Notes

Choosing Sampling Interval Durations for Remotely Classifying Rocky Mountain Elk Behavior

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Abstract

Dual-axis accelerometer global positioning system collars can be used to remotely record the activity level and behavior of free-ranging animals, but inter- and intraspecific variations in motion among behaviors necessitate calibration for each species of interest. To date, little work has been done to determine the best duration for sampling intervals when using activity monitors that incorporate dual-axis accelerometers. However, we expected that the duration of behaviors relative to the duration of sampling intervals could affect the accuracy of calibration and behavior classification models. Furthermore, we considered the potential effect of winter diet supplementation (hay) on behavior classification. We used Lotek 4500 global positioning system collars featuring dual-axis accelerometer activity monitors to collect data for calibration and classification trials on Rocky Mountain elk *Cervus elaphus nelsoni*. We used discriminant function model structures to determine the number of accurately classifiable behaviors that could be derived from data sampled over three sampling interval durations (5 min, 152 s, and 64 s) while also considering the potential effect of hay supplementation on classification. Our results suggest that investigators should ascertain whether their focal elk herd accesses or might access supplemental hay before deployment and analysis of activity sensor data. Similarly, researchers must weigh priorities when choosing a sampling interval, because no optimal solution emerged from our investigation. For example, of our acceptable models, only those constructed using 64-s intervals were able to distinguish short bouts of running. However, only models constructed with 5-min intervals accurately classified browsing while also maximizing the number of behaviors identified.

Keywords: accelerometer; collar; behavior; sampling interval; elk; *Cervus elaphus nelsoni*; Starkey

Received: April 7, 2015; Accepted: March 11, 2016; Published Online Early: March 2016; Published: June 2016

Citation: Gaylord AJ, Sanchez DM, Van Sickle J. 2016. Choosing sampling interval durations for remotely classifying Rocky Mountain elk behavior. Journal of Fish and Wildlife Management 7(1):213-221; e1944-687X. doi: 10.3996/042015-JFWM-034

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Introduction

Collar-mounted activity monitors are an important tool for remotely collecting behavior data of free-ranging animals. Most current models of activity monitors incorporate one or more accelerometers, electronic devices that record animal motion via changes in acceleration along a body axis. Integration of accelerometers into global positioning system (GPS) collars offers a tool with potential to sample location-specific behavior at fine geographic and temporal scales. However, users must balance sampling frequency and duration with the battery life of the collar. Longer sampling intervals tend to allow a longer battery life, but they are also likely to contain more behaviors than a short interval. Intervals containing only one behavior (i.e., pure intervals) tend to have less variable activity monitor values (AMVs) than intervals containing more than one behavior (i.e., mixed intervals) and therefore classify more accurately. It seems intuitive that shorter sampling intervals could allow increased detection of behaviors of shorter duration while also resulting in data sets with low variation in AMVs and higher classification accuracy. However, these issues are largely unexplored.

Passive and active intervals were classified for brown bear *Ursus arctos* with greater than 90% accuracy (Gervasi et al. 2006), whereas feeding, mobile, and stationary behaviors were classified for cheetah *Acinonyx jubatus* with 83–94% accuracy (Grünewälder et al. 2012); both studies used dual-axis GPS collars (Vectronic Aerospace, Berlin, Germany). Resting, feeding plus slow locomotion, and fast locomotion were classified for red deer *Cervus elaphus* with greater than 75% accuracy and for roe deer *Capreolus capreolus* with greater than 89% accuracy by using the same collars (Löttker et al. 2009; Heurich et al. 2012). For all species, comfort movements (e.g., adjusting position) and grooming while resting resulted in underrepresentation of passive behaviors, whereas activities with similar amounts of head movement (e.g., standing vs. lying down or walking vs. feeding) required investigators to group behaviors into broader categories to obtain accurate classification (Coulombe et al. 2006; Löttker et al. 2009). However, none of these studies compared sampling interval when conducting their calibrations.

A few investigators have experimented with sampling interval and have found clear differences in species-specific patterns. Passive behaviors of red deer were classified most accurately using 5-min intervals, rather than 10- and 15-min intervals, when investigators used collars that incorporated two tip-switches (Adrados et al. 2003). In contrast, the active behavior category was classified most accurately over 10-min intervals, which also maximized classification accuracy. Recognition of resting and walking decreased with a stepwise increase of sampling interval from 1 to 20 s for goat *Capra aegagrus*, whereas feeding remained relatively unchanged (Moreau et al. 2009). Besides species-specific issues, we noted that a source of population-scale intraspecific variability might be introduced via particular management activities, such as supplemental feeding. Hay supplementation is a common tool in winter management of elk herds to increase overwinter survival or to alleviate pressure on privately owned hay yards. Field observations of elk eating hay seemed to indicate different head motions than those observed for grazing animals. We wondered whether this different motion might leave a distinguishable signature in remotely collected activity sensor data. Furthermore, we thought it prudent to explore whether such a signature would be significant in choosing sampling interval durations.

We investigated the effects of sampling interval duration when classifying behaviors of Rocky Mountain elk *Cervus elaphus nelsoni* with and without access to hay. We calibrated GPS collars (model 4500; Lotek, Newmarket, Ontario) for Rocky Mountain elk by using 5-min, 152-s, and 64-s sampling intervals. We compared the number of behaviors that could be classified using these sampling intervals and with what accuracy. Based on our previous work (Gaylord 2013), we expected that shorter sampling intervals would result in fewer mixed intervals and thus would allow us to classify a greater number of behaviors with higher accuracy. Specifically, we expected shorter intervals to improve classification for behaviors that tend to be closely interspersed, such as walking and grazing, or of short duration, such as running. In addition to considering the best sampling interval for classification of natural behaviors, we felt it important to include one behavior of anthropogenic origin. Supplying Rocky Mountain elk with supplemental feed (usually hay) to boost overwinter survival has been a common management practice in western states for nearly a century (e.g., Murie 1944; Daniels 1953). Our preliminary observations of hay-supplemented Rocky Mountain elk led us to expect that the data signal from hay eating would differ from other head-down elk behavior, such as grazing on grass. However, we found no previous work considering potential detectability of hay consumption when using tools such as activity monitors. We expect our work will assist future investigators in selecting sampling intervals to best meet their study situation and research objectives.

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

Study animals and animal handling

Experienced personnel used all-terrain vehicles and gated chutes to separate four female Rocky Mountain elk from the rest of the herd. The captive herd at Starkey is comprised of females aged 17–22 y at the time of our work. Individual study animals were selected from this herd based on good body condition. Study animal sample size was restricted by the number of fit individuals and the number of available collars. We collared, recorded body weight, and visually monitored each Rocky Mountain elk for signs of stress (e.g., hyperventilating) before releasing the animals into a recovery pen. Animals used for our measurements ranged in age from 18 to 21 y and weighed 215–307 kg.

We collared the Rocky Mountain elk with Lotek 4500 GPS collars (1 kg) equipped with three accelerometers oriented perpendicular to one another to capture motion along three body planes: a plane across the animal's shoulders (*x* axis), a plane parallel to the animal's spine (*y* axis), and a plane oriented vertically (*z* axis). Accelerometers recorded the difference in acceleration between two consecutive measurements 4 times/s. These values were then averaged over a user-selected sampling interval as an indexed value ranging from 0 to 255 and stored with the associated date, temperature, and start time of the sampling interval. Collars stored

AMVs averaged over the entire sampling interval, rather than individual accelerometer measurements. Users of the Lotek 4500 collars can choose among seven preset modes that record different parameters of motion over different preset sampling intervals. We set our collars to collect data in modes 1, 2, and 3, thereby recording acceleration along only the *x* and *y* axes by using preset 5-min, 152-s, and 64-s sampling intervals, respectively. Other collar modes collect data incorporating head angle. Accelerometer collar technical details are further described in previous work (Gaylord 2013; Gaylord and Sanchez 2014). We collected data during three 2- to 4-wk periods. We collected data during 152-s intervals from September 6 to September 22, 2011; during 64-s intervals from September 22 to October 13, 2011; and during 5-min intervals from April 23 to May 16, 2013. Although some data were collected during rut season, study animals were segregated from other animals, including Rocky Mountain elk bulls. Therefore, it is unlikely that the rut affected the data.

Field observations and data processing

We simultaneously collected accelerometer data via collars and direct observations of behavior. We observed the collared Rocky Mountain elk within the fenced pasture in which the animals were kept during the duration of the study. We observed Rocky Mountain elk at distances ranging from 10 to 30 m by using binoculars when necessary. The captive Rocky Mountain elk at Starkey are regularly fed by U.S. Forest Service staff and are relatively habituated to human presence. Except during handling or when prompting behaviors, observer presence did not seem to influence Rocky Mountain elk behavior. Because collars record physical motions of the animals, the source of stimulation should not influence collar data. For example, the physical motions of a Rocky Mountain elk running, whether in reaction to sighting a predator or to avoid a human on an all-terrain vehicle, should be equivalent in their data signatures.

We used handheld personal digital assistants (Tungsten E2; Palm, Sunnyvale, CA) equipped with personal digital assistant–based software (EVENT-Palm; J. C. Ha, University of Washington, Seattle) to record the start time and duration of each observed behavior. We recorded continuous observations daily during two (morning and evening), 4-h sessions. A single observer was paired to an individual animal and recorded its behaviors into eight classes: bedded, standing, grazing, eating hay, browsing, walking, trotting, and galloping (Tables S1–S3, *Supplemental Material*). Other behaviors, such as grooming and conspecific interaction, were recorded according to the dominant posture or movement of the animal. For example, a Rocky Mountain elk that was grooming while lying down was recorded as bedded. We soon created a ninth category, unknown, to note occasions when we briefly lost sight of an animal. We rotated observers to a different individual animal each observation period to control for potential bias. Most behaviors occurred spontaneously and frequently enough that we were able to obtain adequate samples of those motions. Other behaviors were relatively rare among our study animals for a variety of reasons. Due to prior use of the study pasture, shrub growth and height were limited. Therefore, we induced browsing by attaching locally gathered stems of woody species to fence posts and a wooden tripod. We scattered hay on the ground to induce hay-eating behavior. Finally, trotting and galloping behaviors were prompted when trained, all-terrain vehicle–mounted Forest Service personnel chased individual animals for short periods during sampling for the 64- and 152-s intervals. Due to the age and condition of our study animals, we determined that prompting trotting and galloping for full 5-min sampling intervals was not possible. We postprocessed all collar-collected data to address timing mismatches (as detailed in Gaylord 2013 and Gaylord and Sanchez 2014).

We conducted direct observations of captive female Rocky Mountain elk behavior following review and approval by the Starkey Institutional Animal Care and Use Committee (IACUC), as required by the Animal Welfare Act of 1985 and its regulations. We specifically followed protocols established by the Starkey IACUC for conducting elk research at Starkey Experimental Forest and Range (92-F-0004, Wisdom et al. 1993).

Model building

Activity monitor collars require calibration for each species of interest to determine what behaviors correspond to what AMVs. We paired observed animal behaviors to AMVs recorded by the collars for each sampling interval. We used these pairings to build a predictive model used to classify the activity level or behavior of novel animals based on remotely collected collar data.

We initially categorized all intervals of observed behavior based on the predominant behavior (greatest duration) within an interval. After examining the data, we created a rule for intervals containing greater than or equal to 40 s of running behaviors (trotting or galloping) and recategorized those intervals as run. We also noticed that running often occurred in short bouts of 16–39 s, which temporally dominated mixed 64-s intervals without meeting the 40-s rule. To explore whether our models could detect these potentially important bursts of activity we created a new category, short runs, and then included it in our initial calibration modeling for all three interval durations.

We then constructed classification models for each interval duration. To explore the influence of hay availability, we constructed a parallel set of models that included and excluded observations made while animals had access to hay (Tables S4–S9, *Supplemental Material*). We selected our best models based on the percentage of observed behaviors they classified correctly (i.e., the correct classification rate [CCR]). Each model included AMVs for the *x* axis, *y* axis, and the product of those

Table 1. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled with three different interval durations and without access to supplemental feed (no hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We selected the final model from one of four options: linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. Data were collected using dual-accelerometer Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes during 64-s, 152-s, and 5-min intervals ($n = 13{,}359$, $n = 6{,}210$, and $n = 2{,}795$, respectively) by programming collars to use modes 1, 2, and 3, respectively. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during summer and fall 2011 (64 and 152 s) and spring 2013 (5 min).

Sampling interval	Final model structure	Behavior category							Total	Average
		Bedded	Passive	Graze, walk, stand	Feed/, walk	Browse	Short run	Run		
64 s	LDA_{untr}		89.5		88.4		84.9	71.4	89.2	83.6
152 s	QDA_{log}		87.0		96.7			100.0	90.4	94.6
5 min	QDA_{untr}	93.9		83.2		81.0		81.0	87.7	84.9

AMVs as predictors. For each interval type, we compared the performance of four model structures: linear discriminant function and quadratic discriminant function by using both untransformed and log-transformed AMVs. See Gaylord (2013) for detailed formal model structure. We estimated CCRs that would be expected if classification models were applied to novel data sets by using leave-one-out cross validation. We identified acceptable models based on a best-predictions strategy, as evaluated by CCR, and only considered models acceptable if the CCR for every behavior was greater than or equal to 70%. We grouped behaviorally or mechanically similar behaviors (e.g., standing and bedded, not bedded and running) with CCRs less than 70%. From the acceptable models, we then determined the final model based on the highest total classification rate for all intervals, the highest average behavior classification rate, and highest minimum classification rate for individual behaviors.

Based on previous work (Gaylord and Sanchez 2014), we knew that if behaviors were not correctly classified using models constructed with only pure intervals, then they would not be classified using models constructed with all intervals (both pure and mixed). Therefore, we first constructed models using only pure interval data sets to further combine behaviors. Bedded and standing would not classify greater than or equal to 70% accuracy, so they were grouped into passive for 64- and 152-s intervals and grazing and browsing into feeding for 64-s intervals (Tables S1–S3, *Supplemental Material*). All eight recorded behaviors classified at greater than or equal to 70% accuracy by using pure intervals for 5-min intervals. Using these behavior groupings, we then used full data sets (including both pure and mixed intervals) to construct classification models for each interval duration.

We used leave-one-out cross validation to evaluate model performance for novel animals. We excluded one animal from the calibration of the final model structure, and then used the fitted model to predict behaviors for the excluded animal. We repeated this process for each animal in turn and compared the average CCRs for the four calibration groups of three Rocky Mountain elk vs. the average CCRs for the four excluded individual Rocky Mountain elk. We also compared the standard deviation of CCRs for the group vs. the individual for each behavior to compare classification variability.

Results

Our direct observations of Rocky Mountain elk behavior yielded 30,851, 13,492, and 5,788 samples for 64-s, 152-s, and 5-min sampling intervals, respectively. The number of behaviors classifiable for Rocky Mountain elk differed among the three interval durations for both data sets (Tables 1 and 2). The 152-s intervals distinguished the fewest behavior categories regardless of the presence of hay, but they minimized CCR variability (Figures 1 and 2). Of our acceptable model structures,

Table 2. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled with three different interval durations and with access to supplemental feed (hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We selected the final model from one of four options: linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. Data were collected using Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes during 64-s, 152-s, and 5-min intervals ($n = 17{,}359$, $n = 7{,}127$, and $n = 2{,}993$, respectively) by programming collars to use modes 1, 2, and 3, respectively. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during summer and fall 2011 (64 and 152 s) and spring 2013 (5 min).

Sampling interval	Final model structure	Behavior category								Total	Average
		Bedded	Passive	Hay	Graze, walk, stand	Feed, walk	Browse	Short run	Run		
64 s	LDA_{untr}		86.4			87.1		84.9	71.4	86.7	82.5
152 s	QDA_{untr}		89.9			86.1			100.0	88.4	92.0
5 min	LDA_{log}	91.3		75.0	83.2		83.1		81.0	86.1	82.7

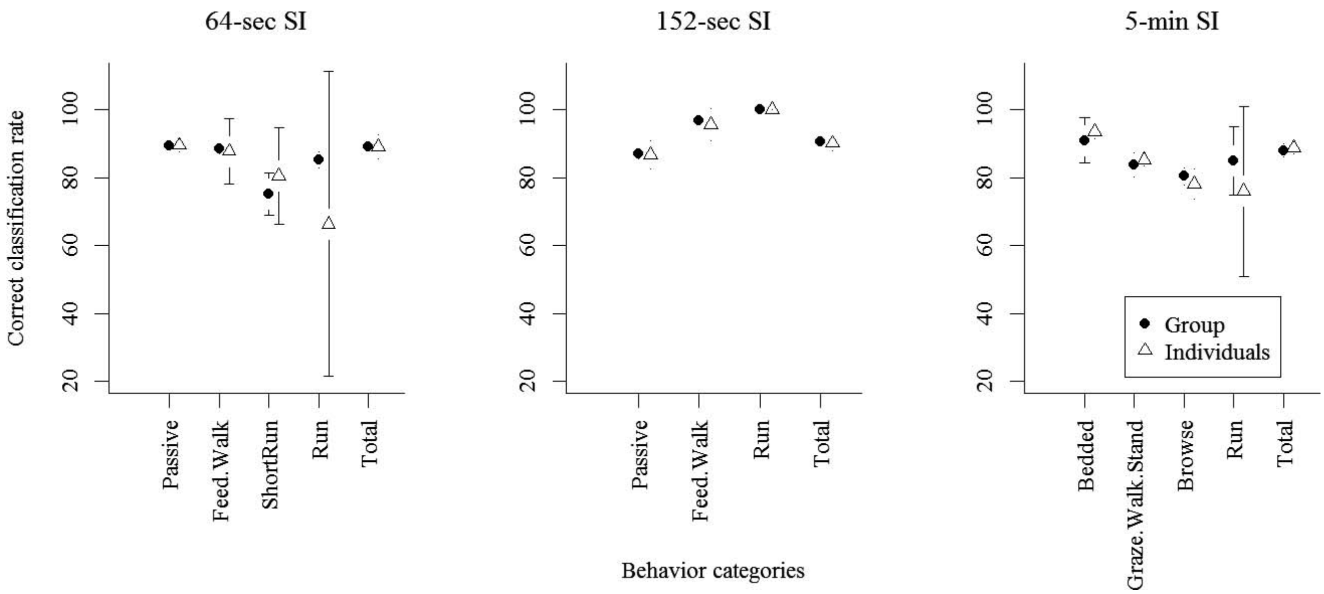

Figure 1. Individual vs. group variability in behavior classification modeled for data collected of 64-s, 152-s, and 5-min sampling intervals by using data sets that excluded supplemental feeding. Data are mean and standard deviation (SD) of correct classification rates (CCRs, %) for behaviors classified using a model calibrated with three animals (Group) and applied to the remaining novel animal (Individual). We calibrated classification models by combining directly observed behaviors of Rocky Mountain elk *Cervus elaphus nelsoni* with simultaneously collected data from activity monitors housed in Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes during 64-s, 152-s, and 5-min intervals ($n = 13{,}359$, $n = 6{,}210$, and $n = 2{,}795$, respectively) by programming collars to use modes 1, 2, and 3, respectively. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during summer and fall 2011 and spring, 2013.

only those constructed using 64-s intervals were able to distinguish short bouts of running (short run), whereas only those constructed using 5-min intervals were able to distinguish browsing and eating hay. Models constructed with 5-min interval data (both with and without hay) classified the greatest number of feeding-related behaviors (three and two, respectively). Models constructed using observations that included eating hay increased classification variability for all intervals (Figures 1 and 2), whereas running had the greatest classification variability among behaviors.

Discussion

Both sampling interval duration and the availability of hay affected classification of Rocky Mountain elk behaviors as sampled on two axes by accelerometer-equipped behavior sensors. Classification models constructed for the three sampling interval durations varied in the number of behaviors they classified, classification accuracy, and classification variability. Similarly, comparison of classification rates for hay and no-hay data sets revealed that addition of hay has a discernible influence on classification variability. We concluded that choice of sampling interval distills to a decision between maximizing the number of distinct behaviors vs. maximizing classification accuracy for a smaller number of behaviors.

Our models were able to distinguish among different feeding behaviors and between different durations of fast locomotion, both firsts for ungulates. Better differentiation of these behaviors could help researchers to generate more informed resource selection or energy budget models. However, like previous work for red deer and roe deer (Löttker et al. 2009; Heurich et al. 2012), we were unable to distinguish grazing from walking at any interval duration. Grazing and walking are closely related for elk and deer, animals rarely do one behavior for long periods without doing the other. Classification of passive behaviors (bedded and stand combined) did not differ appreciably as sampling interval duration increased, thereby differing from findings by Adrados et al. (2003) and Moreau et al. (2009).

Our findings illustrate that choice of sampling intervals should be informed by specific research or management questions. For example, investigators who are most interested in distinguishing among different feeding behaviors (e.g., graze, browse, hay) should set collars to collect data on 5-min intervals. Also, of those we evaluated, only models built with 5-min interval data were able to distinguish the hay-eating behavior. In contrast, if short bursts of fast movement, such as our short runs category, are important to a researcher, then the 64-s interval would be best because it was the only sampling interval able to accurately detect and classify that behavior. We hasten to add a caveat from our prior work that users must consider the microprocessor activation interval of their collar model because of the potential for creating timing offset errors. For the Lotek 4500 collars (8-s microprocessor activation interval), a

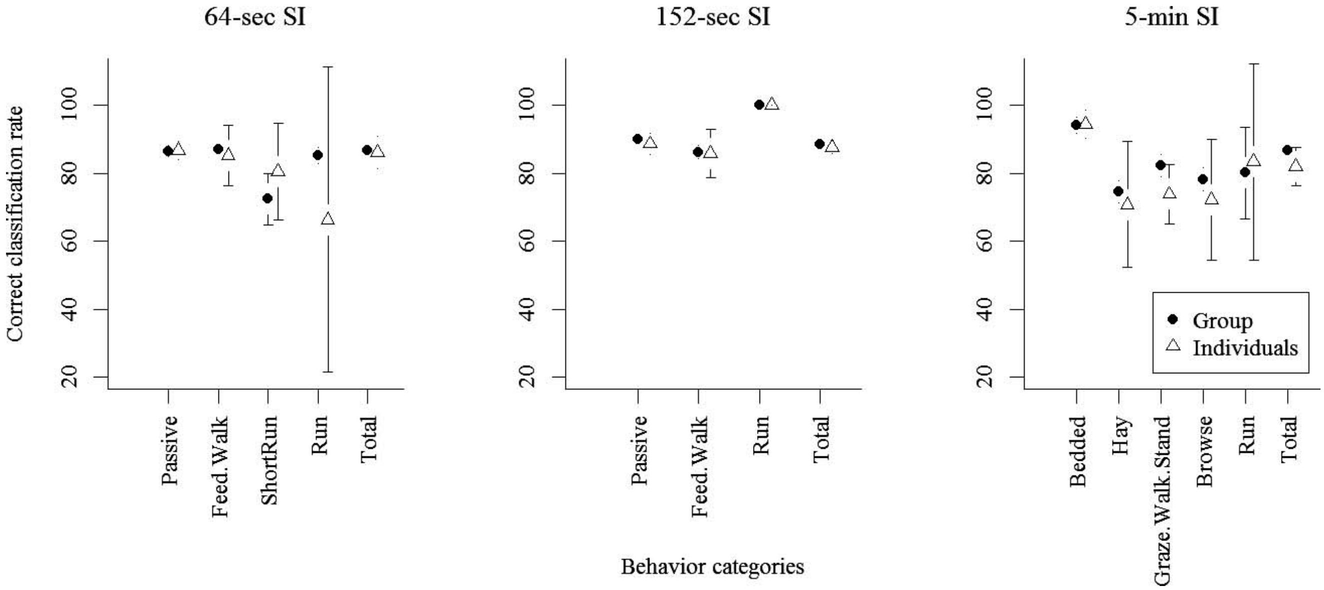

Figure 2. Individual vs. group variability in behavior classification modeled for data collected of 64-s, 152-s, and 5-min sampling intervals by using data sets that included supplemental feeding. Data are mean and standard deviation (SD) of correct classification rates (CCRs, %) for behaviors classified using a model calibrated with three animals (Group) and applied to the remaining novel animal (Individual). We calibrated classification models by combining directly observed behaviors of Rocky Mountain elk *Cervus elaphus nelsoni* with simultaneously collected data from activity monitors housed in Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes during 64-s, 152-s, and 5-min intervals ($n = 17{,}359$, $n = 7{,}127$, and $n = 2{,}993$, respectively) by programming collars to use modes 1, 2, and 3, respectively. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during summer and fall 2011 and spring 2013.

user should set the 5-min sampling interval to last 304 s rather than 300 s (Gaylord and Sanchez 2014).

Exploration of classification variability revealed additional insights. Models that classified a greater number of categories not only distinguished among more behaviors but also offered the ability to increase classification accuracy and decrease variability by further combining behavior categories. For example, 64-s models accurately classified (i.e., CCR > 70%) up to four behaviors (passive, feed plus walk, short run, and run), whereas 152-s models classified only three behaviors (passive, feed plus walk, and run), but with higher accuracy and less variability. When we experimented with further combination of behavior categories for 64-s models (i.e., three behaviors: passive, feed plus walk, run), classification accuracy and variability were comparable to those for 152-s models. This difference suggests that investigators should initially collect finer scale (shorter interval) data and screen for short-duration behaviors (e.g., short runs). They can then experimentally decrease the resolution (i.e., reduce number of behaviors identified) to boost accuracy in a second stage of modeling.

Some of the classification variability we observed was likely due to sampling constraints. We had four animals available during each trial, resulting in small sample sizes when calculating classification for novel animals. This constraint was especially apparent when working with behaviors for which we were able to collect few samples, such as run. For example, during sampling for the 64-s intervals, we observed only two intervals of running for one individual, both of which were misclassified into the short-run category (0% CCR for run for that animal). Similarly, during 5-min sampling, we only obtained running intervals for three of the four Rocky Mountain elk, which undoubtedly contributed to the increased variability we observed. We expect future investigators able to collect larger sample sizes to be able to improve (i.e., lower) on our estimates of behavior-specific interanimal variability.

It is also likely that animals of different age and sex have slightly different motions for the same behavior. For example, increased neck circumference during rut or the weight of antlers might affect head-and-neck movement of males when walking or feeding. Or perhaps younger animals generally exhibit more movement for the same behavior. Furthermore, it is possible that terrain that the animal inhabits, such as steep slopes vs. level plains, may affect head-and-neck movement when walking or running. Further study is necessary to determine to what extent these factors play a role in classifying behavior by using accelerometer collars.

Our work indicates that investigators have several important factors to consider when choosing sampling intervals for their collar-mounted activity sensors. We acknowledge that most users must first balance battery and project duration considerations with other factors. Beyond that basic calculation, however, we urge investigators to consider which behaviors or suites of behaviors are of highest interest for their research questions. We learned that there is no single best option for choosing sampling intervals for every situation. We also learned that feeding the animals hay influenced classification accuracy. Thus, those working on herds known or likely to have access to hay should consider this factor when initially programming collars and again when building initial classification models. We also caution researchers to not use hay as a proxy for grazing when calibrating accelerometer collars because motions associated with these two food sources are distinct. Our models for analysis of 5-min, 152-s, and 64-s sampling intervals collected in either hay or nonhay data sets can be found in the Supplemental Material (Model Package S1, *Supplemental Material*).

Supplemental Material

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Model Package S1. A zipped file containing models to classify Rocky Mountain elk *Cervus elaphus nelsoni* behavior by using data collected from Lotek 4500 global positioning system collars set at 64-s, 152-s, or 5-min intervals. The contents of the zipped file include: instructions for choosing the appropriate behavior classification model (Choosing Classification Models. docx), instructions on how to format collar data for use in a classification model (Elk interval Classification Model Read Me.docx), an R Workspace containing the classification models (ElkIntervalClassificationModels.Rdata), and the R code necessary to run a classification model (Elk Interval Classification R Code.R).

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S1 (43 KB ZIP).

Table S1. Activity monitor data collected at 64-s sampling intervals by using dual-axis global positioning system collars paired with direct behavior observations after shift of interval start times. Data were collected for four captive female Rocky Mountain elk *Cervus elaphus nelsoni* at Starkey Experimental Forest and Range, U.S. Forest Service, Starkey, Oregon, during fall 2011.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S2 (6045 KB XLS).

Table S2. Activity monitor data collected at 152-s sampling intervals using dual-axis global positioning system collars paired with direct behavior observations after shift of interval start times. Data were collected for four captive female Rocky Mountain elk *Cervus elaphus nelsoni* at Starkey Experimental Forest and Range, U.S. Forest Service, Starkey, Oregon, during fall 2011.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S3 (3748 KB XLS).

Table S3. Activity monitor data collected at 5-min sampling intervals using dual-axis global positioning system collars paired with direct behavior observations after shift of interval start times. Data were collected for four captive female Rocky Mountain elk *Cervus elaphus nelsoni* at Starkey Experimental Forest and Range, U.S. Forest Service, Starkey, Oregon, during spring 2013.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S4 (2633 KB XLS).

Table S4. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled at 64-s intervals for animals without access to supplemental feed (no hay). We estimated CCRs by using leave-one-out cross validation for our final model structure. We compared four model structures: linear (LDA) and quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. We grouped behaviors with CCRs less than 70% (italics). Data were collected using dual-accelerometer Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes ($n = 13{,}359$) by programming collars to use mode 1. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during fall 2011.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S5 (49 KB DOC).

Table S5. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled at 152-s intervals for animals without access to supplemental feed (no hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We compared four model structures: linear (LDA) and quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. We grouped behaviors with CCRs less than 70% (italics). Data were collected using dual-accelerometer Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes ($n = 6{,}210$) by programming collars to use mode 2. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during fall 2011.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S6 (50 KB DOC).

Table S6. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled at 5-min intervals for animals without access to supplemental feed (no hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We compared four model structures: linear (LDA) and quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. We grouped behaviors with CCRs less than 70% (italics). Data were collected using dual-accelerometer Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes ($n = 2{,}795$) by programming collars to use mode 3. Observations were made at Starkey

Experimental Forest and Range, La Grande, Oregon, during spring 2013.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S7 (52 KB DOC).

Table S7. Correct classification rates (CCRs, %) of Rocky Mountain elk (*Cervus elaphus nelsoni*) behaviors sampled at 64-s intervals for animals with access to supplemental feed (hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We compared four model structures: linear (LDA) and quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. We grouped behaviors with CCRs less than 70% (italics). Data were collected using Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes ($n = 17{,}359$) by programming collars to use mode 1. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during fall 2011.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S8 (50 KB DOC).

Table S8. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled at 152-s intervals for animals with access to supplemental feed (hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We compared four model structures: linear (LDA) and quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. We grouped behaviors with CCRs less than 70% (italics). Data were collected using Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes ($n = 7{,}127$) by programming collars to use mode 2. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during fall 2011.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S9 (49 KB DOC).

Table S9. Correct classification rates (CCRs, %) of Rocky Mountain elk *Cervus elaphus nelsoni* behaviors sampled at 5-min intervals for animals with access to supplemental feed (hay). We estimated CCRs using leave-one-out cross validation for our final model structure. We compared four model structures: linear (LDA) and quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. We grouped behaviors with CCRs less than 70% (italics). Data were collected using Lotek 4500 global positioning system collars worn by captive female animals. To allow standardized comparisons, we collected data from only the *x* and *y* axes ($n = 2{,}993$) by programming collars to use mode 3. Observations were made at Starkey Experimental Forest and Range, La Grande, Oregon, during spring 2013.

Found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S10 (60 KB DOC).

Reference S1. Rowland MM, Bryant LD, Johnson JK, Noyes JH, Wisdom MJ, Thomas JW. 1997. The Starkey project: history, facilities, and data collection methods for ungulate research. U.S. Department of Agriculture, Forest Service Technical Report PNW-GTR 396:1–62.

Found at DOI: http://www.treesearch..fefsd.us/pubs/4752. Also found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S11 (8015 KB PDF).

Reference S2. Wisdom, MJ, Cook JG, Rowland MM, Noyes JF. 1993. Protocols for care and handling of deer and elk at the Starkey Experimental Forest and Range. General Technical Report PNW-GTR-311. Portland, Oregon: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Found at DOI: http://www.treesearch.fs.fed.us/pubs/4749. Also found at DOI: http://dx.doi.org/10.3996/042015-JFWM-034S12 (3454 KB PDF).

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 L. Ganio, Oregon State University, for providing statistical consulting and M. Henriques and J. Chang at Lotek Wireless, Inc., for teaching us how their collars function. We are grateful to volunteers H. Gaylord, D. Gaylord, C. Gaylord, M. Barton, J. Belk, C. Cappello, J. Coulter, M. Hafsadi, P. Manlick, S. Martinez, and M. Owens who assisted in the data collection phase. D. Taylor assisted with data processing. We thank A.J.G.'s graduate committee members B. McComb and P. Kennedy, the Associate Editor, and three anonymous reviewers for comments that improved previous drafts of this manuscript.

This work was supported by start-up funding provided by Oregon State University College of Agricultural Sciences for D.M.S.

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References

Adrados C, Verheyden-Tixier H, Cargnelutti B, Pepin D, Janeau G. 2003. GPS approach to study fine-scale site use by wild red deer during active and inactive behaviors. Wildlife Society Bulletin 31:544–552.

Coulombe M-L, Massé A, Côté SD. 2006. Quantification and accuracy of activity data measured with VHF and GPS telemetry. Wildlife Society Bulletin 34:81–92.

Daniels TWB. 1953. Winter at Blackrock ... a big game report from a snowbound wilderness. Wyoming Wildlife 17:20–27.

Gaylord A. 2013. Ungulate activity classification: calibrating activity monitor GPS collars for Rocky Mountain elk, mule deer, and cattle. Master's thesis. Corvallis: Oregon State University.

Gaylord AJ, Sanchez DM. 2014 Causes and consequences of timing errors associated with GPS collar accelerometer activity monitors. Journal of Fish and Wildlife Management 5(2):372–379.

Gervasi V, Brunberg S, Swenson JE. 2006. An individual-based method to measure animal activity levels: a test on brown bears. Wildlife Society Bulletin 34:1314–1319.

Grünewälder S, Broekhuis F, Macdonald DW, Wilson AM, McNutt JW, Shawe-Taylor J, Hailes S. 2012. Movement activity based classification of animal behaviour with an application to data from cheetah (*Acinonyx jubatus*). PLoS ONE 7(11):e49120.

Heurich M, Traube M, Stache A, Lottker P. 2012. Calibration of remotely collected acceleration data with behavioral observations of roe deer (*Capreolus capreolus* L.). Acta Theriologica 57:251–255.

Long R, Rachlow J, Kie J. 2008. Effects of season and scale on response of elk and mule deer to habitat manipulation. Journal of Wildlife Management 72:1133–1142.

Löttker P, Rummel A, Traube M, Stache A, Šustr P, Müller J, Heurich M. 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.

Moreau M, Siebert S, Buerkert A, Schlecht E. 2009. Use of a tri-axial accelerometer for automated recording and classification of goats' grazing behaviour. Applied Animal Behaviour Science 119(3):158–170.

Murie OJ. 1944. Our big game in winter. Transactions of the North American Wildlife Conference 9:173–176.

Rowland MM, Bryant LD, Johnson JK, Noyes JH, Wisdom MJ, Thomas JW. 1997. The Starkey project: history, facilities, and data collection methods for ungulate research. USDA Forest Service Technical Report PNW-GTR 396:1–62 (see *Supplemental Material*, Reference S1, http://dx.doi.org/10.3996/042015-JFWM-034S11).

Wisdom MJ, Cook JG, Rowland MM, Noyes JF. 1993. Protocols for care and handling of deer and elk at the Starkey Experimental Forest and Range. General Technical Report PNW-GTR-311. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station, , Portland, Oregon (see *Supplemental Material*, Reference S2, http://dx.doi.org/10.3996/042015-JFWM-034S12).