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Citation	Gaylord, A. J. & Sanchez, D. M. (2014). Causes and Consequences of Timing Errors Associated With Global Positioning System Collar Accelerometer Activity Monitors. Journal of Fish and Wildlife Management, 5(2), 372-379. doi:10.3996/092013-JFWM-060
DOI	10.3996/092013-JFWM-060
Publisher	U.S. Fish and Wildlife Service
Version	Version of Record
Terms of Use	http://cdss.library.oregonstate.edu/sa-termsofuse

Notes

Causes and Consequences of Timing Errors Associated With Global Positioning System Collar Accelerometer Activity Monitors

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Abstract

Direct behavioral observations of multiple free-ranging animals over long periods of time and large geographic areas is prohibitively difficult. However, recent improvements in technology, such as Global Positioning System (GPS) collars equipped with motion-sensitive activity monitors, create the potential to remotely monitor animal behavior. Accelerometer-equipped activity monitors quantify animal motion with different amounts of movement presumably corresponding to different animal activities. Variations in motion among species and differences in collar design necessitate calibration for each collar and species of interest. We paired activity monitor data collected using Lotek GPS_4400 collars worn by captive Rocky Mountain elk *Cervus elaphus nelsoni* with simultaneously collected behavior observations. During our initial data screening, we observed many sampling intervals of directly observed behavior that did not pair to activity monitor data in a logical fashion. For example, intervals containing behaviors associated with little or no motion sometimes aligned with relatively high activity monitor values. These misalignments, due to errors associated with collar timekeeping mechanisms, would likely result in inaccurate classification models. We corrected timing errors by using defined breaks in animal behavior to shift times given by collar output, improving the average correct classification rate 61.7 percentage points for specific behaviors. Furthermore, timing errors were significantly reduced by increasing the GPS fix rate, by using a sampling interval divisible by 8 seconds, and by accurately timing the initial collar activation. Awareness and management of collar timing error will enable users to obtain the best possible estimates of true behavior when calibrating these collars and interpreting data from free-ranging animals.

Keywords: accelerometers; behavior tracking; activity monitors; elk; GPS collars; timing errors

Received: September 6, 2013; Accepted: May 4, 2014; Published Online Early: May 2014; Published: December 2014

Citation: Gaylord AJ, Sanchez DM. Causes and consequences of timing errors associated with GPS collar accelerometer activity monitors. 2014. *Journal of Fish and Wildlife Management* 5(2):372–379; e31944-687X. doi: 10.3996/092013-JFWM-060

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Introduction

Understanding how animals use habitat in space and time is key to predicting and assessing the impacts of management actions, habitat disturbances, and inter- and intraspecies interactions (Reynolds 1964; Rongstad et al. 1969; Gilbert and Kearney 1976; Kie et al. 2005). Knowledge of animal behavior is an important component for development of spatially explicit behavioral landscapes to enhance resource selection modeling efforts (Fryxell 1991; Bakian et al. 2012; Wilson et al. 2012). Global positioning system (GPS) collars equipped with motion-sensitive activity monitors, such as the Lotek GPS_4400 collars (Lotek Engineering, Newmarket, Ontario, Canada), obtain spatially and temporally explicit behavior data and therefore might be of great utility to habitat use–related research questions.

Activity monitors quantify animal motion, but because species vary in their body movements and behaviors, species-specific calibration is necessary to relate numeric collar output (activity monitor values [AMVs]) to actual

Table 1. Sources of timing error associated with dual-axis activity monitors incorporated into Lotek GPS_4400 collars used at Starkey Experimental Forest and Range, USFS, Starkey, summer 2011. The table summarizes the mechanisms by which each type of timing error originates, the duration or magnitude of the error, the evidence by which the error can be recognized in the data set, and the action available to correct or prevent the error.

Source of error	Mechanism	Duration of error[a]	Evidence in data	Action to correct
Internal clock	Drift influenced by age of collar and air temperature	$\pm$0.72 s/h	Label gap or duplicate	Corrected during GPS fix
Activity microprocessor	Drift influenced by age of collar and air temperature	<5 s/h	Label gap or duplicate	None available
Sensor sampling interval not divisible by 8 s	Difference between the duration of the sensor sampling interval and the amount of time between interval start time (IST[b]) time stamps	Depends on chosen sensor sampling interval	Label gap	Choose PSIs divisible by 8 s[c]
Activation offset	Difference between time at which the activity monitor unit is activated and a programmed IST	Up to one interval	No evidence	Activate activity monitor unit at programmed IST

[a] Amount of time the start time of the sampling interval differs from the data time stamp given in the collar output.
[b] The times with which collar data are time stamped in the collar output.
[c] Activity microprocessor activates on an 8-s interval; therefore, a sampling interval not divisible by 8 s results in accumulation of timing error.

behaviors displayed by the species of interest. Calibration is often conducted by observing captive collared animals and then coupling the real-time observed activities to AMVs recorded by the collar over the same sampling interval (Ungar et al. 2005; Löttker et al. 2009; Heurich et al. 2012). Alternatively, investigators working only with free-ranging animals can document behaviors of animals during handling, recovery, and release phases of the initial capture. The temporally aligned paired sets of data (directly observed, remotely sensed) are used to build a behavior classification model that can be used to classify, with a given level of certainty, the behavior or activity level of novel, free-ranging animals.

Users require accurate interval start times (ISTs) established for both the directly observed data and the data (AMVs) collected by the collars. Although use of electronic data loggers with satellite-corrected time allows easy time stamping of direct observations, we discovered that reliance on collar outputs alone is insufficient when attempting to establish the true start times for sampling intervals of collar-collected data. Users must be aware of and prepared to manage sources of potential timing error that affect these data. While calibrating Lotek GPS_4400 collars equipped with dual-axis accelerometers for Rocky Mountain elk *Cervus elaphus nelsoni*, we noted what appeared to be inaccurate temporal pairing of AMVs to behavior(s) that we had directly observed and recorded simultaneously. This problem could result in inaccurate final classification models that would predict the wrong behavior for multiple sampling intervals and ultimately lead to a misunderstanding of space use and resource selection. Our goal was to identify the mechanisms that lead to temporal errors in the data, to learn about solutions to the problem, and to understand how management of the problem might increase the predictive capacity of behavior calibration and classification models.

Activity monitor mechanisms

Activity monitor components measure and store data in a way that results in several potential sources of timing error (Table 1). The sensors within the Lotek GPS_4400 collars were equipped with two accelerometers, an activity microprocessor, and a main microprocessor that includes an internal clock. Accelerometers measure changes in acceleration associated with animal motion along two axes of the body four times per second. Motion data from each accelerometer are averaged over the duration of a user-selected programmed sampling interval (PSI) and result in assignment of a single AMV ranging from 0 to 255 for each axis.

Multiple components interact to record, store, and time stamp data from the accelerometers. The activity microprocessor activates every 8 s, stores the accelerometer data, and tracks how many 8-s periods have elapsed since data were last downloaded by the main microprocessor. When enough 8-s periods have elapsed to cumulatively equal or exceed the duration of the PSI, the activity microprocessor flags the data for storage by the main microprocessor. The main microprocessor averages the activity data for each axis over the duration of the PSI, stores these AMVs along with a temperature measurement, and labels these data with the date and the programmed ISTs that are tracked by the internal clock (J. Chang, Lotek Wireless, Inc., personal communication).

Sources of error

The ideal situation results when the start time of every collar sensor sampling interval matches perfectly with the IST data time stamps (Figure 1, Ideal). In this scenario, an investigator could download collar data and be assured that the AMVs for a given time interval would match the animal's actual behaviors over that period. However, four potential sources of timing error can arise

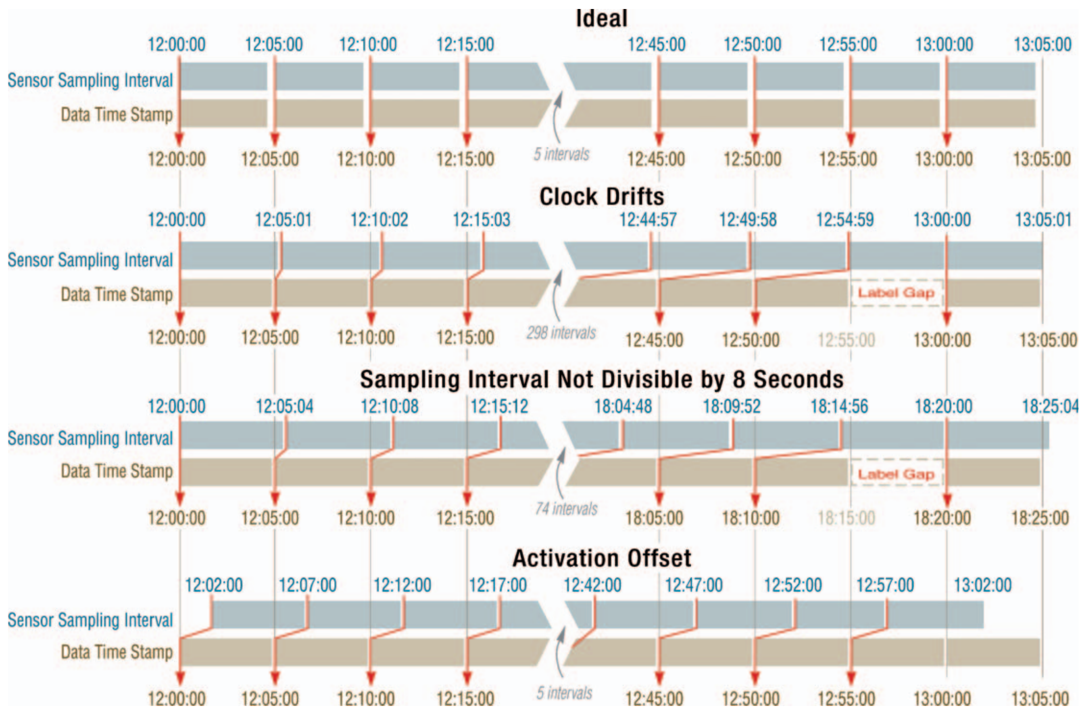

Figure 1. Sources of timing error (Clock Drifts, Sampling Interval Not Divisible by 8 Seconds, and Activation Offset) result in sensor sampling intervals time stamped with incorrect start times for remotely sensed behavior data collected using dual-axis accelerometer activity sensors mounted on Lotek GPS_4400 collars. Accumulation of many small errors can result in a gap in the data time stamps (label gap) which starts the cycle of error accumulation anew.

from mechanical processes and user actions. These errors result in IST time stamps that do not match the actual start time of the sampling interval, which in turn leads to direct behavior observations being inaccurately matched to remotely collected AMVs. If directly observed and remotely collected data are paired using the inaccurate ISTs from the collar output, accuracy of behavior classification models is reduced.

The first sources of timing error derive from what we commonly call clock drift. All timekeeping devices are subject to drift (i.e., they run fast or slow), including two components within the activity monitors: the internal clock (contained within the main microprocessor) and the activity microprocessor. Clock drift in each of these devices can vary by $\pm$0.72 s/h and can be influenced by the age of the collar and by air temperature (J. Chang, personal communication). Clock drift results in differences between the programmed ISTs stamped in the collar output and the actual start time of the interval over which the sensors are sampling movements (Figure 1, Clock Drifts). This difference arises because at the end of a sampling interval, the main microprocessor time stamps data with the preceding programmed IST regardless of when an interval actually started (J. Chang, personal communication). For example, when the PSI is set for 5 min, preset ISTs fall on the hour and at subsequent 5-min intervals. A 5-min PSI starting at 12:05:00 and ending at 12:10:00 would be labeled with the 12:05:00 IST (Figure 1, Ideal). If drift resulted in an interval duration that exceeded the PSI (e.g., 301 s), that sampling interval would have actually started at 12:05:01, would have ended at 12:10:02, and would have been time stamped with the 12:05:00 IST. Uncorrected, the drift accumulates and eventually would result in a gap in the ISTs (i.e., label gap) in the collar output (Table 1; Figure 1, see label gap in Clock Drifts). Similarly, drift that results in a sampling interval that is shorter than the PSI will result in two successive intervals of data that will both be labeled with the same IST. Drift by the internal clock is corrected every time a GPS location fix occurs (J. Chang, personal communication). Thus, the GPS fix rate chosen by the user determines the frequency of correction and therefore the amount of internal clock drift that might accumulate between corrections. However, users should remember that conditions such as cloud cover, vegetative cover, topography, and orientation of the collar can prevent programmed GPS fixes and thus result in extended periods of uncorrected drift (Hulbert and French 2001; Di Orio et al. 2003; Cain et al. 2005; D'Eon and Delparte 2005; Jiang et al. 2008; Mattisson et al. 2010). The activity microprocessor functions independently of the internal clock; therefore, its drift is not corrected by GPS fixes (J. Chang, personal communication). Drift associated with the activity microprocessor will accumulate until a label gap occurs at which time the cycle of drift accumulation will start over (Table 1; Figure 1, see label gap in Clock Drifts).

User choice of PSI can interact with the 8-s activation cycle of the activity microprocessor to create another source of timing error. The activity microprocessor only flags activity data for storage by the main microprocessor once enough 8-s intervals have accumulated to reach or exceed the duration of the PSI. However, some manufacturers, including Lotek Wireless, Inc., offer collars with preset PSI options that are not divisible by 8 s. A user can unknowingly set the collar PSI such that the time at which the activity microprocessor flags the data for storage will not match a preset IST. For example, a common preset PSI option is 5 min (i.e., 300 s). The activity microprocessor would not activate to flag the activity data after 300 s, but instead after the collar sensors had collected data for 304 s (Table 1; Figure 1, Sampling Interval Not Divisible by 8 s). Data would then be labeled with the programmed 300-s (5-min) ISTs, despite having been collected over the 304-s-long period. This error is not corrected by GPS fixes, and the 4-s difference would therefore accumulate until $4n > \text{PSI}$ (where n is the number of intervals) at which time there would be a label gap and the cycle would start over (Figure 1, label gap in Sampling Interval Not Divisible by 8 s).

The final source of error results from the difference between the time at which the activity monitor unit is activated before collar deployment and the first programmed IST. If the activity microprocessor is activated (usually by removing a magnet from the collar housing) at a time that does not match a programmed IST, the start time of the sampling interval will not match the IST with which it is time stamped (Table 1; Figure 1, Activation Offset). Because the activity microprocessor functions independently of the internal clock, the offset between the IST and the start of the sampling interval is not corrected by GPS fixes and will remain consistent throughout the data set. Once we understood the sources of timing deviation and how they contribute to timing error, we developed a method to account for time disparities between observed behaviors and collar data to avoid data loss, decrease mismatched behavior–AMV pairings, and increase accuracy of our behavior classification model.

Study Area

The Starkey Experimental Forest and Range (Starkey) is located in the Blue Mountains 35 km southwest of La Grande, Oregon (45°12′N, 118°3′W). The facility includes a complex of pens, handling facilities, and small pastures that allow safe and efficient animal handling in conjunction with collection of direct observations of tamed Rocky Mountain elk. For details, please see Long et al. (2008).

Methods

We calibrated Lotek GPS_4400 collars worn by Rocky Mountain elk. Collars were equipped with dual-axis activity monitors set to sample over a 5-min PSI. We made detailed observations of five collared captive cow Rocky Mountain elk and recorded observed behaviors using Palm (Sunnyvale, CA) Tungsten E2 handhelds equipped with EVENT-Palm personal digital assistant–based software (J.C. Ha, University of Washington). We conducted field observations in accordance with established Institutional Animal Use and Care Committee protocols (U.S. Forest Service [USFS] Starkey 92-F-0004). We recorded observations daily during two 4-h sessions (morning, evening).

We recorded behaviors into eight classes: bedded, bedded-ruminating, standing, grazing, browsing, walking, trotting, and galloping. To reduce intraobserver variability associated with recognizing and recording behaviors, we trained observers individually over the course of two or three observation sessions and then excluded those observations from the calibration data set. Most behaviors occurred naturally, but three (browsing, trotting, and galloping) had to be prompted. The pasture and corrals in which we worked lacked browse species in sufficient quantities to allow us to collect data on prolonged browsing behavior. To induce this behavior, we collected branches of maple *Acer* spp., willow *Salix* spp., snowberry *Symphoricarpos albus*, and other browse species and attached them to a wooden tripod and wooden fence posts at heights ranging from ground level to the animals' maximum reach (approximately 3 m) to simulate natural conditions. Trotting and galloping were prompted by trained Forest Service personnel using ATVs to chase individual animals for short periods (<3 min). Chasing was limited to early morning sessions to reduce heat stress on the animals.

Correction procedure

We partitioned behavior observations into 5-min (300-s) bouts and then aligned the observations with the activity monitor data (AMVs, $n = 2{,}390$ intervals, Text S1 and Table S1, *Supplemental Material*) based on the (uncorrected) ISTs given by the collar output. Our collar output included both IST label duplicates and label gaps because we used a PSI that was not divisible by 8 s and because of the effects of activity microprocessor drift. We manually corrected label duplicates such that the IST sequence was sequential. For example, when ISTs from our collar output appeared as 12:00:00, 12:05:00, 12:05:00, 12:15:00 …, we changed the duplicate 12:05:00 label to 12:10:00. When we encountered a label gap we paired observed behaviors using the ISTs given by the collar output, resulting in one 5-min period for which no behaviors were paired (Figure 1, label gaps).

Based on previous calibration studies (Ungar et al. 2005; Löttker et al. 2009) and our field observations, we expected that behaviors with relatively low (bedded, bedded-ruminating, and standing) or high (trotting and galloping) amounts of movement associated with them and would be reflected by correspondingly low or high AMVs, respectively. Likewise, we expected other behaviors (grazing, browsing, and walking) to result in intermediate amounts of motion that would be reflected in the AMVs. However, when we initially paired behavior observations to collar-collected data, we noticed a number of intervals associated with low amounts of directly observed movement that aligned with inexplicably high AMVs, and vice versa (Figure 2, Initial Data Screening). These intervals represented mismatched behavior: AMV pairings. The mismatches were most obvious at breaks in behavior from a low or moderate motion activity to a moderate or high motion activity.

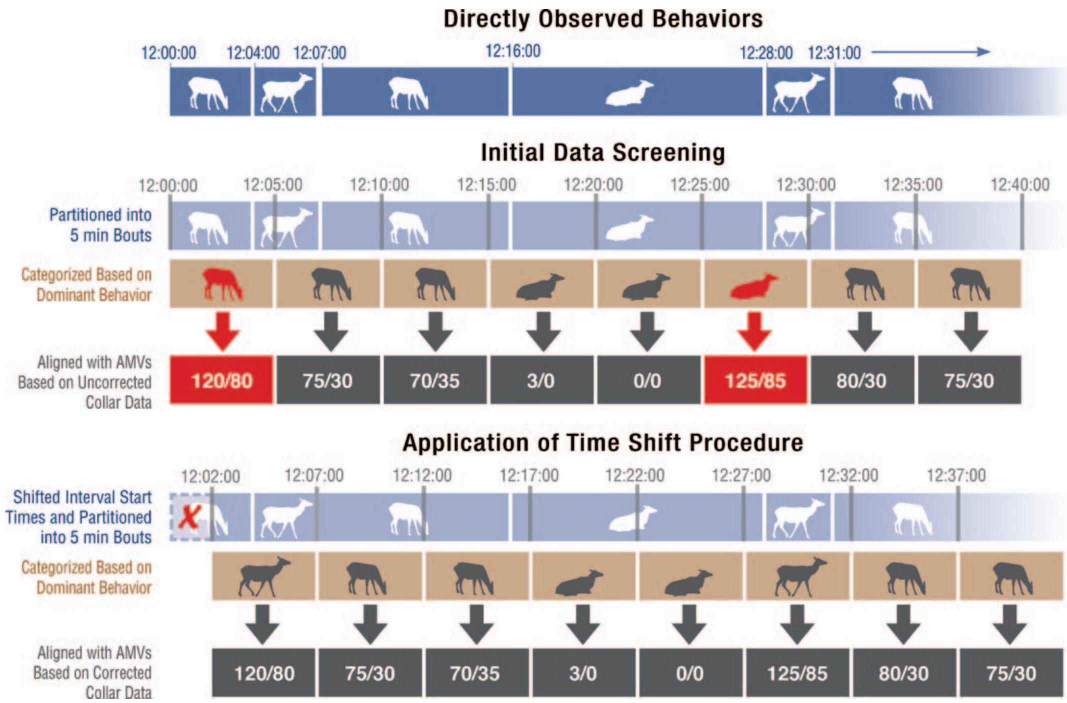

Figure 2. Increase in accurate pairing of directly observed behaviors to Activity Monitor Values (AMVs) after the application of the time shift procedure as compared to the initial data screening. After time shift procedure, behaviors with moderate or no motion are no longer paired with relatively high AMVs (red blocks). X- and Y-axis activity monitor values (X/Y) were collected using dual-axis accelerometers mounted on Lotek GPS_4400 collars worn by cow Rocky Mountain elk *Cervus elaphus nelsoni* observed during summer 2011 at Starkey Experimental Forest and Range, USFS, Starkey, OR.

We sought to address the error through corrective actions. We used the directly observed behaviors as a guide to calculate the number of seconds the collar output time would need to be shifted to achieve an intuitive match with AMVs (Figure 2, Application of Time Shift Procedure). Transitions from behaviors with little motion to behaviors with relatively moderate or high amounts of motion provided the best opportunities to identify these errors because of obvious contrast between expected and collar-recorded AMVs, and they were therefore most useful when calculating time shift. The necessary time shift was consistent over at least one 4-h observation session. The exception to this was when a label gap occurred during an observation session. In these cases, the amount of necessary shift before the gap was greater than that following the gap. This difference was consistent with our understanding of how gaps occur (Figure 1, see examples of label gaps). We shifted collar output times accordingly and realigned the behavior observations to the shifted ISTs. We then completed our originally planned analyses.

Determining impact of time shift procedure

Although our full data set included intervals containing one (pure) or more (mixed) behaviors, the pure intervals provided the best opportunity to examine the effects of timing errors on the accuracy of our classification models. We analyzed the pure intervals (n = 1,342) using linear discriminant function analysis (Tabachnick and Fidell 2001) in R2.11.1 (R Core Team 2014). We used leave-one-out cross-validation to estimate the percentage of correctly classified behaviors (correct classification rate) that one would expect if models were applied to novel pure interval data. To assess the impact of applying the time shift procedure, we compared the percentage of misclassified intervals for both the uncorrected and time-shifted data sets for each of the eight behaviors. Each interval of observed behavior could be misclassified into seven incorrect behavior categories. To examine this behavior-specific misclassification, we calculated the difference in the percentage of intervals of observed behaviors misclassified as specific predicted behaviors. We also compared classification rates achieved when we combined associated behaviors: passive (bedding, bedding-ruminating), feeding (graze, browse, and walk), and running (trot and gallop). We included walk in the feeding category because we observed that our study animals often walked as they fed.

Results

We shifted ISTs from the collar output between 20 and 270 s per observation period (mean = 156.9 s, SE = $\pm$0.66 s). Classification accuracy (correct classification rate) improved up to 61.7 percentage points for six of eight behaviors when we applied the time shift procedure in our modeling of pure interval data (Table 2). Of the eight observed behaviors, six were misclassified into fewer behavior categories using the time-shifted model compared with the uncorrected model (Table 3). The percentage of misclassified intervals

Table 2. Difference in (percentage points) correctly classified pure intervals of individual behaviors (n = 1,341) achieved by application of time shift procedure. Data were collected for five captive cow Rocky Mountain elk *Cervus elaphus nelsoni* wearing Lotek GPS_4400 collars equipped with dual-axis activity sensors at Starkey Experimental Forest and Range, USFS, Starkey, Oregon, summer 2011.

Behavior	Improvement	No change	Decrease
Bedded	2.1	—	—
Bedded-ruminating	3.6	—	—
Standing		0.0	—
Grazing	2.9	—	—
Browsing	25.9	—	—
Walking		—	4.3
Trotting	13.2	—	—
Galloping	61.7	—	—

among combined associated behavior categories was approximately the same for the passive and feeding categories after the time shift, but it improved for the running category. Using the time-shifted data set, the number of running intervals misclassified as passive and feeding decreased by 2 and 17.8 percentage points, respectively.

Discussion

Use of a correction procedure resulted in more accurate final classification of Rocky Mountain elk behaviors. Correction of timing error allowed greater detection and more accurate classification of behaviors that are typically shorter in duration, such as trotting and galloping. However, improvements were relatively small (<5 percentage points) for behaviors that typically occur over longer durations, such as bedding, bedding-ruminating, and grazing. The correct classification rate for browsing did improve markedly using shifted data, but part of this change might reflect an artifact of our methods. Because we were able to present a limited amount of browse to the animals at any given time, bouts of browsing were likely shorter in duration than might be typical in the wild. Only one behavior (walk) was classified more accurately using the uncorrected data, although the difference was small. Standing was often misclassified regardless of time adjustment or lack thereof.

Few investigators have noted evidence or addressed the potential impact of timing errors (Löttker et al. 2009; Heurich et al. 2012). Using data from the middle of relatively long (exceeding two sampling intervals) bouts of a single behavior while discarding data from the intervals at either end avoids the problem (Löttker et al. 2009). However, this approach will not work for behaviors of shorter duration (e.g., running) that are the same behaviors our work show to be the most in need of time correction.

We originally discovered the timing errors described in this paper while conducting work that involved Lotek GPS_4400 collars. However, we subsequently found very similar timing errors when using Lotek GPS_4500 collars (Gaylord 2013), and, based on the literature, we suspect similar errors exist for other collar manufacturers and models. Because different collar manufacturers are likely to use different components as newer models are released, we strongly recommend that users gather and report detailed information about the timekeeping mechanism(s) and technical operating details we have identified here. Specifically, users should assess the likelihood of drift; the magnitude of the drift; and how or when drift correction occurs, if any. Also, users should investigate the possibility of a timing offset due to activity monitor activation and ask what label gaps or duplicates in their collar output will be present in those cases. It should be noted that the time shift procedure described here was developed using data from only a few captive animals of uniform age and a single sex. Further studies with a greater number of animals of

Table 3. Confusion matrix of increases (+) and decreases (−) in misclassification (percentage points) between observed and predicted behaviors after application of the time shift procedure to pure intervals (sampling intervals containing a single behavior) of behavior data collected from Lotek GPS_4400 collars equipped with dual-axis accelerometers and worn by five captive cow Rocky Mountain elk *Cervus elaphus nelsoni*. Data were collected at Starkey Experimental Forest and Range, USFS, Starkey, Oregon, summer 2011. Classification rates were estimated using leave-one-out cross-validation on a linear discriminant model structure applied to activity monitor values collected by activity sensors.

	Predicted behavior							
Observed behavior	Bedded	Bedded-ruminating	Stand	Graze	Browse	Walk	Trot	Gallop
Bedded	0.0	−1.2	0.0	−0.6[a]	−0.1	0.0	0.0	0.0
Bedded-ruminating	−2.4	0.0	0.0	−0.5[a]	−0.7	0.0	0.0	0.0
Standing	+16.7	−11.6	0.0	−13.3[a]	+8.3	0.0	0.0	0.0
Grazing	−0.4[a]	−2.3	0.0	0.0	−0.3	0.0	0.0	0.0
Browsing	0.0	−12.9	0.0	−3.8	0.0	−9.1[a]	0.0	0.0
Walking	0.0	0.0	0.0	+6.1	−1.8	0.0	0.0	0.0
Trotting	−2.8[a]	0.0	0.0	−8.5	0.0	−1.7	0.0	−0.5
Galloping	0.0	0.0	0.0	−14.3[a]	0.0	−22.3	−25.0	0.0

[a] Misclassification in these cases was eliminated by time shift procedure.

multiple ages and both sexes will no doubt benefit our understanding of these issues.

Thus forewarned, users can decrease timing error by addressing its various sources. Users can greatly reduce accumulation of internal clock drift effects by increasing GPS fix rate to increase frequency of internal clock correction and by choosing a GPS fix rate shorter than the chosen PSI. Of course, increasing GPS fix rate will decrease the battery life of the unit, so users will need to balance concerns for internal clock drift and battery life for long-term studies. Users should choose PSIs divisible by 8 s to avoid timing errors associated with conflicts between programmed PSI and the activation interval of the activity microprocessor. Doing so will result in fewer label gaps and label duplicates. Finally, it is important to prevent the error that can result when the activity monitor unit is activated at a time that does not match collar IST. This source of error cannot be corrected by GPS fixes nor is it cyclical in nature; thus, it can defy correction (Figure 1). This error can be reduced or eliminated by timing the first activation of the collar as close to a PSI-dictated IST as possible.

Use of the time shift correction method introduced above is necessary to construct accurate classification models and will be facilitated by accurately noting the start time of changes from observed behaviors with little motion (e.g., bedded down or standing still) to behaviors with relatively moderate (e.g., grazing, browsing, or walking) or high amounts of motion (e.g., running) during the calibration process. To ensure that such breaks occur, it may be necessary to prompt these changes in behavior, for example by chasing an animal that was standing still.

When captive animals are not available for calibration, users have limited opportunity to collect behavior observations for free-ranging animals, generally only during collar deployment and retrieval. These limited observations are then paired with simultaneously collected AMVs to calibrate a classification model used to classify behaviors from the remained of the data set (i.e., when the animal was not being observed). Fewer behavior observation makes it especially important to capture changes from no or little motion to moderate or high amounts of motion. Users should note the start time of changes in behaviors associated with captivity or anesthetization (e.g., standing or lying down) from those associated with capture or to those associated with release (e.g., running) during collar deployment and retrieval. Doing so will provide clear breaks in behavior that are relatively easy to recognize in the data set. These signatures in the downloaded data can allow the investigator to calculate the amount of necessary time shift.

Activity monitor collars offer users the means to record animal behavior on temporal and spatial scales not possible using other techniques. Better understanding of how these collars function and how to proactively plan for data processing will allow scientists and managers to improve accuracy of the use of this tool for research and management. We identified a set of previously undescribed errors in data recorded by dual-axis activity monitors (Lotek GPS_4400). We provide paths by which future investigators can prevent significant amounts of timing error through careful planning and can correct errors in existing data sets. Finally, the time shift procedure and our recommended preventative measures can allow for construction of more accurate behavior classification models. However, some timing error is still possible, so users should exercise caution in attempting to match AMVs to a specific instantaneous locations.

Supplemental Material

Please note: The *Journal of Fish and Wildlife Management* is not responsible for the content or functionality of any supplemental material. Queries should be directed to the corresponding author for the article.

Text S1. Detailed description of the data found in Table S1, including column headings and the overall structure of the data.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-060.S1 (27 KB DOC).

Table S1. Direct behavior observations paired with activity monitor data from dual-axis GPS collars after shift of ISTs. Data were collected for five captive cow Rocky Mountain elk *Cervus elaphus nelsoni* at Starkey Experimental Forest and Range, USFS, Starkey, Oregon, summer 2011.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-060.S2 (1567 KB XLS).

Acknowledgments

We thank M. Wisdom, B. Dick, D. Ray, R. Kennedy, and C. Borum at the Starkey Experimental Forest and Range, U.S. Department of Agriculture, Forest Service Pacific Northwest Research Station, for generous logistical support and collaboration on the project. We thank J. Van Sickle and L. Ganio, Oregon State University, for providing statistical consulting. We thank G. Bracher for excellent collaboration and design of the figures for this manuscript. Thank you to M. Henriques and J. Chang at Lotek Wireless, Inc., for providing the technical details of collars. We are grateful to volunteers H. Gaylord, D. Gaylord, C. Gaylord, and N. Alexander who assisted in our data collection phase. We thank K. Moriarty, members of A.J.G.'s graduate committee B. McComb and P. Kennedy, the Subject Editor, and five anonymous reviewers for comments that improved previous versions of this manuscript.

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