor collars on bears before transitioning to collars containing accelerometers (Costello et al. 2013). The ability to use data from both sensor types in a single analysis would improve opportunities to investigate long-term behavioral patterns. In the current study, we also compared the performance of the 2 lower resolution sensors to a newer tri-axial accelerometer attached externally to collars, which is capable of collecting raw acceleration data in all 3 axes at a higher sampling frequency. Lastly, we evaluated the effect of temporal sampling interval on the accuracy of predicting resting and active behavior to provide recommendations of the optimal sampling frequency for future investigations.

Methods

Collar and sensor deployments on captive bears

One adult female polar bear housed at the Oregon Zoo (Portland, Oregon, USA), 1 adult female polar bear housed at the San Diego Zoo (San Diego, California, USA), 1 adult female and 1 adult male polar bear housed at the Alaska Zoo (Anchorage, Alaska, USA), and 2 adult female brown bears housed at the Washington State University Bear Research, Education, and Conservation Center (Pullman, Washington, USA) were used for this study. Although we sought a larger sample size, in almost all cases collaring of captive bears requires sedation, which is rarely conducted for bears in zoos. We took advantage of the 2 locations (i.e., the Oregon and San Diego Zoos) where captive female polar bears had been trained to be fitted with a collar without sedation. It is common for only adult female bears to be collared in the wild because male morphology prevents the collar from being securely fitted (Amstrup et al. 2001); thus, we also focused on adult female bears in this study. All procedures were approved by the Washington State University, Oregon Zoo, Alaska Zoo, San Diego Zoo, and U.S. Geological Survey Alaska Science Center's Institutional Animal Care and Use Committees and Research Review Committees. Research was permitted under U.S. Fish and Wildlife Service permits

TE047283-0 and MA95406A-0. At Washington State University, bears were housed in pairs in dens (3 m × 3 m × 2.5 m) with access to an outdoor pen (3 m × 5 m × 5 m) and a 0.81-ha outdoor enclosure. The polar bears housed at the Oregon, Alaska, and San Diego Zoos were given access to their normal exhibit enclosures. All bears were exposed to ambient light and temperature cycles during the trial.

The polar bears at the Oregon and San Diego Zoos received positive reinforcement training to voluntarily accept application and removal of the collar without sedation. We anesthetized the 2 brown bears and Alaska Zoo polar bears with 2.5–3.0 mg/kg of tiletamine HCl and zolazepam HCl (Telazol®; Pfizer Animal Health, New York, New York, USA) and 0.006–0.007 mg/kg of dexmedetomidine HCl (Dexdomitor®; Pfizer Animal Health; Teisberg et al. 2014). Following collar placement, we administered 10 mg of atipamezol HCl (Antisedan®; Pfizer Animal Health)/mg of dexmedetomidine intravenously as a reversal agent. We used pre-programmed CO₂ collar-release mechanisms (Lotek Wireless, Inc., Newmarket, Ontario, Canada) to non-invasively detach the collar from the bears.

All bears were fitted with a collar (Telonics, Inc., Mesa, AZ) specifically designed for this study. The collar was identical in shape, weight, and material construction to the Telonics brand collars routinely used in bear species tracking since the 1980s. Each collar included a mercury tip-switch sensor positioned at +7° relative to the horizontal plane in a head-to-tail orientation (included on Gen-III collars from Telonics Inc.), and a tri-axial accelerometer (included on Gen-IV collars from Telonics, Inc.). The mercury tip-switch was triggered by head movement up or down from +7°, whereas the accelerometer was triggered by changes in acceleration and tilt relative to gravity that exceeded the manufacturer's set threshold (about 0.3 g, or 2.87 m/s²). The accelerometer recorded data from all 3 axes every second (1 Hz) and internally summed those values into 1-minute intervals before outputting the data as a single activity value per minute. To mirror the format of historically collected mercury tip-switch data in some ursid studies, raw 1-minute episodes were also summed into 1-hour periods that were assigned to the following bins: 0 = ≤179 active moments, 1 = >179 and ≤359, 2 = >359 and ≤539, 3 = >539 and ≤899, 4 = >899 and ≤1,439, 5 = >1,439 and ≤2,159, 6 = >2,159 and ≤2,879, 7 = >2,879. We also deployed an externally mounted tri-axial accelerometer (hereafter, referred to

as the “3d accelerometer”; Wildlife Computers, Inc., Redmond, Washington, USA) with higher resolution to compare with the mercury tip-switch and internally mounted accelerometer. The 3d accelerometer recorded data continuously at 16 Hz (range ±2 g) for each axis. Raw acceleration data from each axis were smoothed using a 2-second running mean that provided an estimate of static acceleration (acceleration resulting from body angle with respect to gravity). Static acceleration was subtracted from the unsmoothed raw acceleration data to provide dynamic acceleration using SAS version 9.3 (SAS Institute Inc., Cary, North Carolina, USA; Wilson et al. 2006).

We recorded bear behavior (via OpenEye Digital Video Security Solutions, Spokane, Washington, USA; or camcorder Sony model DCR-TRV280, Sony Corp., Tokyo, Japan) to allow classification of resting and active behaviors. Resting included laying, sitting, and standing; we considered all other behaviors “active” (Table 1). A “mixed” category occurred when a bear exhibited both a resting and active behavior within the same minute. These minutes were excluded from the analysis. We documented behaviors for each minute for comparison with the mercury tip-switch and lower resolution accelerometer (i.e., single activity value summed across axes every minute) and each second for the higher resolution accelerometer (i.e., data from each of 3 axes/sec). When a bear performed multiple behaviors within a single minute, we recorded all the behaviors that we observed during that minute. We excluded from analysis all behaviors that were not indicative of natural movements (e.g., stereotypic behaviors, behavior during recovery from anesthesia) or were rare (e.g., digging, fighting, rolling).

Statistical analysis

For the mercury tip-switch and internally housed low-resolution accelerometer, we used a binary logistic regression to examine the accuracy with which cut-offs in sensor readings could be identified that corresponded with resting and active behavior. Because sensor data are often collected from wild bears at various time-intervals, we examined these cut-offs at a range of time scales: 1, 5, 10, 15, 30, and 60 minutes. At 1-minute intervals we used minutes in which bears exhibited either 100% resting or 100% active behaviors. At >1-minute intervals, we examined the accuracy of cut-offs where “resting” was defined as a bear having spent 80% or 100% of the time interval resting. We also examined the effect of head movement (e.g., if a bear moves its head while

Table 1. Description of behavioral categories identified to evaluate the performance of a mercury tip-switch and a tri-axial accelerometer deployed in collars on 2 captive brown bears and 3 captive polar bears. Each behavior type was classified as either a “resting” or “active” behavior for analysis in a binary logistic regression.

Behavior	Resting or active classification	Description
Laying	Resting	Prone or supine resting position, head could be up or down.
Sitting	Resting	Rump down on ground, with or without head movement.
Standing	Resting	Upright quadruped position, with or without head movement.
Eating	Active	Consumption of food during non-grazing periods; could be standing, sitting, or laying while eating.
Grazing	Active	Consumption of foraged plants, could be standing or laying while grazing.
Swimming	Active	Paddling and moving while submerged in water. Floating was excluded. Only observable for the polar bears in this study.
Walking	Active	Movement across any distances, forward or backward.
Head movement	Resting	Up-down or side-to-side movement of the head while engaged in any of the resting behaviors. Head movement was not coded in the active behaviors because it is inherent to those behaviors.

resting, can we still identify that bear as resting?) on our ability to accurately identify resting and active behavior by individually including them in a forward, conditional binary logistic regression and comparing pseudo- R^2 values, P -values of individual effects based on likelihood-ratio, and accuracy of categorizations with and without this single variable in the model. We also included repeated measures of the individual bears as individual effects in the models. Because mercury tip-switch data have often been collected in bins ranging from 0 to 7 as described above, we also used a binary logistic regression to relate bin classification to resting and active behaviors. We examined the relationship between sensor readings and the percent of time bears spent resting at various time intervals by comparing the performance (R^2 - and P -value) of linear and non-linear regressions.

To compare the accuracy of our resting and active classifications of the mercury tip-switch and low-resolution accelerometer with the higher resolution accelerometer, we used a classification system that would provide comparable statistics but that could accommodate data collected in all 3 axes. Therefore, we classified the dynamic acceleration data from the 3d accelerometer as resting and active using a k -nearest neighbor (KNN) algorithm in R (R Core Team 2014) that accommodates multi-dimensional data (Bidder et al. 2014). We randomly used 70% of the resting data and 70% of the active data to “train” the KNN algorithm and used the remaining 30% for validation. The KNN provides both classifications and probability values, which represent the proportion of nearest-neighbor values that belong to the selected classification. Following Bidder et al. (2014), this probability value can then be used as a minimum

majority threshold. The minimum majority threshold is a minimum value for the probability that must be reached in order for the KNN classification to be retained. We compared predicted KNN classifications to the actual behavioral classifications using threshold ranges of ≥ 0.9 , 0.8, 0.7, 0.6, and 0.5. For each threshold range, we calculated the accuracy, precision, and recall between predicted classifications and actual classifications as defined by Bidder et al. (2014).

We examined mercury tip-switch and the low-resolution accelerometer readings using regression analyses to determine whether the 2 sensors performed consistently. Once confirmed, this would allow mercury tip-switch and accelerometer data to be merged via a standardization procedure.

Lastly, we examined the relationship between the percent of time spent resting and activity sensor readings using regression analyses at various time intervals to determine whether a continuous scaling (i.e., % of time resting) could be used to interpret sensor data as opposed to a categorical classification (i.e., resting or active). We excluded head movement from this analysis because these considerations, although potentially significant in affecting readings, cannot be accounted for in data sets collected from wild bears.

Results

The adult male at the Alaska Zoo immediately removed his collar before any behavioral data could be recorded. Thus, all results are for the 3 female polar bears and 2 female brown bears. After removal of rare and atypical behaviors and times when the bears were out of camera view, there were 9,231 total 1-minute observations (153.9 hr). The polar bear at

Table 2. Results of binary logistic-regression classifications of low-resolution (i.e., providing a single value summed across 3 axes) accelerometer activity-sensor data as resting (1 = either 80% or 100% of time spent resting) or active (0) with data collected from collars deployed on 2 captive brown bears and 3 captive polar bears at time intervals ranging from 1 minute to 1 hour. Accuracies of classifying observed resting and active behaviors correctly are provided as percentages. "Overall" is the percent of accurate classifications for the 2 behavioral categories combined. The resting definition is the percent of time a bear spent resting to be categorized as resting (1) in the binary logistic regression. The values provided in columns 3 and 4 represent cut-offs in accelerometer readings corresponding with resting and active behaviors, respectively. The cut-off in the last column is the value set in the logistic regression that minimized the probability of false negatives and false positives.

Data time-scale (min)	Resting definition (%)	Accelerometer values for resting behaviors	Accelerometer values for active behaviors	Accuracy of classifying resting behaviors (%)	Accuracy of classifying active behaviors (%)	Overall accuracy of classification (%)	Cut-off used
1	100	≤9	>9	94.3	86.6	93.2	0.8
5	80	≤41	>41	94.5	92.8	94.3	0.8
5	100	≤33	>33	93.6	89.9	92.9	0.8
10	80	≤73	>73	93.8	92.2	93.5	0.8
10	100	≤51	>51	92.1	89.4	91.4	0.8
15	80	≤96	>96	93.9	92.9	93.7	0.8
15	100	≤63	>63	90.6	92.2	91.1	0.8
30	80	≤185	>185	92.3	95.9	93.2	0.8
30	100	≤108	>108	90.0	92.4	91.5	0.7
60	80	≤355	>355	92.1	92.3	92.2	0.8
60	100	≤127	>127	91.3	93.2	92.2	0.7

the Oregon Zoo was limited to wearing the collar during 1–2-hour periods/day because she was on exhibit. Therefore, data collection for this bear was limited to 2.9 total usable hours (i.e., excluding stereotypic behaviors). The 2 brown bears wore the collar 24 hours/day for a combined 138.8 total hours. The San Diego and Alaska Zoo bears provided 11.9 hours and 64.5 hours, respectively.

The low-resolution accelerometer consistently had a higher accuracy of classifying resting and active behaviors across all time intervals of data collection than did the mercury tip-switch (Tables 2 and 3). For the accelerometer, classifications of resting (defined as having spent 80% or 100% of the time interval resting) and active behaviors across all time intervals (1, 5, 15, 30, and 60 min) had a combined accuracy of ≥91.1%. Classification of resting and active behaviors individually had ≥86.6% accuracy (Table 2). The mercury tip-switch classifications had combined accuracies of classification ranging from 75.5% to 86.3% and accuracy of classifying resting and active behaviors individually ranging from 60.0% to 89.0% (Table 3). Binned tip-switch data were classified into resting and active categories with a similar accuracy as the raw tip-switch data (probability of accurate detection of active behaviors ranged from 68.5% to 83.6% and resting from 76.1% to 90.0%; Table 3). In most cases, active behavior was more likely to be misclassified as resting with the

mercury tip-switch (accuracy of classification ranged from 60.0% to 86.3% across time intervals) compared with the low-resolution accelerometer (86.6–95.9%) although misclassification varied depending on time interval. Mixed behaviors (resting and active) occurred in 8.6% of all observed minutes.

The accuracy of classifying resting and active behaviors using the mercury tip-switch and low-resolution, internal accelerometers was similar to results obtained from the externally mounted 3d accelerometer. Similar to the older activity sensors, resting was more accurately categorized (accuracy ≥94%) than active behaviors (accuracy ≥83%) by the 3d accelerometer (Table 4). Dynamic acceleration (removing the gravity component) increased accuracy by 4% and precision by 1% compared with raw acceleration.

Misclassification of behavior as resting or active using the mercury tip-switch and low-resolution accelerometer could have been associated with the effect of head movement. Using accelerometer data collected at 1-minute intervals, classification of active behavior improved from 86.6% to 95.2% when head movement was included in the model. Similarly, resting classification improved from 94.3% to 98.7% for the accelerometer (Table 5; likelihood ratio = 6,339.8, $P < 0.0001$). The same patterns were observed for the mercury tip-switch (resting classification improved from 76.1% to 93.8% and active classification improved from 72.1% to 84.6%; likelihood

Table 3. Results of binary logistic-regression classifications of mercury tip-switch activity-sensor data as resting (1 = either 80% or 100% of time spent resting) or active (0) with data collected from collars deployed on 2 captive brown bears and 3 captive polar bears at time intervals ranging from 1 minute to 1 hour. Tip-switch data were analyzed using both raw (raw) sensor readings and binned (bin) sensor readings, a common format of tip-switch data. Bins for 1-hour activity-count data were as follows: 0 = 0–179; 1 = 180–359; 2 = 360–539; 3 = 540–899; 4 = 900–1,439; 5 = 1,440–2,159; 6 = 2,160–2,879; 7 = 2,880–3,600; and were scaled to other time intervals. Accuracies of classifying observed resting and active behaviors are provided as percentages. “Overall” is the percent of accurate classifications for the 2 behavioral categories combined. The “resting definition” is the percent of time a bear spent resting to be categorized as resting (1) in the binary logistic regression. The values provided in columns 4 and 5 represent cut-offs in tip-switch readings corresponding with resting and active behaviors, respectively. The cut-off in the last column is the value set in the logistic regression that minimized the probability of false negatives and false positives.

Sensor readings	Time-scale (min)	Resting definition (%)	Mercury tip-switch values for resting behaviors	Mercury tip-switch values for active behaviors	Accuracy of classifying resting behavior (%)	Accuracy of classifying active behavior (%)	Overall accuracy of classification (%)	Cut-off used
Raw	1	100	≤2	>2	76.1	72.1	75.5	0.9
Raw	5	80	≤29	>29	89.0	60.0	84.2	0.8
Raw	5	100	≤23	>23	87.2	64.1	82.8	0.8
Raw	10	80	≤57	>57	86.9	65.9	83.1	0.8
Raw	10	100	≤35	>35	83.6	70.8	80.6	0.8
Raw	15	80	≤64	>64	85.5	70.1	82.3	0.8
Raw	15	100	≤42	>42	82.0	78.9	81.1	0.8
Raw	30	80	≤112	>112	82.1	76.7	80.8	0.8
Raw	30	100	≤82	>82	84.8	80.0	83.1	0.7
Raw	60	80	≤216	>216	83.3	74.4	81.0	0.8
Raw	60	100	≤124	>124	86.3	86.3	86.3	0.6
Bin	1	100	0	>0	76.1	72.1	75.5	0.9
Bin	5	80	0	>0	76.6	77.4	76.7	0.9
Bin	5	100	0	>0	78.2	76.2	77.8	0.9
Bin	10	80	0	>0	76.6	77.4	76.7	0.9
Bin	10	100	0	>0	78.2	76.2	77.8	0.9
Bin	15	80	0	>0	79.7	81.1	80.0	0.8
Bin	15	100	0	>0	83.3	76.5	81.5	0.8
Bin	30	80	0	>0	77.8	83.6	79.2	0.8
Bin	30	100	0	>0	86.8	79.1	84.0	0.7
Bin	60	80	0	>0	77.2	82.1	78.4	0.7
Bin	60	100	0	>0	90.0	68.5	79.7	0.7

ratio = 3,460.6, $P < 0.0001$). There was little or no improvement in classification of resting and active behaviors when adding individual bear identification ($n = 5$) in the logistic regression models compared with excluding individual bear identification (Table 5).

There was not a strong predictive relationship between accelerometer and mercury tip-switch readings collected over 1-minute intervals ($R^2 = 0.41$; Fig. 1A). However, this relationship improved when data were summed over 1 hour ($R^2 = 0.72$; Fig. 1B).

For data collected at 1-minute intervals, the activity levels were observed in all of the mercury tip-switch bins (0–7), but only bins 0–5 were observed in data summed over 1-hour intervals. No activity was sustained over an hour to produce activity equivalent to bins 6 and 7 even prior to excluding any rare behaviors.

Accelerometers more closely reflected the proportion of time spent resting than did mercury tip-switches. Although all relationships were significant, the R^2 for the mercury tip-switch was the highest at the 1-hour interval ($R^2 = 0.50$), whereas the R^2 for the accelerometer ranged from 0.69 to 0.81 between the 5-minute and 1-hour intervals, respectively (Fig. 2; Table S1).

Discussion

Our results demonstrate that the accelerometers built in to many collar systems in use today offer substantial improvement in detecting behavior compared with mercury tip-switches. Low-resolution accelerometer readings were good predictors of the proportion of time bears spent resting ($R^2 = 0.81$) and allowed differentiation of resting and active behavior with a high degree of accuracy (>91%). They were

Table 4. Results of *k*-nearest neighbor analysis using dynamic acceleration data from 3 axes of an accelerometer recording at 16 Hz to predict resting versus active behavior collected from collars deployed on 2 captive brown bears and 3 captive polar bears.

Overall	Accuracy	Precision	Recall
Min. majority threshold			
0.9	0.909	0.988	0.919
0.8	0.939	0.982	0.955
0.7	0.952	0.975	0.976
0.6	0.959	0.968	0.990
0.5	0.961	0.961	1.000
Resting			
0.9	0.943	0.989	0.953
0.8	0.957	0.983	0.972
0.7	0.963	0.978	0.984
0.6	0.966	0.972	0.993
0.5	0.967	0.967	1.000
Active			
0.9	0.832	0.986	0.842
0.8	0.899	0.978	0.917
0.7	0.929	0.969	0.957
0.6	0.943	0.960	0.982
0.5	0.948	0.948	1.000

also able to detect resting behaviors at all timescales of data collection better than mercury tip-switches (Tables 2 and 3). Although resting behavior had a relatively high probability of accurate detection using the mercury tip-switch (76.1–89.0%), certain intervals more frequently resulted in misclassification of active states (60.0–86.3% accuracy). The probabilities of correctly identifying resting versus active behavior based on tip-switch counts in this study were similar to previous work in wild brown and black bears (Schwartz et al. 2009). Individual variation in the accuracy of classifying resting and active behaviors using both sensors was negligible despite our small sample size ($n = 5$).

Table 5. Effects of head movement (hm) and individual bear variation (ind) on accuracy of classifying resting versus active behavior using 2 types of activity sensors (a low-resolution accelerometer and mercury tip-switch) collected at 1-minute intervals from collars deployed on 2 brown bears and 3 polar bears in captivity. R^2 values are Nagelkerke pseudo- R^2 .

Sensor type	Factor added ^a	Accuracy of classifying resting behaviors (%) ^b	Accuracy of classifying active behaviors (%)	R^2	<i>P</i> -value
Accelerometer		94.3	86.6	0.70	<0.0001
Accelerometer	hm	98.7	95.2	0.88	<0.0001
Accelerometer	ind	94.4	86.9	0.71	<0.0001
Mercury tip-switch		76.1	72.1	0.28	<0.0001
Mercury tip-switch	hm	93.8	84.6	0.55	<0.0001
Mercury tip-switch	ind	78.8	71.8	0.32	<0.0001

^a Effects were individually added to a binary logistic model.

^b Accuracy is based on the percent of resting and active observations correctly assigned.

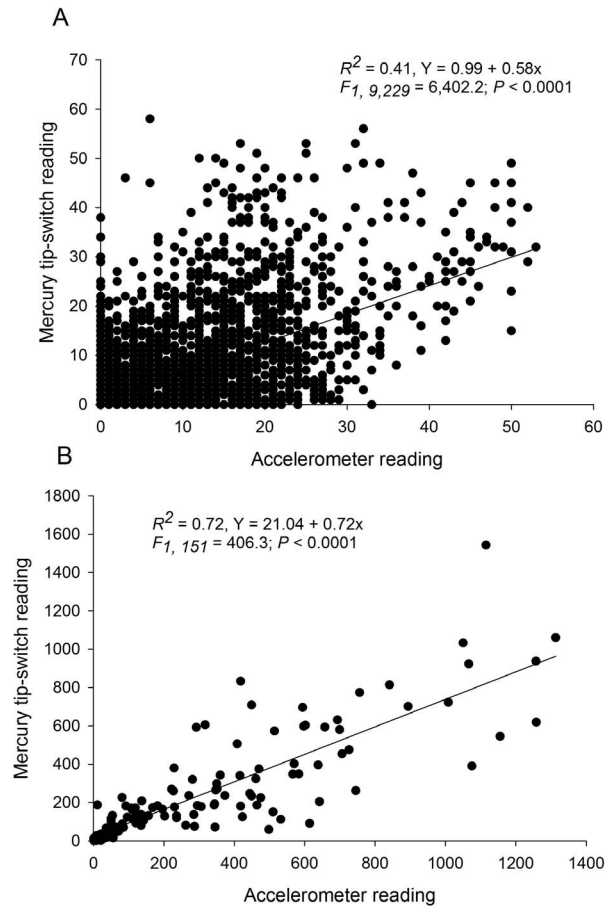


Fig. 1. Relationship between mercury tip-switch and low-resolution accelerometer readings (i.e., an accelerometer that provides a single activity value from measurements made on 3 axes) collected from collars deployed on 2 captive brown bears and 3 captive polar bears over 1-minute (A) and 1-hour (B) intervals.

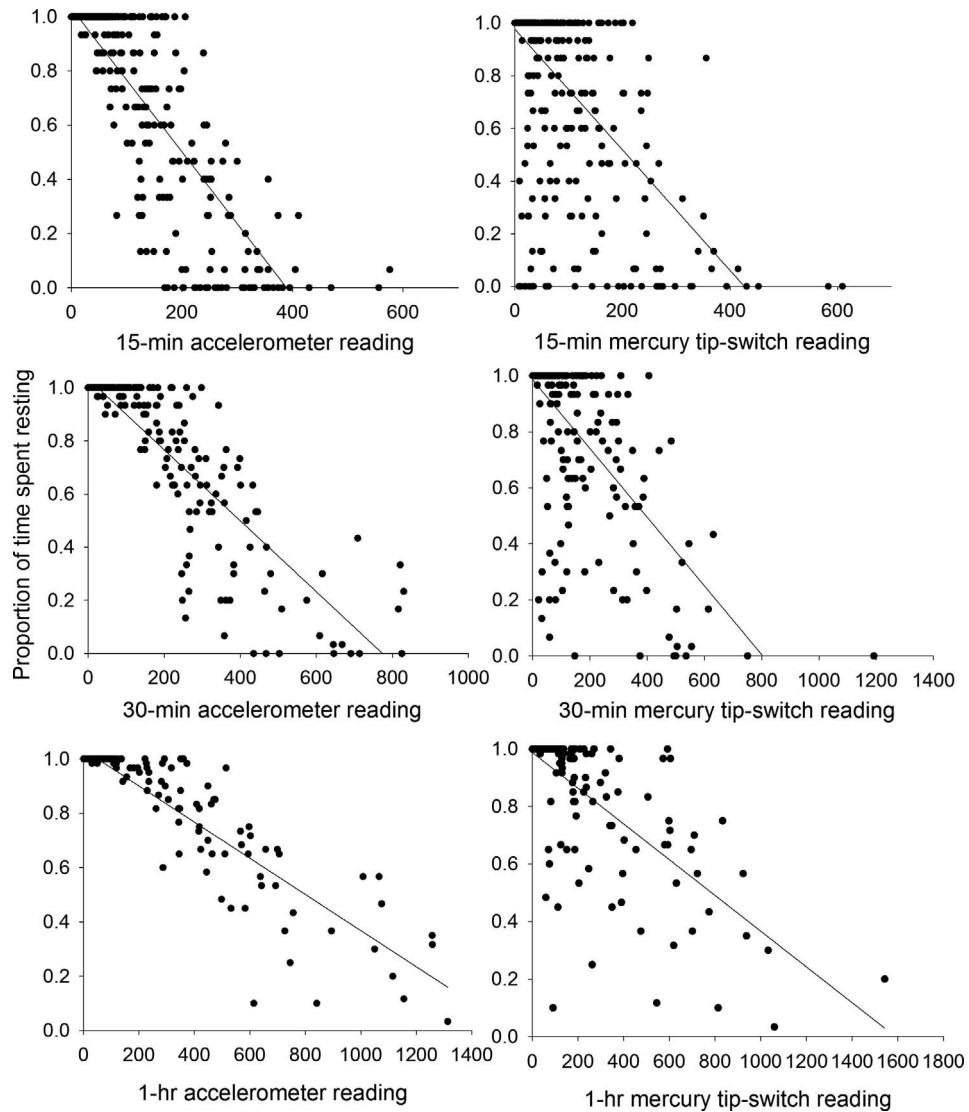


Fig. 2. Relationship between the proportion of a time interval spent resting (e.g., standing, lying, or sitting) and low-resolution accelerometer and mercury tip-switch readings (representing the no. of active seconds) collected from collars deployed on 2 captive brown bears and 3 captive polar bears at 15-minute, 30-minute, and 1-hour intervals. Regression equations and statistics provided in Table S1.

Identification of active behaviors using the mercury tip-switch data improved at longer time intervals of 30 and 60 minutes and when resting was classified as 100% of the time interval versus 80%. Mercury tip-switch readings were relatively poor predictors of the proportion of time a bear spent resting ($R^2 \leq 0.50$). Thus, data from mercury tip-switches are more accurate in identifying resting and active behaviors when more dramatic and temporally persistent changes in behavior are expected, such as when

switching from diurnal to nocturnal activity, hibernation, or seasonal fasting and associated resting.

Accelerometers maintained a relatively high accuracy of identifying resting and active behaviors across all time intervals (>86% for resting and active behaviors individually) and when resting behaviors occurred during 80% of 100% of the time interval. However, the accuracy of identifying active behaviors was somewhat improved at intervals of ≥ 5 minutes (>89%) compared with 1-minute intervals (86%). Although classification

was also somewhat improved for the mercury tip-switch at longer time intervals, accuracy was relatively high for both sensor types across intervals. Because higher temporal resolution data are likely to give a more robust picture of daily activity patterns, decisions about time intervals for data collection should include consideration of study objectives and the classification accuracies reported here.

Classification using the single activity-sensor value generated from low-resolution accelerometers every minute was similar to that generated via the higher resolution accelerometer that collected output from all 3 axes every second. When 1-minute data were summed over longer time periods, the low-resolution accelerometer exhibited accuracy of classifying resting and active behaviors similar to the 3d accelerometers. These results are encouraging for investigators interested in evaluating coarse patterns in resting versus active behaviors because the current, built-in accelerometers upload data through satellites, which eliminates the need to recapture animals to retrieve data.

The primary method for remotely monitoring activity of large terrestrial mammals is to include the activity sensors within a neck-worn collar. There have been concerns that this arrangement (neck-mounted) could distort the reporting of an animal's activity because it mainly measures head and neck movement (Gervasi et al. 2006, Kozakai et al. 2008). However, our current study found only limited improvement when head movement was considered in classification of resting and active behavior for the accelerometer (98.7% and 95.2%, respectively) compared with classifications that did not account for head-movement effects (94.3% and 86.6%, respectively). The mercury tip-switch classifications appeared to improve more dramatically when head movement was considered (accuracy of classifying resting improving from 76.1% to 93.8%). Because the tip-switch registers up or down changes of approximately 7°, it might record higher values during head movement despite little change in velocity (accelerometer values). Although head movements do generate error in classifying resting and active behavior, classification of these behavioral categories was still relatively accurate when head movement was not accounted for.

Accelerometer readings were related to mercury tip-switch readings with an R^2 of 0.72 (Fig. 1A, B). Although this relationship could be used as a correction factor so that mercury tip-switch and accelerometer data can be included in the same data set, such a

correction may introduce bias. Costello et al. (2013) drew a similar conclusion comparing readings from these 2 sensor types for wild bears. Much of the variation between the 2 sensor types occurred for active behaviors because the readings were more closely related for resting behaviors. This consistency among resting behaviors suggests that readings from the 2 sensors similarly reflect resting behaviors but are less comparable among different types of active behaviors. Investigators interested in including mercury tip-switch and accelerometer data in a single data set may minimize bias by using a coarse classification of "resting" or "active" rather than attempting to use a correction factor on raw values.

Given that many ursid research programs have deployed collars, there are vast amounts of previously collected activity data that may inform broad patterns and changes in behavior in response to environmental change and other factors of interest, such as human disturbance. Although movement data can provide important insights into activity, they do not identify active behaviors associated with minimum changes in location, such as foraging on vegetation and berries. Importantly, because polar bears inhabit sea ice, which constantly moves as a result of currents and wind, activity-sensor data are particularly informative of behavior because they are unaffected by ice movement. Despite the small sample size, our results provide support for the use of activity sensors to infer broad patterns of resting and active behavior in bears.

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Literature cited

- AMSTRUP, S.C., G. DURNER, T. McDONALD, D. MULCAHY, AND G. GARNER. 2001. Comparing movement patterns of satellite-tagged male and female polar bears. *Canadian Journal of Zoology* 79:2147–2158.

- BIDDER, O.R., H.A. CAMPBELL, A. GÓMEZ-LAICH, P. URGÉ, J. WALKER, Y. CAI, L. GAO, F. QUINTANA, AND R.P. WILSON. 2014. Love thy neighbour: Automatic animal behavioural classification of acceleration data using the K-Nearest Neighbour algorithm. *PLoS ONE* 9:e88609.
- COOKE, S.J., S.G. HINCH, M. WIKELSKI, R.D. ANDREWS, L. J. KUCHEL, T.G. WOLCOTT, AND P.J. BUTLER. 2004. Biotelemetry: A mechanistic approach to ecology. *Trends in Ecology and Evolution* 19:334–343.
- COSTELLO, C.M., S.I. CAIN, R.M. NIELSON, C. SERVHEEN, AND C.C. SCHWARTZ. 2013. Response of American black bears to the non-motorized expansion of a road corridor in Grand Teton National Park. *Ursus* 24:54–69.
- COULOMBE, M.-L., A. MASSÉ, AND S.D. CÔTÉ. 2006. Quantification and accuracy of activity data measured with VHF and GPS telemetry. *Wildlife Society Bulletin* 34:81–92.
- DURNER, G.M., D.C. DOUGLAS, R.M. NIELSON, S.C. AMSTRUP, T.L. McDONALD, I. STIRLING, M. MAURITZEN, E.W. BORN, Ø. WIIG, E. DEWEAVER, M.C. SERREZE, S. E. BELIKOV, M.M. HOLLAND, J. MASLANIK, J. AARS, D. A. BAILEY, AND A.E. DEROCHE. 2009. Predicting 21st-century polar bear habitat distribution from global climate models. *Ecological Monograph* 79:25–58.
- ELLIOTT, K.H., M. LE VAILLANT, A. KATO, J.R. SPEAKMAN, AND Y. ROBERT-COUDERT. 2013. Accelerometry predicts daily energy expenditure in a bird with high activity levels. *Biology Letters* 9:20120919.
- FISCHBACH, A., S. AMSTRUP, AND D. DOUGLAS. 2007. Landward and eastward shift of Alaskan polar bear denning associated with recent sea ice changes. *Polar Biology* 30:1395–1405.
- FORTIN, J.K., J.V. WARE, H.T. JANSEN, C.C. SCHWARTZ, AND C.T. ROBBINS. 2013. Temporal niche switching by grizzly bears but not American black bears in Yellowstone National Park. *Journal of Mammalogy* 94: 833–844.
- GARSHELIS, D.L., H.B. QUIGLEY, C.R. VILLARRUBIA, AND M.R. PELTON. 1982. Assessment of telemetric motion sensors for studies of activity. *Canadian Journal of Zoology* 60:1800–1805.
- AND ———. 1980. Activity of black bears in the Great Smoky Mountains National Park. *Journal of Mammalogy* 61:8–19.
- GEORGII, B. 1981. Activity patterns of female red deer (*Cervus elaphus L.*) in the Alps. *Oecologia* 49:127–136.
- GERVASI, V., S. BRUNBERG, J.E. SWENSON, AND J. BOWMAN. 2006. An individual-based method to measure animal activity levels: A test on brown bears. *Wildlife Society Bulletin* 34:1314–1319.
- GILLINGHAM, M.P., AND F.L. BUNNELL. 1985. Reliability of motion-sensitive radio collars for estimating activity of black-tailed deer. *Journal of Wildlife Management* 49:951–958.
- GLEISS, A.C., R.P. WILSON, AND E.L. SHEPARD. 2011. Making overall dynamic body acceleration work: On the theory of acceleration as a proxy for energy expenditure. *Methods in Ecology and Evolution* 2:23–33.
- GOTTARDI, E., F. TUA, B. CARGNELUTTI, M.-L. MAUBLANC, J.-M. ANGIBAULT, S. SAID, AND H. VERHEYDEN. 2010. Use of GPS activity sensors to measure active and inactive behaviours of European roe deer (*Capreolus capreolus*). *Mammalia* 74:355–362.
- GREEN, R.A., AND G.D. BEAR. 1990. Seasonal cycles and daily activity patterns of Rocky Mountain elk. *Journal of Wildlife Management* 54:272–279.
- HALSEY, L.G., J. GREEN, R. WILSON, AND P. FRAPPELL. 2009. Accelerometry to estimate energy expenditure during activity: Best practice with data loggers. *Physiological and Biochemical Zoology* 82:396–404.
- KACZENSKY, P., D. HUBER, F. KNAUER, H. ROTH, A. WAGNER, AND J. KUSAK. 2006. Activity patterns of brown bears (*Ursus arctos*) in Slovenia and Croatia. *Journal of Zoology* 269:474–485.
- KOZAKAI, C., S. KOIKE, K. YAMAZAKI, AND K. FURUBAYASHI. 2008. Examination of captive Japanese black bear activity using activity sensors. *Mammal Study* 33:115–119.
- LARIVIÈRE, S., J. HUOT, AND C. SAMSON. 1994. Daily activity patterns of female black bears in a northern mixed-forest environment. *Journal of Mammalogy* 75:613–620.
- LÖTTKER, P., A. RUMMEL, M. TRAUBE, A. STACHE, P. ŠUSTR, J. MÜLLER, AND M. HEURICH. 2009. New possibilities of observing animal behaviour from a distance using activity sensors in GPS-collars: An attempt to calibrate remotely collected activity data with direct behavioural observations in red deer *Cervus elaphus*. *Wildlife Biology* 15:425–434.
- MACHUTCHON, A.G., S. HIMMER, H. DAVIS, AND M. GALLAGHER. 1998. Temporal and spatial activity patterns among coastal bear populations. *Ursus* 10:539–546.
- MESSIER, F., M. TAYLOR, AND M. RAMSAY. 1992. Seasonal activity patterns of female polar bears (*Ursus maritimus*) in the Canadian Arctic as revealed by satellite telemetry. *Journal of Zoology* 226:219–229.
- MOEN, R., J. PASTOR, AND Y. COHEN. 1996. Interpreting behavior from activity counters in GPS collars on moose. *Alces* 32:101–108.
- MUNRO, R.H.M., S.E. NIELSEN, M.H. PRICE, G.B. STENHOUSE, AND M.S. BOYCE. 2006. Seasonal and diel patterns of grizzly bear diet and activity in West Central Alberta. *Journal of Mammalogy* 87:1112–1121.
- R CORE TEAM. 2014. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org>. Accessed 31 Jan 2014.
- RATNAYEKE, S., F.T. VAN MANEN, AND U. PADMALAL. 2007. Home ranges and habitat use of sloth bears *Melursus*

- ursinus inornatus* in Wasgomuwa National Park, Sri Lanka. *Wildlife Biology* 13:272–284.
- SCHWARTZ, C.C., S.L. CAIN, S. PODRUZNY, S. CHERRY, AND L. FRATTAROLI. 2010. Contrasting activity patterns of sympatric and allopatric black and grizzly bears. *Journal of Wildlife Management* 74:1628–1638.
- , S.L. CAIN, AND S. CHERRY. 2009. Performance of spread spectrum Global Positioning System collars on grizzly and black bears. *Journal of Wildlife Management* 73:1174–1183.
- SHEPARD, E.L., R.P. WILSON, F. QUINTANA, A.G. LAICH, N. LIEBSCH, D.A. ALBAREDA, L.G. HALSEY, A. GLEISS, D.T. MORGAN, AND A.E. MYERS. 2008. Identification of animal movement patterns using tri-axial accelerometry. *Endangered Species Research* 10:47–60.
- , W.G. REES, E. GRUNDY, S.A. LAMBERTUCCI, AND S.B. VOSPER. 2013. Energy landscapes shape animal movement ecology. *The American Naturalist* 182:298–312.
- SMITH, T.R. 1986. Activity and behavior of denned black bears in the lower Mississippi River Valley. *Bears: Their Biology and Management* 6:137–143.
- TE WONG, S., C.W. SERVHEEN, AND L. AMBU. 2004. Home range, movement and activity patterns, and bedding sites of Malayan sun bears *Helarctos malayanus* in the rainforest of Borneo. *Biological Conservation* 119:169–181.
- TEISBERG, J., S. FARLEY, O. NELSON, G. HILDERBRAND, M. MADEL, P. OWEN, J. ERLBACH, AND C. ROBBINS. 2014. Immobilization of grizzly bears (*Ursus arctos*) with dexmedetomidine, tiletamine, and zolazepam. *Journal of Wildlife Diseases* 50:74–83.
- WATANABE, S., M. IZAWA, A. KATO, Y. ROPERT-COUDERT, AND Y. NAITO. 2005. A new technique for monitoring the detailed behaviour of terrestrial animals: A case study with the domestic cat. *Applied Animal Behaviour Science* 94:117–131.
- WILSON, A.M., J. LOWE, K. ROSKILLY, P.E. HUDSON, K. GOLABEK, AND J. MCNUTT. 2013. Locomotion dynamics of hunting in wild cheetahs. *Nature* 498:185–189.
- WILSON, R.P., C.R. WHITE, F. QUINTANA, L.G. HALSEY, N. LIEBSCH, G.R. MARTIN, AND P.J. BUTLER. 2006. Moving towards acceleration for estimates of activity-specific metabolic rate in free-living animals: The case of the cormorant. *Journal of Animal Ecology* 75:1081–1090.
- YAMAZAKI, K., C. KOZAKAI, S. KASAI, Y. GOTO, S. KOIKE, AND K. FURUBAYASHI. 2008. A preliminary evaluation of activity-sensing GPS collars for estimating daily activity patterns of Japanese black bears. *Ursus* 19:154–161.

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Supplemental material

Table S1. Regressions of the proportion of time a captive bear spent resting (y) relative to low-resolution accelerometer and mercury tip-switch activity-sensor readings (x) at various time intervals of data collection.

Time interval	Accelerometer				Mercury tip-switch			
	Equation	R ²	F	P	Equation	R ²	F	P
5 min	1.03 – 0.008x	0.69	4,161.4	<0.0001	0.96 – 0.006x	0.32	864.3	<0.0001
10 min	1.03 – 0.004x	0.73	2,479.4	<0.0001	0.97 – 0.003x	0.36	515.5	<0.0001
15 min	1.03 – 0.003x	0.76	1,958.2	<0.0001	0.98 – 0.002x	0.40	402.9	<0.0001
30 min	1.03 – 0.001x	0.78	1,069.9	<0.0001	0.99 – 0.001x	0.47	270.0	<0.0001
1 hr	1.03 – 0.0007x	0.81	659.2	<0.0001	0.99 – 0.0006x	0.50	151.6	<0.0001