Ungulate Activity Classification: Calibrating Activity Monitor GPS Collars for Rocky Mountain Elk, Mule Deer, and Cattle

by
Adam J. Gaylord

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Ungulate behavior has been studied extensively but direct observation of free-ranging animals over long periods of time and large geographic areas is often prohibitively difficult. Improved technology, such as GPS collars fitted with motion-sensitive activity monitors, provides researchers with a potential tool to remotely collect fine scale activity and location data. Activity monitors record animal movement along one or more axes with different amounts of motion presumably corresponding to different animal behaviors. Inter- and intraspecific variations in motion among behaviors necessitate calibration for each focal species. Calibration generally consists of making detailed behavioral observations of captive collared animals and then pairing observed behaviors with collar activity data for the same sampling interval. This process results in a mathematical model that can be used to classify the activity level or behavior of novel free-ranging animals using remotely collected collar data.

During the calibration process, we discovered that several factors associated with the time-keeping mechanisms of these collars can result in mismatches between collar

activity monitor data and direct behavior observation. This results in inaccurate classification models. To correct for these timing errors, we used defined breaks in animal behavior to shift collar output times, improving the average correct classification rate up to 61.7 percentage points for specific behaviors. We also learned that timing errors can be minimized by activating a collar's GPS unit, increasing the GPS fix rate, and using a sampling interval divisible by 8 seconds. Awareness and management of collar timing issues will enable managers and researchers to best classify animal behavior when using these collars and interpreting data from free-ranging animals.

No activity monitor calibration had been conducted for Lotek 4400 GPS collars featuring dual-axis activity monitors for Rocky Mountain elk (*Cervus elaphus nelsoni*), mule deer (*Odocoileus hemionus*), or cattle (*Bos taurus*). We used discriminant function models to determine what behaviors can be accurately classified using these collars. Additionally, we constructed models using only pure intervals (sampling intervals during which only one behavior occurred) and applied them to datasets containing only mixed intervals (sampling intervals during which >1 behavior occurred) to determine the effect of excluding the latter from the calibration process. Final full-dataset models accurately classified (correct classification rates > 70%) up to 4 behavior categories for elk, 3 for deer, and 2 for cattle. Our results showed that classification models constructed with only pure intervals can result in misclassification rates of up to 61% for mixed intervals of some behaviors.

When remotely collecting data, researchers must balance sampling frequency with the battery life of the recording device. The duration of each behavior relative to sampling interval length might play an important role in activity monitor calibration. To date no efforts have been made to determine the optimal sampling interval duration to use with these sensors. Similarly, Lotek 4500 GPS collars featuring accelerometer activity monitors had not been calibrated for Rocky Mountain elk. We examined discriminant function model structures for 3 sampling interval durations (5-min, 152-sec, and 64sec) to determine what behaviors can be accurately classified for animals with and without access to supplemental feed in the form of hay. Models constructed using 5-min sampling intervals performed best, accurately classifying (≥ 70% classification rate) up to 5 behaviors for animals without access to supplemental feed and 4 behavior categories for those with access to supplemental feed. All of our calibration models will be made available on-line, allowing managers and researchers to interpret data from novel free-ranging animals for use in ongoing and future studies of ungulate ecology and management.

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Adam J. Gaylord, Author

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Dr. John Van Sickle provided statistical instruction and guidance for the calibration of the classification models described in Chapters 2 and 3. He also provided valuable feedback on early drafts of the manuscripts for those chapters.

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DEDICATION

For my mom and dad, Sherry and Brian Gaylord, who stirred my love of learning and of the great outdoors. For my grandpa, Lloyd Gaylord, who inspires me. For my brother, Aaron Gaylord, who supports me. And to my wife, Hilary Gaylord, whose love I'm grateful for beyond words. I dedicate this to my family.

CHAPTER 1: GENERAL INTRODUCTION

Knowledge of animal behavior provides information necessary for making informed management decisions. Although Global Positioning System (GPS) technology has enabled biologists to analyze animal use of space over a range of temporal and spatial scales, animal behavior at these locations has been unknown. Direct observation of free-ranging animals is prohibitively difficult, especially as sample size and species-specific mobility increase. Direct observations of animal behavior can also be at risk of various kinds of observer bias (Martin and Beteson 2007). Therefore, many researchers are turning to collar-mounted devices to track and record behavior remotely.

Users of early models relied on changes in the signal strength of Very High Frequency (VHF) collars to infer changes in activity (Roth and Meslow 1983, Carranza et al. 1991). These techniques have been criticized due to the potential for substantial bias from signal modulation (Lindzey and Meslow 1977, Singer et al. 1981) and signal interference caused by the environment between the animal and the antenna (Rouys et al. 2001). Other investigators used the distance between successive GPS points per unit time to measure velocity and to infer activity (Nelson and Sargeant 2008, Proffitt et al. 2010). However cloud cover, vegetative cover, topography, and the orientation of the collar can reduce GPS fix rates by half (Hulbert and French 2001, Di Orio et al. 2003, Cain III et al. 2005, D'Eon and Delparte 2005, Jiang et al. 2008, Mattisson et al. 2010), substantially affecting location accuracy and resulting in underestimates of travel in active animals and overestimates of travel in stationary animals (Ganskopp and Johnson 2007). Likewise, because animals seldom move in straight lines for significant periods of time, distances traveled between GPS locations are likely to be underestimated unless samples (i.e., "fixes") are taken very frequently. High fix rates decrease the lifespan of collar batteries so collar users must balance location frequency with the duration of their study. Location-dependent errors can contribute to inaccuracies when calculating energy budgets or estimating habitat utilization.

Later collar designs included a single tip-switch consisting of a small metal ball in a metal tube with metal pins on each end. When tipped, the ball rolled to one end of the tube and completed the circuit between the tube and the pin. The tube was oriented such that a change in animal posture (e.g., head up vs. head down) would tip the switch and change the pulse rate emitted by the radio transmitter. Behavior was inferred from differences in pulse rate or from the number of changes in pulse rate per unit time. Inferred behaviors agreed with observed behaviors when distinguishing between active and inactive behaviors 98% and 96% of the time for white-tailed deer (*Odocoileus virginianus*) and 88.5% and 93.8% of the time for mountain lions (*Puma concolor*), respectively (McCullough and Beier 1988, Janis and Clark 1999). However, further discrimination among active behaviors was not successful. Other researchers used changes in pulse rate and variation in radio-signal strength to distinguish resting, feeding, and moving in Rocky Mountain elk (*Cervus elaphus nelsoni*) with 94% accuracy (Green and Bear 1990). Similarly, resting, feeding, and other activities of mule deer (*Odocoileus hemionus*) were correctly identified 94.5%, 96.5%, and 95% of the time, respectively (Kufeld et al. 1988).

Rather than signal strength, distance traveled, or pulse rate, the subsequent generation of collars functioned on the premise that different behaviors vary in how much movement occurs along multiple body axes. These collars incorporated devices that record quantified measures of animal motion in multiple spatial planes. One type of motion sensing collar included 2 tip switches mounted perpendicular to one another. Each switch records the number of tips (0–255) that occur during a user-defined sampling interval. Early versions of these collars, including Lotek Model 1000 (Newmarket, Ontario, Canada), were used to correctly classify inactive and active behaviors up to 76% and 91% of the time in moose (*Alces alces*) and 97% and 86% of the time in red deer (*Cervus elaphus*), respectively (Moen et al. 1996, Adrados et al. 2003). Rest (84.1%), grazing (95.8%), and travel (78.3%) behaviors of cattle were correctly inferred when investigators incorporated the tip switch data with the distance traveled between successive GPS locations (*Bos taurus*, Ungar et al. 2005) sampled by Lotek model 2200 collars. These collars were more accurate than VHF variable pulse sensor collars when distinguishing between periods of inactivity (92%) and activity (90.3%) in white-tailed deer (Coulombe et al. 2006). Similarly, periods of inactivity and activity were correctly classified 87.3% and 85.4% of the time in free-ranging mouflon (*Ovis melini musimon* x *Ovis* spp.) and 97% and 84% of the time in roe deer (*Capreolus capreolus*, Bourgoin et al. 2008, Gottardi et al. 2010), using Lotek model 3300 collars. Another type of motion sensing collar included a single omnidirectional accelerometer that recorded changes in acceleration on multiple planes. These collars were used to classify resting, feeding, and travel with 88% accuracy for Rocky Mountain elk (Naylor and Kie 2004).

The most recent generation of collars incorporate 2 accelerometers which record motion via changes in acceleration such as Lotek model 4400 GPS collars. Similar collars have been used to infer passive, feeding plus slow locomotion, and fast locomotion for red deer and roe deer with >75% accuracy (Löttker et al. 2009, Heurich et al. 2012). Differences in motion for different behaviors within and among species necessitate that these types of collars be calibrated in order to determine which specific behaviors correspond to what range of activity monitor values (AMVs). No prior calibrations exist for dual-axis activity monitors for Rocky Mountain elk, mule deer, or cattle. Our goals were to calibrate this type of collar for these 3 species and to determine optimal sampling interval for use in future behavior studies.

To build calibration models for our focal species, we needed to pair directly observed behaviors to AMVs recorded by collars during the same 5-min sampling intervals. It was during this process we noted a series of timing errors, which if not addressed, could lead to inaccurate classification models. After identifying the mechanisms behind these timing errors, we developed a procedure to correct for these timing errors and created a guide to help users recognize and manage errors in their own data (Chapter 1).

After applying the correction procedure, we proceeded with model building to classify collar data into specific behavior categories. Most previous collar calibrations have used datasets containing only pure intervals (sampling intervals containing only 1 behavior) and have excluded mixed intervals (those containing > 1 behavior) from the calibration process. Calibrations that did include mixed intervals were for 2 tip-switch collars and were only able to distinguish passive from active behaviors (Adrados et al. 2003, Gervasi et al. 2006, Gottardi et al. 2010). Also, no quantification of the effect of excluding mixed intervals from the model calibration process has been conducted. Since datasets from free-ranging animals inherently contain mixed intervals, and because there is no way to distinguish which intervals are mixed and therefore no way to exclude them, we suspected that excluding mixed intervals from calibration could decrease classification accuracy. We calibrated Lotek model 4400 dual-axis accelerometer GPS collars for Rocky Mountain elk, mule deer, and cattle using both pure interval datasets and full datasets (including both pure and mixed intervals). We compared the correct classification rates for 4 discriminant function models to determine the number of behaviors that could be classified and with what accuracy. We also examined the effect of excluding mixed intervals from the calibration process by comparing the classification rates from the cross-validated pure intervals models to those obtained by applying the same models to datasets containing only mixed intervals (Chapter 2).

Having calibrated the collars for our 3 focal species, we then determined the optimal sampling interval for these types of collars. Most previous collar calibrations have used 5-min sampling intervals but shorter sampling intervals might allow greater classification accuracy by better capturing behaviors that are typically of shorter duration. New models of GPS-activity monitor collars allow users numerous choices of sampling interval duration and other sensor settings. However, very few comparisons have been conducted to determine the relative merits of different sampling intervals for activity monitor collars. For 2 tip-switch collars, 10-min intervals allowed higher total classification rate and better classification of active behaviors when compared to 5- and 10-min intervals but 5-min intervals allowed better classification of passive behaviors (Adrados et al. 2003). To date, no sampling interval comparisons have been conducted for dual-axis accelerometer collars. We addressed this issue for elk behaviors as recorded by Lotek model 4500 GPS collars. To determine whether shorter sampling intervals would increase the number of behaviors we were able to distinguish, classification accuracy, or both, we compared classification performance for 5-min, 152-sec, and 64-sec sampling intervals (Chapter 3).

LITERATURE CITED

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

Bourgoin, G., M. Garel, B. Van Moorter, D. Dubray, D. Maillard, E. Marty, and J. M. Gaillard. 2008. Determinants of seasonal variation in activity patterns of mouflon. Canadian Journal of Zoology 86:1410-1418.

Cain III, J. W., P. R. Krausman, B. D. Jansen, and J. Morgart. 2005. Influence of topography and GPS fix interval on GPS collar performance. Wildlife Society Bulletin 33:926-934.

Carranza, J., J. H. d. T. Sebastian, M. Rosario, V. Juliana, D. Jose, and S. J. Hidalgo-de-Trucios. 1991. Space use by red deer in a mediterranean ecosystem as determined by radio-tracking. Applied Animal Behaviour Science 30:363-371.

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.

D'Eon, R. G., and D. Delparte. 2005. Effects of radio-collar position and orientation on GPS radio-collar performance, and the implications of PDOP in data screening. Journal of Applied Ecology 42:383-388.

Di Orio, A. P., R. Callas, and R. J. Schaefer. 2003. Performance of two GPS telemetry collars under different habitat conditions. Wildlife Society Bulletin 31:372-379.

Ganskopp, D. C., and D. D. Johnson. 2007. GPS error in studies addressing animal movements and activities. Rangeland Ecology and Management 60:350-358.

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

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: International Journal of the Systematics, Biology & Ecology of Mammals 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.

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

Hulbert, I. A. R., and J. French. 2001. The accuracy of GPS for wildlife telemetry and habitat mapping. Journal of Applied Ecology 38:869-878.

Janis, M. W., and J. D. Clark. 1999. Predicting mountain lion activity using radiocollars equipped with mercury tip-sensors. Wildlife Society Bulletin 27:19.

Jiang, Z., M. Sugita, M. Kitahara, S. Takatsuki, T. Goto, and Y. Yoshida. 2008. Effects of habitat feature, antenna position, movement, and fix interval on GPS radio collar performance in Mount Fuji, central Japan. Ecological Research 23:581-588.

Kufeld, R. C., C. B. David, and L. S. Donald. 1988. Habitat selection and activity patterns of female mule deer in the front range, Colorado. Journal of Range Management 41:515-522.

Lindzey, F. G., and E. C. Meslow. 1977. Home range and habitat use by black bears in Southwestern Washington. Journal of Wildlife Management 41:413-425.

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.

Martin, P., and P. Beteson. 2007. Measuring behavior: An introductory guide. 3rd edition. Cambridge University Press, Cambridge, UK.

Mattisson, J., H. Andrén, J. Persson, and P. Segerström. 2010. Effects of species behavior on global positioning system collar fix rates. Journal of Wildlife Management 74:557-563.

McCullough, D. R., and P. Beier. 1988. Motion-sensitive radio collars for estimation white-tailed deer activity. Journal of Wildlife Management 52:11-13.

Moen, R., J. Pastor, and Y. Cohen. 1996. Interpreting behavior from activity counters in GPS collars on moose. Alces 32:101-108.

Naylor, L. M., and J. G. Kie. 2004. Monitoring activity of Rocky Mountain elk using recording accelerometers. Wildlife Society Bulletin 32:1108-1113.

Nelson, M. E., and G. A. Sargeant. 2008. Spatial interactions of yarded white-tailed deer, *Odocoileus virginianus*. Canadian Field-Naturalist 122:221-225.

Proffitt, K. M., J. L. Grigg, R. A. Garrott, K. L. Hamlin, J. Cunningham, J. A. Gude, and C. Jourdonnais. 2010. Changes in elk resource selection and distributions associated with a late-season elk hunt. Journal of Wildlife Management 74:210-218.

Roth, H. U., and C. H. Meslow. 1983. Diel activity of a remnant population of European brown bears. Pages 223-229 *in* P. Zager, editor. Bears: Their biology and management. International Association for Bear Research and Management, Brookeville, MD.

Rouys, S., J. Theuerkauf, and M. Krasinska. 2001. Accuracy of radio-tracking to estimate activity and distances walked by European bison in the Bialowieza Forest, Poland. Acta Theriologica 46:319-326.

Singer, F. J., A. R. Tipton, C. P. Hable, and D. K. Otto. 1981. Home ranges, movements, and habitat use of European wild boar in Tennessee. Journal of Wildlife Management 45:343-353.

Ungar, E. D., Z. Henkin, M. Gutman, A. Dolev, A. Genizi, and D. Ganskopp. 2005. Inference of animal activity from GPS collar data on free-ranging cattle. Rangeland Ecology and Management 58:256-266.

CHAPTER 2: ACTIVITY MONITORS IN GPS COLLARS REQUIRE CORRECTION FOR TIMING ERRORS

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ABSTRACT

Direct behavior observation of multiple free-ranging animals over long periods of time and large geographic areas is prohibitively difficult. However, recent improvements in technology, such as GPS collars equipped with motion-sensitive activity monitors, create the potential to monitor animal behavior remotely. Activity monitors record animal motion along one or more axes with different amounts of motion presumably corresponding to different animal activities. Variations in motion among species necessitate calibration for each species of interest. Calibration generally involves making detailed behavioral observations of captive collared animals and then pairing observed behaviors with collar data. During the pairing process we discovered that several factors associated with the time-keeping mechanisms of these collars can result in mismatched behavior observations and collar data resulting in inaccurate classification models. We corrected for these timing errors using defined breaks in animal behavior to shift times given by collar output, improving the average correct classification rate up to 61.7 percentage points for specific behaviors. Also, timing errors can be minimized by activating a collar's GPS unit, increasing the GPS fix rate, and using a sampling interval divisible by 8 seconds. 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.

KEY WORDS

accelerometers, activity sensor, behavior, *Cervus elaphus*, error estimation, GPS collar, Rocky Mountain elk.

INTRODUCTION

Global positioning system (GPS) collars equipped with motion-sensitive activity monitors have the potential to be an important tool for wildlife researchers and managers. This technology has been touted as one that will greatly expand our ability to understand habitat selection of free-ranging wildlife. Activity monitor collars have been used to study habitat utilization in red deer (*Cervus elephus*, Löttker et al. 2009) and activity patterns in Asiatic black bear (*Ursus thibetanus*, Hwang and Garshelis 2007), brown bear (*U. arctos*, Gervasi et al. 2006), rhesus monkeys (*Macaca mulatta*, Papailiou et al. 2008) and cattle (*Bos taurus*, Ungar et al. 2005). Because species vary in their motions and behaviors, species-specific calibration is necessary to relate numeric collar output to actual behaviors. Calibration is generally conducted using captive animals and results in a model that can be used to classify, with a given level of certainty, the behavior or activity level of free-ranging animals. Calibration is conducted by observing collared animals and then coupling the real-time observed activities to activity data recorded by the collar over the same sampling interval.

One potential factor influencing the accuracy of the calibrations is time-keeping which is important at multiple scales when seeking to record and then accurately translate collar data into knowledge of animal behavior. To accurately pair observations with collar data, users need the accurate start time of both. Time-stamping the direct observations of behavior is relatively easy using electronic data loggers featuring satellite-corrected time. However, we discovered that establishing the true interval start times (ISTs) for data collected by the collars is not possible using collar outputs alone.

Although previous investigators noted evidence of timing errors, few have addressed these issues (Löttker et al. 2009). Use of data from sampling intervals within long periods of a single behavior while discarding the data at the beginning and end of that behavior avoids the problem (Löttker et al. 2009) but can result in significant data loss. This approach is only effective for behaviors that exceed two sampling intervals in duration. For many species, behaviors of interest such as running are unlikely to exceed two sampling intervals.

While conducting a calibration study of Rocky Mountain elk (*C. e nelsoni*, hereafter elk), we noted discrepancies between real time and “data time” which result in inaccurate pairing of activity monitor values (AMVs) to observed behavior(s). This increased behavior classification error could hinder our ability to accurately classify behaviors of free-ranging animals. We created a procedure to adjust collar data ISTs for timing errors and determined whether correct classification rates (CCRs) differed between models built with raw versus time-corrected data.

Inside activity monitors

Recent generations of GPS collars incorporate activity monitors that measure and store activity data in a way that results in several potential sources of timing error (Table 2.1). Activity monitor components that contribute potentially to timing errors include one or more accelerometers, an activity microprocessor, and a main microprocessor that includes an internal clock.

Table 2.1 Sources of timing error associated with activity monitor GPS collars, specifically Lotek model 4400 dual-axis accelerometer GPS collars.

Source of error	Mechanism	Duration of error	Evidence in data	Action to correct
Internal clock	Drift influenced by age of collar and air temperature.	± 0.72 sec/hr	Not apparent	Corrected during GPS fix
Activity microprocessor	Drift inherent in all clocks.	< 5 sec/hr	Label gap or duplicate	None available
Programmed sampling interval (PSI) duration	Difference between actual start time of a sampling interval and the interval start time (IST) dictated by the PSI.	Depends on chosen PSI	Label gap	Choose PSIs divisible by 8 sec[a]
Collar activation offset	Difference between microprocessor activation and the IST dictated by the PSI.	Up to one interval	Label gap	Activate collar at IST

[a] Activity microprocessor activates on an 8 second interval, therefore PSIs not divisible by 8 seconds result in an accumulation of timing error with each interval.

Accelerometers are used to measure changes in acceleration associated with animal motion. Currently, many collars that include activity-sensing options record animal movement along 2 or 3 axes, each of which is equipped with an accelerometer. Motion data from accelerometers is averaged over the duration of a programmed sampling interval (PSI) resulting in a single AMV, ranging from 0 to 255 for each axis. Several manufacturers allow users to set the PSI to either 5 minutes or any multiple of 8 seconds between 64 – 896 seconds.

The activity monitor microprocessors track and record elapsed time and store motion data from the accelerometers at specific intervals. Changes in acceleration are measured by the accelerometers four times per second. The activity microprocessor activates every 8 seconds, stores the accelerometer data, and tracks how many 8-second periods have elapsed since data were last downloaded by the main microprocessor. Once the activity microprocessor recognizes that enough 8-second periods have elapsed to cumulatively equal or exceed the PSI, it 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 and stores these AMVs along with a temperature measurement. The main microprocessor labels these data with the date and IST that are supplied by the internal clock (J. Chang, Lotek Wireless, Inc., personal communication).

Sources of error

All timekeeping devices are subject to drift (i.e., they may run fast or slow). Time drift by the internal clock can vary by ± 0.72 seconds/hour and can be influenced by the age of the collar and by air temperature (J. Chang, Lotek Wireless, Inc., personal communication). Internal clock drift results in differences between “data time”, with which the activity data are labeled, and the “true time” with which behavior observations are time-stamped. This can result in behavior observations that are not accurately matched to the appropriate AMVs and reduce the accuracy of classification models. Drift is corrected every time a GPS location fix occurs (J. Chang, Lotek Wireless, Inc., personal communication). Thus, user-programmed GPS fix rate will determine the frequency of correction and the amount of drift accumulating between corrections. However, cloud cover, vegetative cover, topography, and orientation of the collar can prevent programmed GPS fixes (Hulbert and French 2001, Di Orio et al. 2003, Cain III et al. 2005, D'Eon and Delparte 2005, Jiang et al. 2008, Mattisson et al. 2010).

The activity microprocessor also produces time drift, but because it functions independently of the internal clock, this drift is not corrected by GPS fixes. Drift by the activity microprocessor results in sampling intervals that are longer or shorter than the PSI (J. Chang, Lotek Wireless, Inc., personal communication). Sampling intervals are not likely to differ from the PSI by more than a few seconds, therefore the difference in duration between the sampling interval and the duration of observed behaviors for a given PSI is negligible. However, this small difference can accumulate over time and result in direct behavior observations that are not accurately matched to the appropriate AMVs, further reducing the accuracy of the classification model. The mismatch results from how the main microprocessor stores and labels activity data. If the activity microprocessor flags activity data for storage at a time that does not match an IST, the activity data will be labeled by the main microprocessor with the preceding IST (J.

Chang, Lotek Wireless, Inc., personal communication). Once drift results in a sampling interval that is longer than the PSI, an IST will be skipped, resulting in a label gap. For example, if the PSI is set for 5 minutes, ISTs would be on the hour (e.g., 12:00:00) and at subsequent 5-minute intervals (e.g., 12:05:00, 12:10:00…). However if activity microprocessor drift results in a PSI that exceeds 300 seconds, the drift will accumulate such that a sampling interval ends at 12:04:59. The activity data for that sampling interval will be labeled with the IST 12:00:00. The next sampling interval will then end at 12:10:01 and be labeled with 12:10:00. Although there is no gap in activity data, the 12:05:00 IST will not be present in the collar output. Similarly, activity microprocessor 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. Regardless of whether it results in a label gap or a duplicate label, activity microprocessor drift will result in behavior observations that are not accurately matched to the appropriate AMVs if data are paired using the ISTs from the collar output alone.

The 8-second activation interval of the activity microprocessor creates another source of potential timing error. The activity microprocessor only flags activity data for storage by the main microprocessor once enough 8-second intervals have accumulated to reach or exceed the PSI. However, some manufacturers offer collars with preset PSI options that are not divisible by 8 seconds, resulting in PSIs that cannot be equaled; only exceeded. For example, a common preset PSI option is 5 minutes (i.e., 300 sec). The activity microprocessor will not activate to flag the activity data at 300 seconds but instead at 304 seconds. The collar output will list activity data at 5-minute intervals although the data were recorded over 304-second periods. This 4-second difference results in a disparity between the actual start time of the sampling interval and the ISTs dictated by the PSI and tracked by the internal clock. For example, if the PSI is set for 5 minutes, ISTs would be on the hour (e.g., 12:00:00) and at subsequent 5-minute intervals (e.g., 12:05:00, 12:10:00…). However because the intervals are 304 seconds long, if the first interval starts at 12:00:00, the second interval will start at 12:05:04 and the next at 12:10:08 and so on. The 4-second difference will accumulate until 4n > PSI (where n = no. of intervals) at which time there will be a label gap. In this case, the gap will occur every 76 intervals (approximately 6.25 hrs.). At that time, one interval will end at 18:14:56 (IST labeled 18:10:00) and the next interval will end at 18:20:00 (IST labeled 18:20:00). The 18:15:00 IST will not be included in the collar output. Therefore, behavior observations will not be accurately matched to the appropriate AMVs if paired using the ISTs from the collar output.

Finally, potential for significant timing error results from the difference between the time at which the activity microprocessor is activated prior to deployment (usually by removing a magnet) and the IST dictated by the PSI and tracked by the internal clock. As stated above, if the activity microprocessor flags activity data for storage at a time that does not match an IST, the activity data will be labeled with the preceding IST. This will result in activity data that occurs over the course of two IST-defined intervals. Using the above example, if the PSI is set for 5 minutes, ISTs would be on the hour (e.g., 12:00:00) and at subsequent 5-minute intervals (e.g., 12:05:00, 12:10:00…). However if the activity microprocessor were activated at 12:02:00, the activity data would be flagged for storage at 12:07:04 (after 304 sec) and the main microprocessor will store the averaged accelerometer data labeled with the IST of 12:05:00. As a result, behavior observations will be mismatched with AMVs if paired using ISTs from the collar output. Further, the offset between the IST and the start of the sampling interval will not be consistent over time due to drift of the internal clock, internal clock correction by the GPS satellite, and label gaps or duplicates associated with using PSIs not divisible by 8 seconds.

Once we understood these mechanisms and how they contribute to timing error, we developed a method to account for time disparities between observed behaviors and collar data in order to avoid data loss, minimize mismatched behavior-AMV pairings, and increase accuracy of our behavior classification model. We also developed a key to help users recognize and adjust for timing errors in data from activity sensor collars.

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) and consists of a 10,125 ha mosaic of grassland, regenerating forests, and older forest stands. Elevations range from 1,122-1,500 m with varied topography. The climate is continental and characterized by relatively consistent mean monthly precipitation. Total annual precipitation averages 42.9 cm with about 52.8 cm of average snow fall (Western Regional Climate Center 2010).

Starkey is divided into 4 study areas designed to facilitate large-scale studies on free-ranging ungulates. Within 1 of these, the 265-ha Winter Area includes a complex of pens and handling facilities as well as several small pastures. We conducted our behavior observations in the handling pens and Wing Pasture (2.6 ha) within the Winter Area.

These facilities allow safe and efficient animal handling, close observation of captive ungulates, and addition of foods and other stimuli to the observation areas. Canopy in the pasture is dominated by Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*). Forage species consist mainly of bluebunch wheatgrass (*Pseudoregneria spicatum*), Sandberg bluegrass (*Poa secunda*) and Idaho fescue (*Festuca idahoensis*, Rowland et al. 1997).

SAMPLING DESIGN

We calibrated Lotek Engineering Model 4400 GPS collars (Lotek Engineering, Newmarket, Ontario, Canada) for elk. Collars were equipped with dual-axis activity monitors set for a 5-minute PSI. We made detailed observations of 5 collared captive female elk and recorded observed behaviors using Palm (Sunnyvale, CA, USA) Tungsten E2 handheld PDAs equipped with Palm PDA-based software (EVENT-Palm, J. C. Ha, University of Washington). Field observations were conducted in accordance with established Institutional Animal Use and Care Committee (IACUC) protocols (USFS Starkey 92-F-0004). We recorded observations daily during two (morning, evening) 4-hour sessions. We initially recorded behaviors into nine classes: bedded, bedded-ruminating, standing, standing-ruminating, grazing, browsing, walking, trotting, and galloping (Table 3.1). However, we observed very little standing-ruminating so we excluded that class from analysis and model construction.

Most behaviors occurred naturally but three (i.e., browsing, trotting, and galloping) had to be prompted. The pasture and corrals where we worked lacked browse species in sufficient quantities to allow us to collect data on prolonged browsing behavior. To prompt 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 3m) 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 minimize heat stress on the animals.

Correction procedure

We partitioned behavior observations into 5-minute (300-sec) bouts and then paired the observations to the activity monitor data (n = 2,390 intervals) based on the (uncorrected) ISTs given by the collar output. Due to the use of a PSI not divisible by 8 seconds and activity microprocessor drift our collar output included both IST label duplicates and label gaps. For label duplicates, we corrected the labeling such that the IST sequence was sequential. For example, when ISTs from the collar output were 12:00:00, 12:05:00, 12:05:00, 12:15:00…, we changed the second 12:05:00 label to 12:10:00 to facilitate appropriate pairing. When we encountered label gaps, we paired observed behaviors using the ISTs given by the collar output, resulting in one 5-minute period for which no behaviors were paired.

Based on previous calibration studies (Ungar et al. 2005, Löttker et al. 2009) and our field observations, we expected that some behaviors would have relatively low (i.e., bedded, bedded-ruminating, and standing) or high (i.e., trotting and galloping) amounts of movement associated with them and therefore have correspondingly low or high

AMVs, respectively. Likewise, we expected other behaviors (i.e., grazing, browsing, and walking) to result in moderate amounts of motion that would be reflected by their AMVs. However, when we paired behavior observations to collar activity data we noticed a number of pure intervals (those containing a single behavior) associated with low amounts of movement that had inexplicably high AMVs, and vice-versa. These intervals represented mismatched behavior:AMV pairings. The mismatches occurred consistently at breaks in behavior from a low or moderate motion activity to a moderate or high motion activity, respectively. As such, the mismatched intervals were directly adjacent to intervals for which their AMV would be more appropriate.

We calculated the number of seconds the collar output time would need to be shifted to achieve a logical match with the behaviors of the direct observation intervals. Shifts from behaviors with little motion to behaviors with relatively moderate or high amounts of motion were easiest to identify due to an obvious contrast between their expected and collar-recorded AMVs and were therefore most useful when calculating time shift. The necessary time shift was consistent over ≥ one, 4-hour 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 consistently smaller than the shift necessary after the gap. This difference is consistent with our understanding of how gaps occur. Collar output times were shifted accordingly and the behavior observations re-paired to the shifted ISTs. We then completed our originally planned analyses.

We analyzed the pure intervals (n = 1,342) using linear discriminant function analysis (Tabachnick and Fidell 2001) with leave-one-out cross validation in R2.11.1. To assess the impact of timing errors, we calculated the difference in CCRs between the uncorrected and time-shifted datasets and compared the misclassification rates of each for eight individual 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 - 270 seconds per observation period (average = 156.9 sec, SE = ± 0.66 sec). Classification accuracy (CCR) improved for six of eight behaviors when we applied the time-shift procedure in our modeling of pure interval data (Table 2.2).

Table 2.2 Effect of time shift procedure on correct classification rate (CCR, %) of individual behaviors within pure intervals of activity data (n = 1,341). Data were collected for five captive female Rocky Mountain elk (*Cervus elaphus nelsoni*) wearing GPS collars equipped with dual-axis activity sensors at Starkey Experimental Forest and Range, USFS, Starkey, OR, Summer 2011.

Behavior	Improvement	No change	Decrease
Bedded	2.1%		
Bedded-Ruminating	3.6%		
Stand		0.0%	
Graze	2.9%		
Browse	25.9%		
Walk			4.3%
Trot	13.2%		
Gallop	61.7%		

Of the eight observed behaviors, six were misclassified into fewer behavior categories using the time-shifted model when compared to the uncorrected model while two were misclassified into an equal number of categories (Table 2.3).

Table 2.3 Increase (+) and decrease (-) in behavior-specific misclassification (%) after applying the time shift procedure to pure intervals of behavior data collected from dual-axis activity sensor GPS collars (Lotek Model 4400) worn by five captive female Rocky Mountain elk (*Cervus elaphus nelsoni*). Data were collected at Starkey Experimental Forest and Range, USFS, Starkey, OR, Summer 2011. Data were analyzed using linear discriminant function analysis and validated using leave-one-out validation.

	Predicted Behaviors							
Observed Behaviors	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
Stand	+16.7	-11.6	0.0	-13.3 [a]	+8.3	0.0	0.0	0.0
Graze	-0.4[a]	-2.3	0.0	0.0	-0.3	0.0	0.0	0.0
Browse	0.0	-12.9	0.0	-3.8	0.0	-9.1 [a]	0.0	0.0
Walk	0.0	0.0	0.0	+6.1	-1.8	0.0	0.0	0.0
Trot	-2.8 [a]	0.0	0.0	-8.5	0.0	-1.7	0.0	-0.5
Gallop	0.0	0.0	0.0	-14.3 [a]	0.0	-22.3	-25.0	0.0

[a] No intervals misclassified as this behavior after time shift procedure.

Fewer intervals of every observed behavior were misclassified as bedding-ruminating, walk, trot, and gallop. Further, of 56 possible misclassifications, 22 behavior categories had fewer interval misclassifications, three had more, and 36 had an equal number. The percent of misclassified intervals among associated behavior categories was approximately the same for passive and feeding after the time shift (Table 2.4). Using the time-shifted dataset 2% fewer running intervals were misclassified as passive and 17.8% fewer were misclassified as feeding.

Table 2.4 Increase (+) and decrease (-) in misclassification (%) after applying the time shift procedure to pure intervals of behavior data where individual behaviors were grouped as passive (bedded, bedded-ruminating, stand), feeding (graze, browse, walk), or running (trot and gallop). Data were collected from dual-axis activity sensor GPS collars (Lotek Model 4400) worn by five captive female Rocky Mountain elk (Cervus elaphus nelsoni) at Starkey Experimental Forest and Range, USFS, Starkey, OR, Summer 2011. Data were analyzed using linear discriminant function analysis and validated using leave-one-out validation.

	Passive	Feeding	Running
Passive	0.0	-1.0	0.0
Feeding	+0.1	0.0	0.0
Running	-2.0 [a]	-17.8	0.0

[a] No intervals misclassified as this behavior after time shift procedure.

DISCUSSION

Differences between CCRs using the classification models constructed using the uncorrected data and the shifted data were relatively small (< 5%) for behaviors that are typically long in duration such as bedding, bedding-ruminating, and grazing. However, for behaviors that are typically shorter in duration, such as trotting and galloping, the time shift procedure improved CCRs by 13.2% and 61.7%, respectively. The CCR for browsing also improved markedly using shifted data (25.9%) but this may be due to an artifact of our methods. Due to the limited amount of browse we were able to present 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 (3.3%). Standing was not generally correctly classified regardless of time adjustment or lack thereof.

Correction of timing errors reduced misclassification of individual behaviors and increased the precision with which most individual behaviors were classified. Notable difference between the two models included browse, which was misclassified as bedded-ruminating 12.9% and as walk 9.1% less often, and gallop, which was misclassified as graze 14.3% and as walk 22.3% less often. Due to the latter decreases in misclassification, far fewer intervals of the running associated behavior group were misclassified into such behaviorally and energetically different groups as passive and feeding. Study animals were often observed engaging in either passive or feeding behaviors immediately prior to running. As such, intervals of the former were directly adjacent to the latter in the collar output accounting for the decrease in misclassification observed using the time-shifted model.

When deploying collars with activity monitors, users can minimize several of the sources of timing error we have discussed. First, although the activity monitor can function without the GPS unit having been activated, to minimize internal clock drift users should enable the collar GPS and increase GPS fix rate (more frequent) to increase frequency of internal clock correction and thus decrease accumulation of drift by the internal clock. Furthermore, intervals between GPS fixes shorter than the PSI of the activity monitor should result in negligible internal clock drift. However, increasing GPS fix rate will decrease the battery life of the unit. Thus, users will need to balance concerns for internal clock drift and battery life for long-term studies.

Users should use PSIs divisible by 8 seconds to eliminate timing errors associated with activation interval of the activity microprocessor. Doing so will result in fewer label gaps and label duplicates. Error associated with activity microprocessor activation can be minimized or eliminated by timing the first activation of the activity microprocessor as close to a PSI-dictated IST as possible. To do this, activate the collar's activity monitor for a period of time and then download activity data to determine what ISTs are for a chosen PSI. Before deploying the collar on an animal, the activity monitor should then be activated as close to an IST as possible using a satellite-corrected timekeeping device such as a cell phone. This will minimize or eliminate the differences between PSI-dictated ISTs and the actual start times of intervals.

Some of the timing errors we discovered can be minimized, but others such as those associated with activity microprocessor drift, cannot be minimized or corrected. Controlling for and correcting as many of these sources as possible will maximize accuracy of behavior classifications. Use of the time-shift method introduced above will be facilitated by accurately noting the start time of changes from 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). To assure that such breaks occur, it may be necessary to prompt these changes in behavior, for example by chasing an animal that was standing still. Similarly, when calibrating collars being worn by free-ranging animals, note the start time of changes in behaviors associated with captivity or anesthetization (e.g. standing or lying down) to those associated with release (i.e., running). Doing so will provide clear breaks in behavior that are relatively easy to recognize. These signatures in the downloaded data would then allow the investigator to calculate the amount of necessary time-shift for pairing observed behaviors to AMVs for classification modeling.

While models calibrated using time-shifted data will classify intervals of unknown activity from free-ranging animals, due to the timing errors associated with these collars, the AMVs given by the collar output will not be labeled with their true ISTs. The steps described above can minimize but not eliminate the entire difference between true time and “data time”. As such, users need to be cautious when attempting to pair AMVs, and their corresponding activity, to a time-stamped event such as a particular GPS location. Doing so could result in pairing an incorrect behavior with a particular location.

Different collar manufacturers may use different components and settings and changes can be expected as newer models are released. Therefore, we recommend that users closely question the manufacturer of their specific collars concerning the time keeping mechanism(s) as well as technical operating details we have identified. Specifically, users should learn about the likelihood of drift, the range of that 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.

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.

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LITERATURE CITED

Cain III, J. W., P. R. Krausman, B. D. Jansen, and J. Morgart. 2005. Influence of topography and GPS fix interval on GPS collar performance. Wildlife Society Bulletin 33:926-934.

D'Eon, R. G., and D. Delparte. 2005. Effects of radio-collar position and orientation on GPS radio-collar performance, and the implications of PDOP in data screening. Journal of Applied Ecology 42:383-388.

Di Orio, A. P., R. Callas, and R. J. Schaefer. 2003. Performance of two GPS telemetry collars under different habitat conditions. Wildlife Society Bulletin 31:372-379.

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

Hulbert, I. A. R., and J. French. 2001. The accuracy of GPS for wildlife telemetry and habitat mapping. Journal of Applied Ecology 38:869-878.

Hwang, M. H., and D. L. Garshelis. 2007. Activity patterns of Asiatic black bears (Ursus thibetanus) in the Central Mountains of Taiwan. Journal of Zoology 271:203-209.

Jiang, Z., M. Sugita, M. Kitahara, S. Takatsuki, T. Goto, and Y. Yoshida. 2008. Effects of habitat feature, antenna position, movement, and fix interval on GPS radio collar performance in Mount Fuji, central Japan. Ecological Research 23:581-588.

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.

Mattisson, J., H. Andrén, J. Persson, and P. Segerström. 2010. Effects of Species Behavior on Global Positioning System Collar Fix Rates. Journal of Wildlife Management 74:557-563.

Papailiou, A., E. Sullivan, and J. L. Cameron. 2008. Behaviors in rhesus monkeys (Macaca mulatta) associated with activity counts measured by accelerometer. American Journal of Primatology 70:185-190.

Rowland, M. M., L. D. Bryant, J. K. Johnson, J. H. Noyes, M. J. Wisdom, and J. W. Thomas. 1997. The Starkey project: History, facilities, and data collection methods for ungulate research. USDA Forest Service Technical Report PNW-GTR 396: 1-62.

Tabachnick, B., A., and L. S. Fidell. 2001. Using multivariate statistics Allyn & Bacon, Needham Heights, MA.

Ungar, E. D., Z. Henkin, M. Gutman, A. Dolev, A. Genizi, and D. Ganskopp. 2005. Inference of animal activity from GPS collar data on free-ranging cattle. Rangeland Ecology and Management 58:256-266.

CHAPTER 3: CLASSIFICATION OF UNGULATE BEHAVIOR USING ACCELEROMETER ACTIVITY MONITOR COLLARS

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ABSTRACT

Ungulate behavior has been widely studied but direct observation of free-ranging animals over long periods of time and large geographic areas is prohibitively difficult. Improved technology, such as GPS collars equipped with motion-sensitive activity monitors, provides researchers with a means to remotely collect activity data. Variations in motion among behaviors necessitate calibration for each species of interest. No calibration has been conducted for Lotek 4400 GPS collars featuring dual-axis activity monitors for Rocky Mountain elk (*Cervus elaphus nelsoni*), mule deer (*Odocoileus hemionus*), or cattle (*Bos taurus*). We made detailed behavioral observations of captive animals and then coupled these observations with data collected simultaneously by collars worn by those same animals. We partitioned observed behaviors into 5-minute bouts to match the sampling interval of the activity monitors and corrected timing errors based on defined breaks in behavior. We used discriminant function models to determine the number of behaviors that can be accurately classified using these collars. We also constructed models using only pure intervals (sampling intervals during which only one behavior occurred) and applied them to datasets containing only mixed intervals (sampling intervals during which >1 behavior occurred) to determine the effect of excluding mixed intervals from the calibration process. Final full-dataset models accurately classified (correct classification rates > 70%) up to 4 behavior categories for elk, 3 for deer, and 2 for cattle. Our results showed that classification models that use only pure intervals can result in misclassification rates of up to 61% for mixed intervals of some behaviors. Our calibration models will be made available on-line, allowing managers and researchers to

interpret data from free-ranging animals for use in ongoing and future studies of ungulate ecology and management.

KEY WORDS

accelerometers, activity monitor collars, behavior classification, cattle, elk, mule deer.

INTRODUCTION

Direct observation of animal behavior is labor intensive, time consuming, and often prohibitively difficult, especially for multiple free-ranging individuals over long periods of time and large geographic areas. Various radio-telemetry and Global Positioning System (GPS) collars have reduced dependence on direct observations of animals and provided a promising tool for monitoring animal activity and behavior. Passive and active animal behaviors have been inferred using variation in the signal strength of collar-mounted Very High Frequency (VHF) radio transmitters (Roth and Meslow 1983, Carranza et al. 1991), the distance between successive GPS collar derived locations (Nelson and Sargeant 2008, Proffitt et al. 2010), collars with a single tip switch (McCullough and Beier 1988, Janis and Clark 1999), and collars with 2 tip switches (Coulombe et al. 2006, Bourgoin et al. 2008, Gottardi et al. 2010). Rest, grazing, and travel have also been inferred when incorporating 2 tip switches and the distance traveled between successive GPS locations (Ungar et al. 2005).

Subsequent generations of collars include activity sensor devices that record quantified measures of animal motion in multiple spatial planes. Due to inter- and intra-specific variation in motion (e.g., between species or among sex and age classes, respectively), collar manufacturers do not provide standard calibrations for these activity sensors. Therefore researchers and managers must calibrate collars for their focal species, a process which consists of correlating activity monitor output to observed (known) animal activity for each sampling interval. This process allows the user to determine what activity monitor values (AMVs) correspond to which observed behaviors. Calibration results in a model that can be used to predict (i.e., classify) the behaviors of novel animals based on remotely-collected collar data.

We worked with dual-axis accelerometer collars for which few calibrations have been conducted. Passive and active intervals were classified for brown bears (*Ursus arctos*) with > 90% accuracy (Gervasi et al. 2006) by investigators using Vectronic Aerospace (Berlin, Germany) dual-axis GPS collars. Resting, feeding plus slow locomotion, and fast locomotion were classified for red deer with > 75% accuracy and > 89% accuracy for roe deer 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, while 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 in order to obtain accurate classification (Coulombe et al. 2006, Löttker et al. 2009).

The relationship between the duration of a sampling interval and the duration of natural bouts of animal behavior is important to consider when conducting calibrations. Classification models predict only 1 behavior category for each sampling interval. Because of this, calibration is simplified considerably by the use of only pure intervals (those containing only 1 behavior) for model construction (e.g.,Coulombe et al. 2006, Löttker et al. 2009). However, because some behaviors rarely last as long as an entire sampling interval (e.g., running), a given sampling interval may contain > 1 behavior (hereafter "mixed interval"). To include mixed intervals in model calibration, each must first be assigned into a single category, usually based on the behavior that temporally dominates the interval. Although this process is labor-intensive, the exclusion of mixed intervals can introduce potential sampling bias and result in significant data loss. This issue is especially important when working with free-ranging animals using energetically expensive behaviors that are typically of short duration. In these circumstances researchers cannot know how many behaviors are included in any given sampling interval. No previous calibrations of dual-axis accelerometers have included mixed-intervals. Several calibrations of 2 tip-switch collar have used mixed intervals, but the final models only distinguished active from passive behaviors (Adrados et al. 2003, Gervasi et al. 2006, Gottardi et al. 2010). Finally, no prior work has quantified the impact of including mixed intervals in the calibration process.

We calibrated Lotek model 4400 GPS collars equipped with dual axis accelerometers for Rocky Mountain elk, mule deer, and cattle using both pure and mixed sampling intervals. We determined the number of behaviors that can be accurately classified using these collars. We also examined the consequence of excluding mixed intervals from the calibration process. We chose a threshold of 70% correct classification rate (CCR) as the minimum acceptable classification accuracy based on consultation with colleagues involved in studies that employ similar collars (M. Wisdom, US Forest Service, personal communication). Based on preliminary observations of the motions exhibited by our study species and previous calibration studies, we expected that no single classification model would be applicable to all three species. We anticipated that our final models would be able to distinguish at least 3 behavior categories for elk (passive, feeding plus walking, and running), 4 for deer (passive, feeding plus walking, running, and stotting), and 4 for cattle (passive, feeding, walking, and running) with ≥ 70% accuracy using mixed intervals.

STUDY AREAS

Starkey Experimental Forest and Range

The Starkey Experimental Forest and Range (Starkey) is located 35 km southwest of La Grande, OR (45°12’N, 118°3’W) in the Blue Mountains. The climate is continental and characterized by relatively consistent mean monthly precipitation averaging 42.9 cm annually (Western Regional Climate Center 2010). Vegetation of the Starkey study area is a 10,125 ha mosaic of grassland and coniferous forest. The research facility is divided into several study areas, including a 265 ha Winter Area consisting of several small pastures and a complex of pens and handling facilities. We conducted our behavior observations in the relatively flat (< 20% grade) handling pens and Wing Pasture (2.6 ha) within the Winter Area. Douglas fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*) dominate the canopy and bluebunch wheatgrass (*Pseudoregneria spicatum*), Sandberg bluegrass (*Poa secunda*) and Idaho fescue (*Festuca idahoensis*) are the primary forage species (Rowland et al. 1997).

Eastern Oregon Agricultural Research Center, Hall Ranch

The Hall Ranch of Oregon State University's Eastern Oregon Agricultural Research Center is located 19.3 km southeast of Union, Oregon (43° 12' N, 117° 53' W) and is comprised of 809 ha of riparian meadow and upland pine forest. Annual precipitation averages 34.8 cm, with the majority falling October through June (Western Regional Climate Center 2010). We conducted our field observation in a 109 ha pasture surrounding a 2.4 km section of Milk Creek, a tributary of Catherine Creek. Topography here ranges from flat meadow (< 10% grade) to steep woodland (< 100% grade). The area is divided into 2 smaller pastures that consist of riparian meadow dominated by Kentucky bluegrass (*Poa pratensis*) and elk sedge (*Carex geyeri*) with dense patches of Douglas hawthorn (*Crataegus douglasii*) along the creek and upland forest dominated by Douglas-fir and ponderosa pine. The smaller (38 ha) southern pasture (Upper) has a denser canopy than the larger (71 ha) northern pasture (E-Pasture) and a higher percentage of shrubs consisting primarily of snowberry (*Symphoricarpos albus*).

Washington State University, Wild Ungulate Facility

The Wild Ungulate Facility (WUF) is located on the campus of Washington State University in Pullman, WA (46° 43' N, 117° 9' W). Average annual precipitation is 50.5 cm, most of it in the form of snow (112.3 cm on average) during December and January (Western Regional Climate Center 2010). The WUF is a 3.2 ha double-fenced treeless area that includes animal handling facilities, covered feeding structures, and 5 pastures. The largest of these pastures is 2.2 ha of rolling hills (0 to 50% grade) and consists of a mix of bare soil and grasses including meadow foxtail grass (*Alopecurus pratensis*), red fescue (*Festuca rubra*), bulbous bluegrass (*Poa bulbosa*), tall wheatgrass (*Agropyron elongatoum*), and orchardgrass (*Dactylis glomerata*).

METHODS AND MATERIALS

Study animals and animal handling

We conducted direct behavior observations of captive Rocky Mountain elk, mule deer, and beef cattle from Starkey, the WSU WUF, and the Hall Ranch, respectively. We conducted our elk field observations 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). Our research with mule deer and cattle was approved by the WSU IACUC (Protocol #3705) and OSU Hall Ranch (ACUP #3799), respectively.

We collared animals with Lotek 4400 GPS collars equipped with two accelerometers oriented perpendicular to one another: one across the shoulder axis (X-axis) and the other parallel to the spine (Y-axis). Each accelerometer is an electronic device that records the difference in acceleration between 2 consecutive measurements 4 times/second. This value is then averaged over a user-selected sampling interval as an indexed value between 0–255. The resulting AMV for each axis is stored with the associated date, temperature, and start time of the sampling interval. It is important to note that collars only store averaged AMVs and not individual accelerometer measurements. We set the collars to record activity at 5-minute sampling intervals which is a commonly used interval duration. Collars weighed 500 g (deer), 1 kg (elk), and 1.2 kg (cattle).

We used existing animal handling facilities and established animal handling procedures to collar the elk at Starkey (Wisdom et al. 1993). Experienced personnel separated 4 elk from the rest of the herd using ATVs and then separated the animals using a series of gated chutes. We used a partitioned handling chute to weigh and collar the animals. During the collaring procedure we visually monitored the elk for signs of stress (e.g., hyperventilating) and then released the animals into a recovery pen once collared. We collared the elk on June 9, 2011 and removed the collars July 11, 2011. We removed 1 animal from the study at the first sign of lameness on June 22 and replaced it with another animal. Elk ranged in age from 18–20 years old and weighed 246–298 kg.

At the Hall Ranch, workers used ATVs to separate 3 Black Angus and 1 Red Angus cow-calf pairs from the herd. Personnel then used a series of chutes to separate individuals and used a mobile squeeze chute to restrain and collar each cow. During the procedure personnel monitored the animals for signs of stress and then released them back into the herd. We collared the cattle on July 19, 2011 and removed the collars August 26, 2011. One cow dropped its collar on August 15 and was re-collared on August 17. Cattle ranged from 4–5 years old and averaged 590 kg.

We collared mule deer at the WSU facility on October 18, 2011. We immobilized 4 adult female mule deer in conjunction with annual medical procedures. We used anesthetization in the form of Xylazine (0.5-1 mLs) delivered via a CO_2-powered dart gun. We physically restrained the animals and visually monitored them for signs of stress. Once medical procedures were complete and the animal collared, we intravenously administered a reversal agent (Tolazoline, 2-3 mLs) and released the animal. We monitored each deer for signs of stress or injury for 30 minutes after release. All deer were 9 years old and weighed 71–92 kg. We removed the collars November 17, 2011. During collar removal, we immobilized 1 deer via manual injection, 1 by blow dart, and 1 by CO2-powered dart gun. We immobilized the fourth deer using a makeshift squeeze chute without anesthetization. We followed the same reversal and post capture monitoring protocol as previously described.

Field observations

We observed animals daily during 4-hour morning and evening sessions. To minimize observer bias, observers rotated focal animals each session. We recorded the start time and duration of each observed behavior using Palm Tungsten E2 handheld PDAs (Sunnyvale, CA, USA) equipped with Palm PDA-based software (EVENT-Palm, J. C. Ha, University of Washington). We initially recorded behaviors into 11 classes: bedded, bedded-ruminating, standing, standing-ruminating, grazing, salt-lick (cattle only), browsing, walking, trotting, stotting (deer only), and galloping (Table 3.1). When we lost sight of an animal we labeled that behavior as “unknown”. Most behaviors occurred naturally but several had to be prompted, including browsing for elk and deer, stotting for deer, and trotting and galloping for all 3 species. Our observation areas lacked browse material in sufficient quantities to allow prolonged browsing behavior by elk and deer. To prompt this behavior, we collected branches of maple (*Acer* spp.), willow (*Salix* spp.), snowberry, and other locally available browse species and attached them to fence posts and a wooden tripod at heights ranging from ground level to the animals' maximum reach (2.5 m) to simulate natural conditions. Trotting, galloping, and stotting were prompted by chasing individual animals for short periods (< 3 min). Trained Forest Service personnel briefly chased elk using an ATV. We chased cows both on foot and using an ATV and we chased deer on foot only. Chasing sessions were limited to early morning or late evening hours to minimize heat stress on the animals.

Table 3.1 Behavior definitions used when calibrating Lotek 4400 GPS collars equipped with dual-axis accelerometers for Rocky Mountain elk, mule deer, and cattle. Observations were made at Starkey Experimental Forest and Range, La Grande, OR (elk), Washington State University Wild Ungulate Facility, Pullman, WA (deer), Eastern Oregon Agricultural Research Center Hall Ranch, Union, OR (cattle) during summer and fall, 2011.

Behavior $_a$	Description	May contain < 10 sec of other behavior $_b$:	Duration defining pure interval $_d$
Bedded	Animal lying on ground	Bedded-ruminating	300 sec
Bedded-ruminating	Animal is chewing cud while lying	Bedded	300 sec
Standing	Animal standing	Standing-ruminating, graze, browse, walk	300 sec
Standing-ruminating	Standing while animal is chewing cud	Standing, graze, browse, walk	300 sec
Salt-lick (cattle only)	Cow actively licking salt block	Standing, standing-ruminating, walk	≥ 240 sec
Graze	Animal feeding on herbaceous vegetation	Standing, standing-ruminating, walk	300 sec

Browse	Animal feeding on woody vegetation	Standing, standing-ruminating, walk	300 sec (elk), ≥ 180 sec (deer), ≥ 240 sec (cattle)
Walk	Animal walking without feeding	Standing, standing-ruminating, graze, browse	300 sec (elk), ≥ 240 sec (deer), ≥ 180 sec (cattle)
Trot	Animal running at 2-beat gait faster than walk but slower than gallop	≤ 5 sec of walk	≥ 40 sec (elk and deer), ≥ 60 sec (cattle)
Gallop	Animal running at 3- or 4-beat gait near or at top speed	≤ 5 sec of trot	≥ 40 sec (elk and deer), ≥ 60 sec (cattle)
Stott (mule deer only)	Mule deer bounding at 2-beat gait near or at top speed	≤ 5 sec of gallop	≥ 40 sec
Run [c]			≥ 40 sec of trot, gallop, and stott (elk and deer), ≥ 60 sec (cattle)

[a] All behaviors may include grooming, nursing, acts of elimination, and comfort movements.
[b] Less than 10 seconds of one behavior preceded and followed by ≥ 10 seconds (≥ 5 sec for trot, gallop, and stott) of the dominant behavior.
[c] Run category was created during data analysis phase to reflect sampling intervals that contained a mixture of fast locomotion behaviors.
[d] Statistical robustness for discriminant function analysis can be expected with ≥ 20 cases (intervals) in the smallest group (behavior category) when using ≤ 5 predictor variables. To include behaviors that never lasted the entire pre-set 5-minute sampling interval in our pure interval analysis, we determined the duration of these behaviors that, if used to define a "pure" interval, would result in at least 20 pure intervals of that behavior.

Data processing

We downloaded collar data and behavioral observations into a spreadsheet in order to address behavior recording issues, timing errors, and to pair collar data with behavior observations. The behavior classes we initially used (Table 3.1) represented the most detailed categorization of potential activities we expected to observe. Some behaviors, such as grazing, inherently contained brief bouts of related activity, such as standing and walking. When conducting our direct behavior observations, we recorded changes in activity as soon as they occurred rather than risk underestimating the duration of a behavior. This sometimes resulted in brief bouts of 1 activity (≤ 5 sec for running activities, ≤ 10 sec for non-running activities) contained within a bout of another behavior of greater duration (≥ 5 sec for stotting, ≥ 10 sec for all other activities, Table 3.1). In these instances, we coded those minor breaks to match the longer related behavior in which they occurred.

To begin the model-building process it was necessary to partition the direct observation data into 5-minute intervals to pair with the corresponding collar data for the simultaneous interval. To do so accurately, it was necessary to ensure that the interval start times matched across datasets. We learned that the mechanics of the collar timekeeping system cause timing errors that can result in temporally mismatched collar data and behavior observations that decrease calibration and classification accuracy. We created a time shift procedure to align interval start times of the direct observations and the collar data (Chapter 1). We then used the corrected interval start times to align collar activity data with our direct behavior observations in preparation for model construction.

Several behaviors never lasted the entire pre-set 5-minute sampling interval. Statistical robustness for discriminant function analysis can be expected with ≥ 20 cases (intervals) in the smallest group (behavior category) when using ≤ 5 predictor variables (Tabachnick and Fidell 2001). To include these behaviors in our pure interval analysis, we determined the duration of these behaviors that, if used to define a “pure” interval, would result in at least 20 pure intervals of that behavior (see Duration defining pure interval, Table 3.1). We discarded any intervals that contained “unknown” in a great enough duration that those unknown seconds could have been pivotal in the categorization of that interval for analysis. We also added an additional behavior class, “run”, for intervals that contained a mixture of running behaviors (i.e., trot, gallop, and stott) but in which no 1 of these behaviors was dominant (Table 3.1).

Model building

We calibrated 2 complete sets of classification models for each species. One set of models was calibrated on pure interval datasets and the other was calibrated on full dataset (both pure and mixed intervals).

Pure interval models – Our behavior observations yielded sufficient samples of pure intervals for elk (n = 1,342), mule deer (n = 1,227), and cattle (n = 1,182). We calibrated discriminant function models (Tabachnick and Fidell 2001) using pure interval datasets to classify the behavior of pure intervals. We based prior probabilities of behavior category occurrences on activity pattern and foraging preference studies conducted on each species (elk: Craighead et al. 1973, Green and Bear 1990, Wichrowski et al 2005; cow: Ungar et al 2005, Walburger et al 2007, MacKay et al 2012, Aharoni et al 2009, Kilgour 2012; deer: Kuzyk and Hudson 2007, Kufelk et al 1988, Kie et al 1991; 3 species: Findholt et al. 2005). For each species we compared model performance (CCRs) for 4 model structures: linear discriminant function (LDA) and quadratic discriminant function (QDA) using predictor variables consisting of untransformed ($_{untr}$)

and log-transformed ($_{log}$) X, Y, and X*Y axis AMVs. We used leave-one-out cross validation to estimate the CCRs that one would expect if models were applied to novel pure interval data. We considered models acceptable if the CCRs for all behaviors were ≥ 70%. After reviewing the differing assumptions for LDA and QDA models, we chose the best model based on a "best-predictions" strategy, as evaluated by CCR. From the acceptable models we determined the best model based on the highest total classification rate (the percentage of all intervals correctly classified) for all intervals, the highest average behavior classification rate (the average classification rate among behavior), and highest minimum (lowest classification rate among behaviors) behavior classification rate. More consideration was given to the latter 2 parameters because total classification rates were greatly influenced by the number of intervals within each behavior category. For example, our datasets were dominated by passive and grazing intervals so if the CCRs for those behaviors were high, the total classification rate would also be high even if CCRs for other behaviors (e.g. browsing and running) were low.

Our initial models yielded CCRs < 70% for many behaviors for all 3 species. Therefore, we grouped 4 behaviors (bedding, bedding-ruminating, standing, and standing-ruminating) together as "passive" for all subsequent analyses. We also grouped trotting and galloping (and stotting for deer) together as "run". Even after these categorizations, several cattle behaviors continued to yield CCRs < 70%, forcing us to attempt other behavior groupings. In our final classification of pure intervals for cattle, we grouped graze, browse, salt lick, walk, and run as "active".

Full-dataset models – We used the behavior categories derived from our analyses of pure intervals to categorize the full dataset (including both pure and mixed intervals, n = 2,391, 3,454, and 2,382 for elk, mule deer, and cattle, respectively), based on the predominant behavior (greatest duration) within an interval. The exceptions were any intervals containing ≥ 40 seconds of run (deer and elk) or ≥ 60 seconds of run (cattle) which we categorized as run or active, respectively. Using the categorized full datasets, we calibrated the 4 discriminant function model structures and grouped behaviors based on cross-validated CCRs using the same criteria as those used for the pure models. We then identified the final, best full-dataset model for each species.

Subsequent analysis

To examine the consequence of excluding mixed intervals during calibration of classification models, we compared cross-validated CCRs from the pure interval models to those obtained by using those models to predict behaviors for the mixed interval datasets (containing only mixed intervals) for each species. The difference in CCRs for each behavior represents additional misclassification resulting from the use of pure interval models to classify mixed intervals, such as those inherently included in datasets from free ranging animals.

To evaluate the ability of our models to correctly classify behaviors of novel animals, we first calibrated the final full-dataset models using data from 3 animals (4 for elk) and then applied this model to data from the remaining animal. We repeated this process for each animal and compared the average CCR for the group (4 for elk, 3 for deer and cattle) vs. the average CCR for individuals. We also examined classification variability by comparing the standard deviation of the CCRs for the group vs. the individual for each behavior.

RESULTS

Rocky Mountain Elk

Our best, final model structure for the full dataset (QDA_{untr}) had cross-validated CCRs ≥ 70% for up to 4 categories (passive, graze plus walk, browse, and run, Table 3.2). The use of only pure intervals for calibration resulted in a model (LDA_{untr}) that allowed us to classify our pure interval dataset into 5 categories (passive, graze, browse, walk, and run). Application of this model to classify the mixed (only) interval dataset resulted in additional misclassification rates of up to 24.5% for individual behaviors (Table 3.3). Average CCRs for behaviors of individual elk ranged from 6.7% lower to 2.4% higher when compared to the 4-animal calibration dataset (Figure 3.1). Variability of CCRs (± 1 standard deviation) ranged from 1.9 to 9.2 percentage points higher for individual elk behaviors than for those of the group.

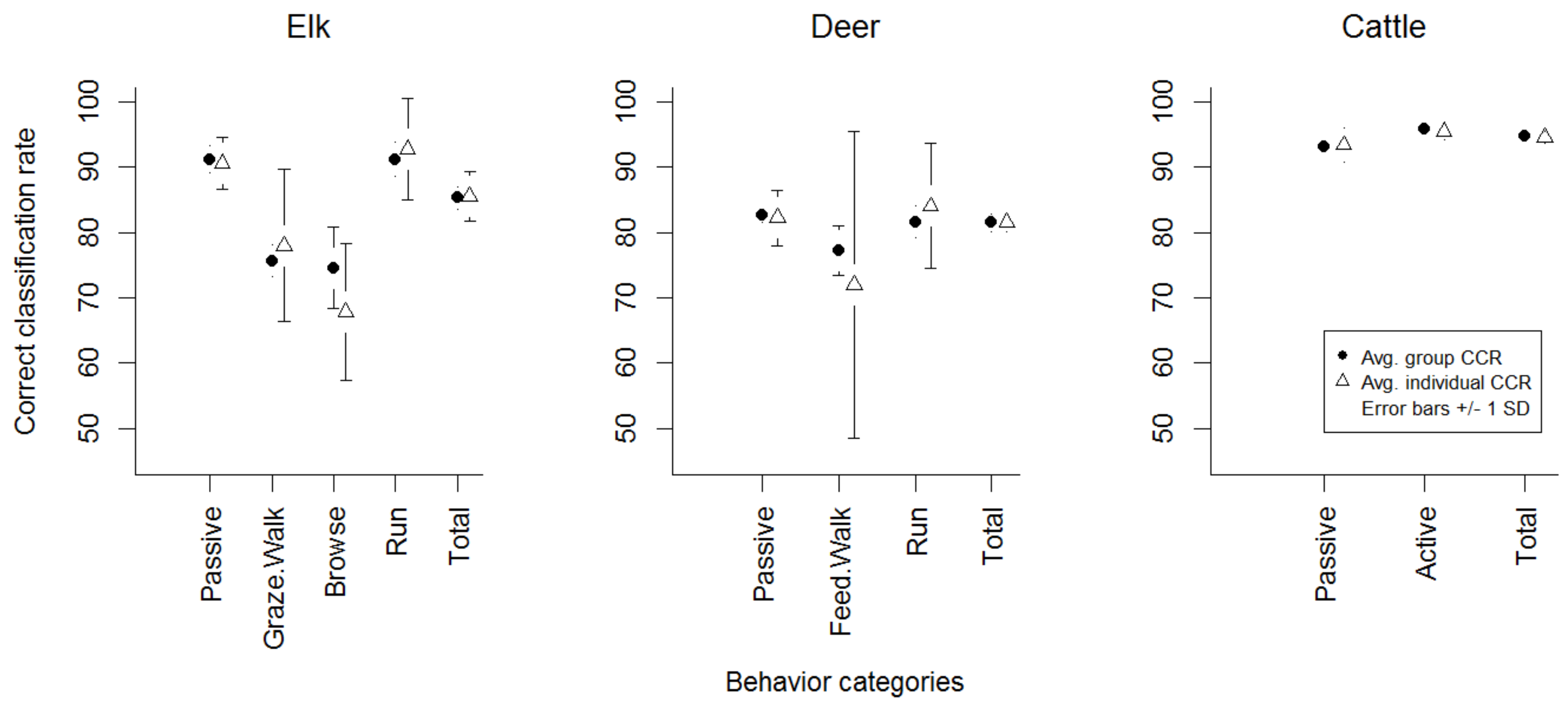
Mule Deer

Our best, final model structure for the full dataset (LDA_{untr}) had cross-validated CCRs ≥ 70% for up to 3 categories (passive, feed plus walk, and run, Table 3.2). The use of only pure intervals for calibration resulted in a model (QDA_{log}) that classified behaviors into 5 categories (passive, graze, browse, walk, and run). Application of this model to classification of the mixed (only) interval dataset resulted in additional misclassification rates of up to 63.1% for some behaviors (Table 3.3). Average CCRs for behaviors of individuals ranged from 5.2% lower to 2.4% higher when compared to the 3-animal calibration dataset (Figure 3.1). Variability of CCRs (standard deviation) ranged from 3.3 to 19.7 percentage points higher for individual deer behaviors than for those of the group.

Cattle

Our best, final model structure for the full dataset (LDA_{untr}) had cross-validated CCRs ≥ 70% for 2 categories (passive and active, Table 3.2). The use of only pure intervals for calibration resulted in a model (QDA_{untr}) that allowed us to classify behaviors into the same 2 categories (passive and active). Use of this model to classify our mixed interval dataset resulted in additional misclassification rates of up to 24.3% for individual behaviors (Table 3.3). Average CCRs for behaviors of individual cattle ranged from 0.3% lower to 0.3% higher when compared to the 3-animal calibration dataset (Figure 3.1). Variability of CCRs (standard deviation) ranged from 0.5 to 2.3 percentage points higher for individual cow behaviors than for those of the group.

Figure 3.1



Means and standard deviations (SD) of correct classification rates (CCRs, %) for behaviors classified using 1 of 4 models structures: linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. The best final model was calibrated to all but one animal (Group) and applied to the remaining novel animal (Individual). We calibrated classification models by combining directly observed behaviors of Rocky Mountain elk (QDA_{untr}, *n*=5), mule deer (LDA_{log}, *n*=4) and cattle (LDA_{untr}, *n*=4) with simultaneously-collected data from activity monitors housed in Lotek 4400 GPS collars worn by captive female animals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR (elk), Washington State University Wild Ungulate Facility, Pullman, WA (deer), Eastern Oregon Agricultural Research Center Hall Ranch, Union, OR (cattle) during summer and fall, 2011.

Table 3.2 Correct Classification Rates (CCRs, %) for behaviors classified using final models calibrated with full datasets collected for Rocky Mountain elk, mule deer, and cattle. We estimated CCRs using leave-one-out cross validation for our final model structure, either linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values collected using Lotek 4400 GPS collars worn by captive female animals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR (elk), Washington State University Wild Ungulate Facility, Pullman, WA (deer), Eastern Oregon Agricultural Research Center Hall Ranch, Union, OR (cattle) during summer and fall, 2011.

		Behavior category							
Species	Final model structure	Passive	Graze-Walk	Feed-Walk	Browse	Run	Active	Total	Average
Elk	QDA_{untr}	92.0	76.3		70.0	91.2		85.5	82.4
Deer	LDA_{log}	82.8		76.9		82.6		81.6	80.8
Cattle	LDA_{untr}	92.4					96.4	94.8	94.4

Table 3.3 Correct Classification Rates (CCRs, %) for behaviors classified using models calibrated with only pure intervals (pure) and then applied to datasets containing only mixed intervals (mixed) for Rocky Mountain elk, mule deer, and cattle. We estimated CCRs for pure using leave-one-out cross validation for our final model structure, either linear or quadratic discriminant functions on untransformed or log-transformed activity monitor values collected using Lotek 4400 GPS collars worn by captive female animals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR (elk), Washington State University Wild Ungulate Facility, Pullman, WA (deer), and Eastern Oregon Agricultural Research Center Hall Ranch, Union, OR (cattle) during summer and fall, 2011.

		Behavior categories							
Species	Dataset	Passive	Graze	Browse	Walk	Run	Active	Total	Average
Elk	Pure	96.4	89.5	94.7	70.6	80.0		94.2	86.3
	Mixed	77.1	73.8	79.5	46.1	77.2		72.0	70.7
Deer	Pure	96.8	71.2	83.7	85.7	73.0		92.4	82.1
	Mixed	33.7	40.2	94.3	50.7	74.4		38.6	58.7
Cattle	Pure	98.9					99.0	99.0	99.0
	Mixed	97.1					74.7	90.9	85.9

DISCUSSION

We were able to accurately classify (≥ 70% CCRs) up to 4 behavior categories for Rocky Mountain elk, 3 for mule deer, and 2 for cattle. Similar to previous efforts to classify remotely-sensed behavior data, we were unable to discriminate among behaviors associated with little to no motion such as bedding, standing, or ruminating (Ungar et al. 2005, Löttker et al. 2009). Likewise, we were unable to distinguish between feeding and walking activities in mule deer and cattle, likely because these behaviors are frequently interspersed. We succeeded in distinguishing elk browsing, likely because the elk we observed often browsed by biting the base of a stem or twig and then stripping the leaves along its length in one motion. The cattle and deer, in contrast, bit off discrete mouthfuls of leaves, a motion which produced a data signature (AMVs) similar to that produced by grazing. While the elk and deer browsed most often on willow, maple, and cottonwood branches we attached to a wooden tripod, the cattle browsed exclusively on naturally occurring snowberry. The potential effect of browse source on calibration is unclear. Intervals that included ≥ 40 seconds of running behaviors resulted in AMVs consistently higher than those for other behaviors in deer and elk, allowing for classification rates exceeding 80%. Running by cattle, on the other hand, resulted in relatively low AMVs which overlapped significantly with those associated with feeding and walking, despite the higher proportion of running within each interval (≥ 60 sec). We suspect this was because cattle trot with relatively level backs and little neck motion compared with the vigorous neck motions they employ while feeding. It should be noted that although we categorized observed behaviors into a relatively broad spectrum, some rarely occurring behaviors (e.g. parturition or combat) were not observed and will be misclassified by our models.

Few calibration studies have successfully discriminated among active behaviors. Running and feeding in cattle have been classified using models that incorporate distance traveled during an interval (Ungar et al. 2005). However, these analyses only involved pure intervals, so classification accuracy for a full (including both pure and mixed intervals) dataset is unknown. Similarly, the only previous effort to calibrate dual-axis accelerometers succeeded in discriminating among active behaviors (Löttker et al. 2009), but also used only pure intervals. Further, previous studies incorporating mixed intervals of any kind were only successful in distinguishing between passive and active behavior categories (Gervasi et al. 2006, Gottardi et al. 2010). Our results show that models calibrated with datasets that include mixed intervals can accurately distinguish among active behaviors for some species.

Our work also demonstrates that the use of pure-interval models may be inappropriate when classifying behavior for free-ranging ungulates. We discovered that use of models built solely with pure intervals can result in increased misclassifications. Pure-interval models applied to mixed (only) intervals resulted in CCRs up to 24.5%, 63.1%, and 24.3%, lower than cross-validated pure-interval CCRs for elk, mule deer, and cattle, respectively. The impact of this difference when working with full datasets (those that include pure and mixed intervals) such as those from free-ranging animals, would depend on the proportion of mixed intervals within a dataset. For example, using a pure interval model to classify our full mule deer dataset (64.5% of the intervals were mixed) would have decreased total classification 35.8% and resulted in actual CCRs 39.8%, 27.3%, and 21.8% lower for passive, graze, and walk behavior categories, respectively. Unknown to the user, these 3 behaviors would actually classify below our 70% acceptable CCR threshold. A user relying on pure (only) interval models could be classifying behaviors into an inflated number of acceptable categories and with an appreciably inflated estimate of accuracy. Further, both the inflated number of categories and decreased classification are unknown to a user basing their classification accuracy on cross-validated pure interval CCRs. These unknown effects could strongly bias results when behavior classifications are used to explore habitat utilization or as part of energy-budget models.

We note that topography or conditions that affect animal motion, such as steep slopes or deep snow, and which differ significantly from those in our study, could affect classification. Also, the age and sex of an animal can affect the amount of movement associated with different behaviors and therefore affect AMVs (Coulombe et al. 2006, Gervasi et al. 2006). For example, Löttker et al. (2009) observed considerably lower AMVs for male red deer than for females for the same behavior categories. Additionally, age and sex specific differences in foraging ecology, time budgeting, alertness behaviors, etc. could result in differences in classification. Therefore, our classification models might be less accurate for juveniles or males. Additionally, despite only observing mature females for each species, we did find relatively high amounts of variability in classification rates for novel animals for some behaviors. That variability did not correspond to animal weight but might be due to some other variable we did not measure such as neck or leg length. Future calibrations that are based on greater sample sizes might allow investigators to identify and model the effect of such animal-specific factors might improve classification. The variability we observed was likely also influenced by the small number of individuals available for our model-building sample. However, given the relatively small amount of classification variability found for novel cattle, choosing models with fewer behavior categories (e.g. 3 categories for elk) might result in less classification variation. Researchers and managers will need to decide whether greater precision or a greater number of behaviors is more appropriate for their study. The classification tools that resulted from this study allow for that flexibility.

We constructed tools for users to classify dual-axis accelerometer data from free ranging elk, deer, and cattle. We offer the final full-dataset models for the highest number of accurately classified behavior categories (4 for elk, 3 for deer, and 2 for cattle) and those full-dataset models that classify fewer behavior categories (2-3 for elk and 2 for deer) with greater accuracy. The classification tool consists of an R workspace containing these models and an R script with instructions for how to format and upload data and then classify it using the models. This classification tool is available at http://fwl.oregonstate.edu/About%20Us/personnel/faculty/sanchez.html.

MANAGEMENT IMPLICATIONS

Activity monitors in GPS collars that feature dual-axis accelerometers allow managers and researchers to remotely sense, store, and download animal behavior data while collecting fine-scale spatial locations. The combination of these data types can allow the study of activity patterns, foraging behavior, and fine-scale habitat use. Once calibrated, these data can be used to calculate energy budgets, thus allowing researchers to explore animal responses to management actions, for example. Researchers and managers must weight demands for high classification accuracy (CCRs) against maximization of the number of individual behaviors a model can discern. Using sampling intervals of different durations might help address some of these issues (Chapter 4). Given the timing errors associated with these collars (Chapter 1), users must also be cautious when associating behaviors from specific sampling intervals with point-in-time locations recorded by the collar GPS. Future calibration efforts should incorporate mixed intervals in their model building to avoid the high misclassification rates resulting from dependence on pure intervals.

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LITERATURE CITED

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

Aharoni, Y., Z. Henkin, A. Ezra, A. Dolev, A. Shabtay, A. Orlov, Y. Yehuda, and A. Brosh. 2009. Grazing behavior and energy costs of activity: A comparison between two types of cattle. Journal of Animal Science 87:2719-2731.

Bourgoin, G., M. Garel, B. Van Moorter, D. Dubray, D. Maillard, E. Marty, and J. M. Gaillard. 2008. Determinants of seasonal variation in activity patterns of mouflon. Canadian Journal of Zoology 86:1410-1418.

Carranza, J., J. H. d. T. Sebastian, M. Rosario, V. Juliana, D. Jose, and S. J. Hidalgo-de-Trucios. 1991. Space use by red deer in a mediterranean ecosystem as determined by radio-tracking. Applied Animal Behaviour Science 30:363-371.

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.

Craighead, F. C., Jr., J. J. Craighead, C. E. Cote, and H. K. Buechner. 1973. Satellite and ground radio tracking of elk. Pages 99-111 *in* S. R. Galler, editor. Animal orientation and navigation. University Press of the Pacific, Honolulu, Hawaii.

Findholt, S. L., B. K. Johnson, D. Damiran, T. DelCurto, and J. G. Kie. 2005. Diet composition, dry matter intake, and diet overlap of mule deer, elk, and cattle. . Pages 159-169 *in* M. J. Wisdom, editor. The Starkey Project: a synthesis of long term studies of elk and mule deer. Lawrence, Kansas, USA, Alliance Communications Group.

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

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: International Journal of the Systematics, Biology & Ecology of Mammals 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.

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

Janis, M. W., and J. D. Clark. 1999. Predicting mountain lion activity using radiocollars equipped with mercury tip-sensors. Wildlife Society Bulletin 27:19.

Kie, J. G., C. J. Evans, E. R. Loft, and J. W. Menke. 1991. Foraging behavior by mule deer: The influence of cattle grazing. Journal of Wildlife Management 55:665.

Kilgour, R. J. 2012. In pursuit of "normal": A review of the behaviour of cattle at pasture. Applied Animal Behaviour Science 138:1-11.

Kufeld, R. C., C. B. David, and L. S. Donald. 1988. Habitat selection and activity patterns of female mule deer in the front range, Colorado. Journal of Range Management 41:515-522.

Kuzyk, G. W., and R. J. Hudson. 2007. Twenty-four-hour activity budgets of mule deer, *Odocoileus hemionus*, in the Aspen Parkland of Eastcentral Alberta. Canadian Field-Naturalist 121:299-302.

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.

MacKay, J. R. D., J. M. Deag, and M. J. Haskell. 2012. Establishing the extent of behavioural reactions in dairy cattle to a leg mounted activity monitor. Applied Animal Behaviour Science 139:35-41.

McCullough, D. R., and P. Beier. 1988. Motion-sensitive radio collars for estimation white-tailed deer activity. Journal of Wildlife Management 52:11-13.

Nelson, M. E., and G. A. Sargeant. 2008. Spatial interactions of yarded white-tailed deer, *Odocoileus virginianus*. Canadian Field-Naturalist 122:221-225.

Proffitt, K. M., J. L. Grigg, R. A. Garrott, K. L. Hamlin, J. Cunningham, J. A. Gude, and C. Jourdonnais. 2010. Changes in elk resource selection and distributions associated with a late-season elk hunt. Journal of Wildlife Management 74:210-218.

Roth, H. U., and C. H. Meslow. 1983. Diel activity of a remnant population of European brown bears. Pages 223-229 *in* P. Zager, editor. Bears: Their biology and management. International Association for Bear Research and Management, Brookeville, MD.

Rowland, M. M., L. D. Bryant, J. K. Johnson, J. H. Noyes, M. J. Wisdom, and J. W. Thomas. 1997. The Starkey project: History, facilities, and data collection methods for ungulate research. USDA Forest Service Technical Report PNW-GTR 396: 1-62.

Tabachnick, B., A., and L. S. Fidell. 2001. Using mulivariate statistics Allyn & Bacon, Needham Heights, MA.

Ungar, E. D., Z. Henkin, M. Gutman, A. Dolev, A. Genizi, and D. Ganskopp. 2005. Inference of animal activity from GPS collar data on free-ranging cattle. Rangeland Ecology and Management 58:256-266.

Walburger, K. J., T. DelCurto, and M. Vaura. 2007. Influence of forest management and previous herbivory on cattle diets. Rangeland Ecology & Management 60:172-178.

Wichrowski, M. W., D. S. Maehr, J. L. Larkin, J. J. Cox, and M. P. O. Olsson. 2005. Activity and movements of reintroduced elk in southeastern Kentucky. Southeastern Naturalist 4:365-374.

Wisdom, M. J., J. G. Cook, M. M. Rowland, and J. H. Noyes. 1993. Protocols for care and handling of deer and elk at the Starkey Experimental Forest and Range. General Technical Report PNW-GTR-311, Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

CHAPTER 4: CHOOSING SAMPLING INTERVAL LENGHS FOR REMOTELY CLASSIFYING ELK BEHAVIOR

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ABSTRACT

Dual-axis accelerometer GPS 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. The duration of each behavior relative to sampling interval length could play an important role in calibration but to date no work had been done to determine optimal interval duration to use with these sensors. Similarly, no calibration had been conducted for Lotek 4500 GPS collars featuring accelerometer activity monitors for Rocky Mountain elk (*Cervus elaphus nelsoni*). We examined discriminant function model structures for 3 sampling interval durations (5-min, 152-sec, and 64-sec) to determine the number of behaviors that can be classified and to what level of accuracy for novel animals with and without access to supplemental feed. Models constructed using 5-min intervals performed best for animals with and without access to supplemental feed, accurately classifying (≥ 70% classification rate) 5 and 4 behavior categories, respectively.

KEY WORDS accelerometers, activity monitors collars, behavior classification, elk, hay, sampling interval.

INTRODUCTION

Collar-mounted activity monitors are an important tool for remotely collecting data on the behavior of far-roaming species. Accelerometers are electronic devices that record animal motion via changes in acceleration. Integration of accelerometers into Global Positioning System (GPS) collars offers researchers the opportunity to sample behavior and locations at fine temporal and geographic scales. Dual-axis accelerometer collars have been used to accurately classify passive and active behaviors for brown bears (*Ursus arctos*) and cattle (Gervasi et al. 2006, Chapter 2), resting, feeding plus slow locomotion, and fast locomotion for red deer (*Cervus elaphus*), roe deer (*Capreolus capreolus*), and mule deer (*Odocoileus hemionus*, Löttker et al. 2009, Heurich et al. 2012, Chapter 2), and resting, grazing plus walking, browsing, and running for Rocky Mountain elk (*Cervus elaphus nelsoni*, Chapter 2).

Accelerometer collars require calibration for each species of interest to determine what behaviors correspond to what activity monitor values (AMVs). The calibration process consists of correlating observed animal behaviors to AMVs for each sampling interval and results in a mathematical model that can be used to predict (i.e., classify) the activity level or behavior of novel animals based on remotely-collected collar data. Classification models are validated by calibrating with some portion of a dataset and then determining the percentage of correctly classified sampling intervals for each behavior category when that model is applied to the remainder of the dataset.

Construction of classification models is simplified by the exclusion of mixed intervals (sampling intervals containing > 1 behavior) from model calibration and validation. Mixed intervals are typically categorized according to the most abundant behavior within an interval. Because they contain multiple behaviors with different data signatures, mixed intervals tend to exhibit more variable AMVs than pure intervals (those containing only 1 behavior). Thus, models constructed and validated using only pure interval datasets (i.e., pure-interval models) classify a greater number of behaviors more accurately than models constructed and validated using both pure and mixed intervals (i.e., full-dataset models). However, application of pure-interval models to mixed intervals can result in additional misclassification rates of $\leq$ 61% for some behaviors (Chapter 1). Because datasets from free-ranging animals inherently include mixed intervals and given that there is no way to distinguish pure from mixed intervals and therefore no way to exclude the latter, reliance on pure-interval models to classify behaviors of free-ranging animals should be avoided. It is possible, however, that shorter sampling intervals could better capture behaviors of shorter duration and result in mixed interval datasets with less variable AMVs that can be used to construct full-dataset models that classify more behaviors more accurately.

Few researchers have explored the effect of sampling interval duration on accuracy of classification models. Passive behavior of red deer were classified most accurately using 5-min intervals, in comparison to 10- and 15-min intervals, when investigators used collars that incorporated 2 tip-switches (Adrados et al. 2003). However, the active behavior category was classified most accurately over 10-min intervals, which also had the highest total classification rate. At this writing, no sampling interval comparisons have been conducted for accelerometer-based activity monitors.

We calibrated Lotek model 4500 GPS collars (Newmarket, Ontario, Canada) for Rocky Mountain elk using 5-min, 152-sec, and 64-sec sampling intervals. We compared the number of behaviors that can be classified using these sampling intervals and with what accuracy. Consultation with colleagues using similar collars led us to choose a threshold of a 70% correct classification rate as the minimum acceptable rate of classification (M. Wisdom, US Forest Service, personal communication). Based on our previous work (Chapter 1) we expected that shorter sampling intervals would allow us to classify a greater number of behaviors with higher accuracy. We expected the greatest improvement in classification for behaviors that tend to be closely interspersed, such as walking and grazing, or of short duration, such as running. Our exploration of the effect of varying sampling interval lengths on classification accuracy will improve application of these tools in studies of animal behavior.

In addition to exploring how to best classify natural behaviors, we felt it important to consider one behavior of anthropogenic origin. Supplying elk with supplemental feed (usually hay) to boost overwintering survival has been a common management practice in several western states for nearly a century (Murie 1944, Daniels 1953). However, we found no previous work considering potential detectability of hay-consumption using tools such as activity monitors. We explored whether hay feeding would affect classification by comparing the performance of models constructed using datasets that both included and excluded eating hay.

STUDY AREA

Starkey Experimental Forest and Range (Starkey) is located in the Blue Mountains 35 km southwest of La Grande, OR (45°12'N, 118°3'W). It consists of a 10,125 ha divided into several study areas including a 265-ha Winter Area consisting of several small pastures and a complex of pens and handling facilities. We conducted our behavior observations in Wing pasture and the handling pens within the Winter Area. Canopy in the pasture was dominated pine and forage species consisted of upland grasses (Rowland et al. 1997).

METHODS AND MATERIALS

Study animals and animal handling

We conducted direct observations of captive 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). Experienced personnel used ATVs and gated chutes to separate 4 female elk from the rest of the herd. We collared, recorded body weight, and visually monitored each elk for signs of stress (e.g., hyperventilating) before releasing the animals into a recovery pen. Elk ranged in age from 18–21 years old and weighed 215–307 kg.

We collared the elk with Lotek 4500 GPS collars (1 kg) equipped with 3 accelerometers oriented perpendicular to one another to capture motion along 3 body planes: one across the animal's shoulders (X-axis), one parallel to the animal's spine (Y-axis), and one oriented vertically (Z-axis). Accelerometers record the difference in acceleration between 2 consecutive measurements 4 times/sec. These values are averaged over a user-selected sampling interval as an indexed value ranging 0–255 and are stored with the associated date, temperature, and start time of the sampling interval. Collars store AMVs averaged over the entire sampling interval and not individual accelerometer measurements. This collar model allows users to choose among 7 preset modes that record different parameters of motion over a variety of sampling intervals. We used modes 1, 2, and 3 which record acceleration along the X and Y axes using 5-min, 152-sec, and 64-sec sampling intervals, respectively. To offer users the best comparison possible to similar collar models that incorporate 2 accelerometers, we did not use collar modes that incorporated the Z axis. Accelerometer collar technical details can be found in our previous publications (Chapter 2 and Chapter 3). We collected data during 3, 2–4 week periods. We collected data using 152-sec intervals September 6-22, 2011, using 64-sec intervals September 22- October 13, 2011, and using 5-min intervals April 23- May 16, 2013.

Field observations and data processing

Direct field observations were conducted in accordance with Chapter 3. We used Palm Tungsten E2 handheld PDAs (Sunnyvale, CA, USA) equipped with Palm PDA-based software (EVENT-Palm, J. C. Ha, University of Washington) to record the start time and duration of each observed behavior. We initially recorded behaviors into 10 classes: bedded, bedded-ruminating, standing, standing-ruminating, grazing, eating hay, browsing, walking, trotting, and galloping. When we lost sight of an animal we labeled that time as “unknown”. Most behaviors occurred naturally but several had to be prompted. We prompted browsing by providing locally gathered woody species attached to fencepost and a wooden tripod. We prompted eating hay by scattering hay bales on the ground. Trotting and galloping were prompted by trained ATV-mounted Forest Service personnel chasing individual animals for short periods for the 64- and 152-sec intervals. Due to the age and condition of our study animals, we determined that prompting trotting and galloping for 5-minute sampling intervals was not possible. We completed data processing in order to format data, correct timing errors, and pair observations to activity monitor data as described in Chapter 3.

Model building

Our direct observations of elk behavior yielded 17,359, 7,127, and 2,993 intervals for 64-sec, 152-sec, and 5-min sampling intervals, respectively. We categorized all intervals based on the predominant behavior (greatest duration) within an interval. The exceptions were any intervals containing ≥ 40 seconds of running behaviors (trotting or galloping) which we classified as "run". Several 64-sec mixed intervals for which running was temporally the dominant behavior (≥ 16 seconds) contained < 40 seconds of running behaviors. We categorized these intervals as "short runs". To include the same behavior categories in model calibration, any intervals for the 152-sec and 5-min sampling intervals that contained 16-39 seconds of running were also initially categorized as "short runs". During our direct observations we had noted that grazing and eating hay appeared to be associated with different head motions. To address the question of optimal sampling interval for herds with and without access to supplemental feed (i.e., hay), we compared classificaiton models using intervals that included “eating hay” as well as models that excluded those intervals.

We completed model construction as described in Chapter 3. We used full datasets (both pure and mixed intervals) to construct classification models for each interval duration and compared performance based on the percentage of correctly classified intervals (i.e., the Correct Classification Rate, CCR). For each interval type we compared the performance of 4 model structures: linear discriminant function (LDA) and quadratic discriminant function (QDA) using both untransformed ($_{untr}$) and log-transformed ($_{log}$) X-axis, Y-axis, and X*Y AMVs. We estimated CCRs that would be expected if classification models were applied to novel datasets using leave-one-out cross validation. We identified the best model based on a “best-predictions” strategy, as evaluated by CCR, and only considered models acceptable if the CCRs for all behaviors were ≥ 70%. We chose the best model from the acceptable models based on the highest total classification rate (the percentage of all intervals correctly classified), the highest average behavior classification rate (the average classification rate among behaviors), and highest minimum (lowest classification rate among behaviors) behavior classification rate. Because total classification rates were greatly influenced by the number of intervals within each behavior category, highest average and minimum CCRs were given greater consideration in this process. For example, our datasets were dominated by passive and grazing intervals so high CCRs for those behaviors corresponded to high total classification rates regardless of CCRs of the other behaviors (e.g. browsing and running).

Subsequent analysis

To evaluate the ability of our models to correctly classify behaviors of novel animals, we calibrated the best model structure for each interval duration using data from 3 animals and then applied this model to data for the remaining animal. We repeated this process for each animal and compared the average CCRs for the group (3 elk) vs. the average CCRs for individual elk. We also compared the standard deviation of CCRs for the group vs. the individual for each behavior to compare classification variability.

RESULTS

Rocky Mountain elk behavior sampled over 64-sec intervals had cross-validated CCRs ≥ 70% for the final, best model structure (LDA_{untr}) for up to 4 categories (passive, feed plus walk, short run, and run) using datasets that excluded (Table 4.1) and included (Table 4.2) eating hay. The bedded behavior category was expanded to include bedded and bedded-ruminating because the two behaviors were indistinguishable for all interval durations and datasets. The "passive" behavior category included bedded and standing. No intervals of standing-ruminating were observed for any interval duration.

Neither the 152-sec nor the 5-min models were able to classify "short run" at an acceptable CCR, therefore we eliminated the category from further analyses of those datasets. The final model structure for 152-sec intervals (QDA_{log}) classified up to 3 behaviors (passive, feed plus walk, and run) for both hay and no-hay datasets. Final model structures for 5-min interval for datasets excluding and including hay (QDA_{unt} and LDA_{log}, respectively) classified up to 4 (bedded, graze plus walk plus stand, browse, and run) and 5 behaviors (bedded, hay, graze plus walk plus stand, browse, and run), respectively.

For the hay-free datasets, average CCRs for individual elk behaviors differed from 3-animal group averages by -18.8% to +5.2% for 64-sec intervals, -1.3% to 0.0 for 152-sec intervals, and -9.1% to +2.7% for 5-min intervals (Figure 4.1). Variability of CCRs (±1 standard deviation) ranged from -0.8 to +42.5 percentage points (pps), 0.0 to +4.4 pps, and -4.4 pps to +15.0 pps for individual elk behaviors than for those of the group for 64-sec, 152-sec, and 5-min intervals, respectively. For the datasets that included hay, average CCRs for individual elk behaviors differed from 3 animal group averages by -18.8% to +8.0% for 64-sec intervals, -1.4% to 0.0 for 152-sec intervals, and -8.5% to +3.3% for 5-min intervals (Figure 4.2). Variability of CCRs (±1 standard deviation) ranged from +1.1 to +42.5 pps, 0.0 to +5.2 pps, and +1.8 to +15.5 pps for individual elk behaviors than for those of the group for 64-sec, 152-sec, and 5-min intervals, respectively.

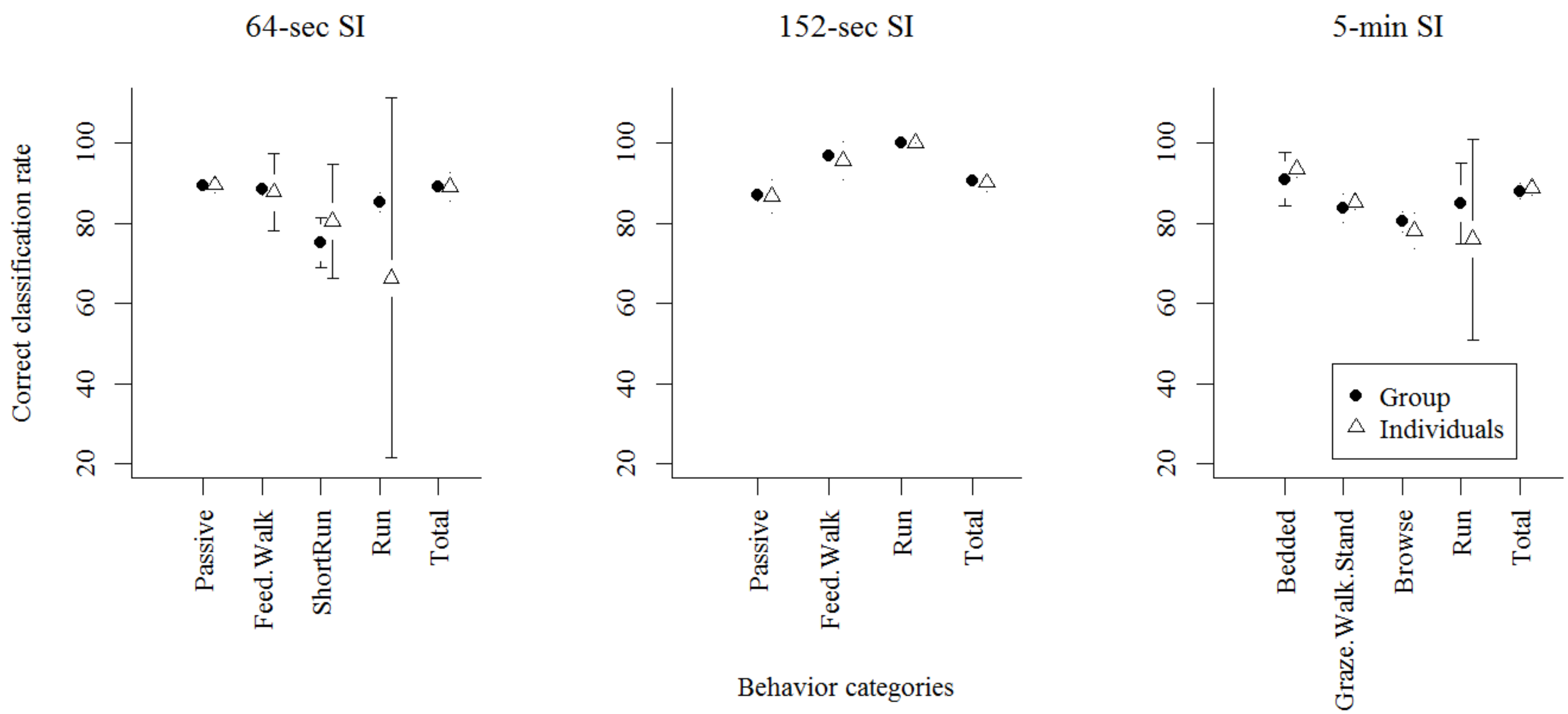
Table 4.1 Correct Classification Rates (CCRs, %) of behaviors classified over 3 different sampling intervals. Models were calibrated with datasets that excluded supplemental hay for Rocky Mountain elk. We estimated CCRs using leave-one-out cross validation for our final model structure, either linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values collected using Lotek 4500 GPS collars worn by captive female animals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR, during summer and fall, 2011 and spring, 2013.

		Behavior category								
Sampling interval	Final model structure	Bedded	Passive	Graze/Walk/ Stand	Feed/ Walk	Browse	Short run	Run	Total	Average
64-sec.	LDA_{untr}		89.5		88.4		84.9	71.4	89.2	83.6
152-sec.	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

Table 4.2 Correct Classification Rates (CCRs, %) of behaviors classified over 3 different sampling intervals. Models were calibrated with datasets that included supplemental hay for Rocky Mountain elk. We estimated CCRs using leave-one-out cross validation for our final model structure, either linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values collected using Lotek 4500 GPS collars worn by captive female animals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR, during summer and fall, 2011 and spring, 2013.

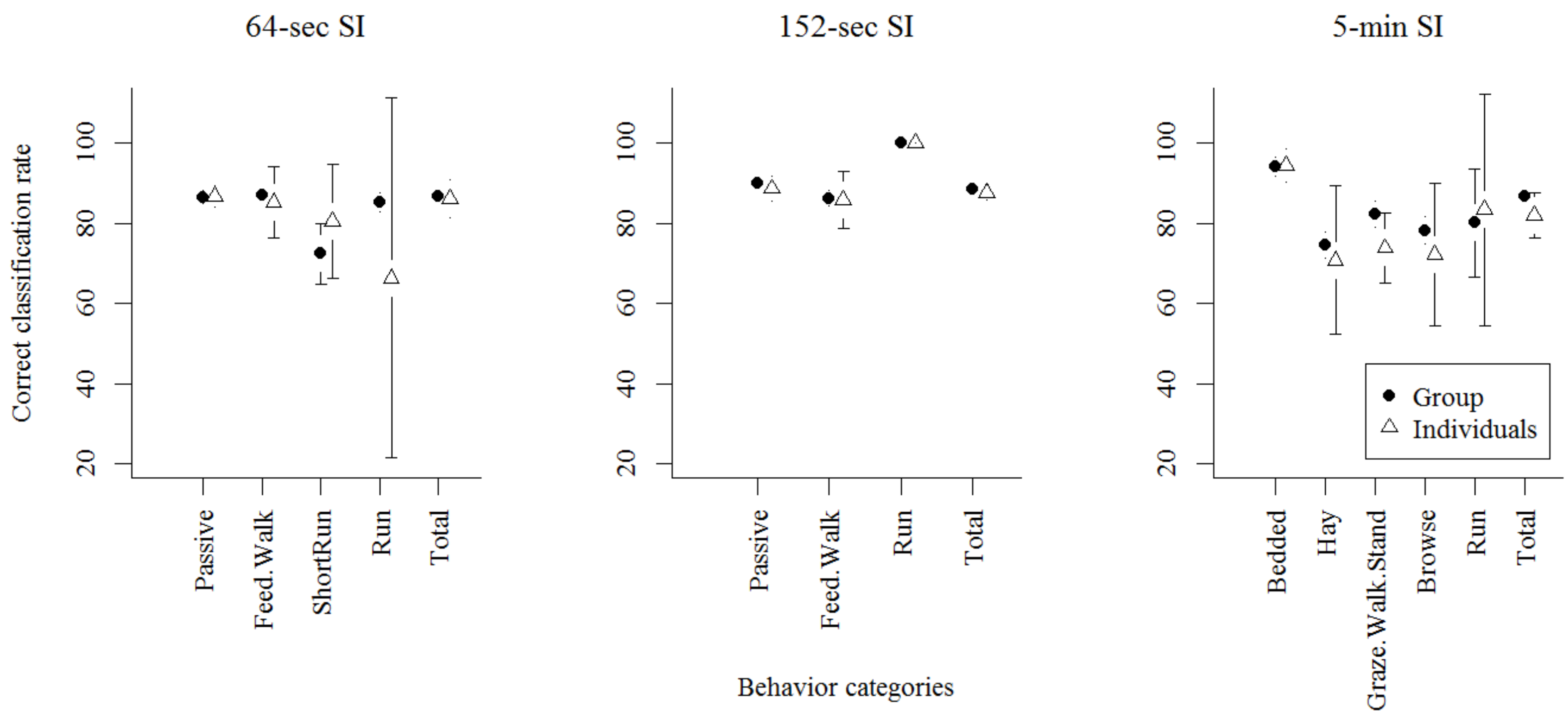
		Behavior category									
Sampling interval	Final model structure	Bedded	Passive	Hay	Graze/Walk/ Stand	Feed/ Walk	Browse	Short run	Run	Total	Average
64-sec.	LDA_{untr}		86.4			87.1		84.9	71.4	86.7	82.5
152-sec.	QDA_{log}		89.9			86.1			100.0	88.4	92.0
5-min.	LDA_{log}	91.3		75.0	83.2		83.1		81.0	86.1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

Figure 4.1



Means and standard deviations (SD) of correct classification rates (CCRs, %) for behaviors classified using 1 of 4 models structures: linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. The best final model was calibrated to all but one animal (Group) and applied to the remaining novel animal (Individual) using datasets that excluded supplemental feeding. We calibrated classification models by combining directly observed behaviors of Rocky Mountain elk (*n*=4) with simultaneously-collected data from activity monitors housed in Lotek 4500 GPS collars worn by captive female animals and set on 64-sec (LDA_{untr}), 152-sec (QDA_{log}), and 5-min (QDA_{untr}) sampling intervals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR during summer and fall, 2011 and spring, 2013.

Figure 4.2



Means and standard deviations (SD) of correct classification rates (CCRs, %) for behaviors classified using 1 of 4 models structures: linear (LDA) or quadratic (QDA) discriminant functions on untransformed ($_{untr}$) or log-transformed ($_{log}$) activity monitor values. The best final model was calibrated to all but one animal (Group) and applied to the remaining novel animal (Individual) using datasets that included supplemental feeding. We calibrated classification models by combining directly observed behaviors of Rocky Mountain elk (*n*=4) with simultaneously-collected data from activity monitors housed in Lotek 4500 GPS collars worn by captive female animals and set on 64-sec (LDA_{untr}), 152-sec (QDA_{log}), and 5-min (LDA_{log}) sampling intervals. Observations were made at Starkey Experimental Forest and Range, La Grande, OR during summer and fall, 2011 and spring, 2013.

DISCUSSION

Classification models varied in classification accuracy, variability, and the number of behaviors classified among sampling interval durations and between hay and no-hay datasets. For collar users, sampling interval choice comes down to a decision between high accuracy and low variability or a greater number of classifiable behaviors. Models that classified fewer behaviors had higher total and average CCRs and less classification variability for novel animals. However, models that classify a greater number of categories not only distinguish among more behaviors but offer the ability to increase classification accuracy and decrease variability by further combining behavior categories. For example, 64-sec models accurately classified up to 4 behaviors (passive, feed plus walk, short run, and run) while 152-sec models classified only 3 (passive, feed plus walk, and run) but with higher accuracy and less variability. When we further combined behavior categories for 64-sec models (3 behaviors: passive, feed plus walk, run), classification accuracy and variability were comparable to those for 152-sec models. The flexibility between more behaviors or fewer behaviors with higher accuracy and less variability makes intervals that allow classification of the greatest number of categories the best option for accelerometer GPS collars. Therefore, we recommend that users select 5-min sampling intervals when deploying their collars.

Some of the classification variability we observed was likely due to sampling constraints. We were only able to observe 4 animals during each trial which resulted in small sample sizes when calculating classification for novel animals. This was especially apparent for behaviors with relatively few intervals such as run. For 64-sec models, we only observed 2 intervals of running for 1 animal, both of which were misclassified into the short-run category (0% CCR for run for that animal). For 5-min models, we only observed running intervals for 3 of the 4 elk which further decreased our already small study animal sample size and contributed to the increased variability we observed.

We note that the age and sex of an animal can affect the movement associated with different behaviors and therefore affect AMVs (Coulombe et al. 2006, Gervasi et al. 2006). For example, considerably lower AMVs have been observed for male red deer than for females for the same behavior categories (Löttker et al. 2009). Additionally, sex and age specific differences in time budgeting, foraging ecology, alertness behaviors, etc. could result in different classifications. As such, our classification models might be less accurate for males or juveniles. Additionally, although we only observed females of similar age for each species, we did find relatively high amounts of CCR variability for novel animals for some behaviors. Variability did not correspond to animal weight but might be due to other variables we did not measure. Future calibrations that are based on greater sample sizes might allow researchers to identify and model the effect such animal-specific factors have on classification. The variability we observed was also likely affected by the limited observation animal sample size. It should also be noted that conditions that affect animal motion, such as deep snow or steep slopes, and which differ significantly from those in our study, could affect classification. Finally, although we categorized behavior observations into a relatively broad spectrum, some behaviors that occur rarely (e.g. parturition or combat) were not observed and will be misclassified by our models.

Animal motion associated with feeding on hay was distinct enough that the behavior was distinguishable when using models constructed with 5-min intervals. Classification models for elk herds with access to hay need to include this behavior when calibrating their models or else risk biasing their results. Also, researchers should not use eating hay as a proxy for grazing when calibrating accelerometer collars because their motions are distinct.

We plan to make our classification models available on-line for 5-min, 152-sec, and 64-sec sampling interval durations for both hay and non-hay datasets. This tool will include a suite of models that accurately classify the greatest number of behaviors and those that classify fewer (more combined) behavior categories. Users will need to decide what model is most appropriate for their study. Classification models will enable users to derive accurate behavior categorizations from their collar data for these 3 sampling intervals.

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LITERATURE CITED

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

Daniels, T. W. B. 1953. Winter at Blackrock...a big game report from a snowbound wilderness. Wyoming Wildlife 17:20-27.

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

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

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.

Murie, O. J. 1944. Our big game in winter. Transactions of the North American Wildlife Conference 9:173-176.

Rowland, M. M., L. D. Bryant, J. K. Johnson, J. H. Noyes, M. J. Wisdom, and J. W. Thomas. 1997. The Starkey project: History, facilities, and data collection methods for ungulate research. USDA Forest Service Technical Report PNW-GTR 396: 1-62.

Wisdom, M. J., J. G. Cook, M. M. Rowland, and J. H. Noyes. 1993. Protocols for care and handling of deer and elk at the Starkey Experimental Forest and Range. General Technical Report PNW-GTR-311, Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

CHAPTER 5: THESIS SUMMARY

Knowledge of animal behavior is crucial for making informed management decisions and activity-monitor collars are increasingly the tool of choice for studying the behavior of free-ranging species. During our efforts to calibrate accelerometer activity-monitor collars, several challenges arose that we detailed in this thesis. Understanding and accounting for these issues will allow managers and researchers to use these tools properly and, through their successful use, lead to a better understanding of animal behavior.

Ideally, users should familiarize themselves with the operations of any remote sensing or analysis tool they employ. Accelerometer activity-monitors are a critical case in point. Before deploying collars, users must actively engage manufacturers' engineering personnel to discover and understand exactly how the sensors work. For our work, the relatively straightforward calibration process of pairing behavior observations to activity monitor values for the same sampling interval was complicated considerably by internal clock errors caused by multiple components within the activity sensors themselves. Further, these errors are largely ignored in user guides provided by collar manufacturers. Not recognizing or understanding these problems will result in inaccurate behavior classification models when calibrating activity monitor collars. Also, location errors can result if pairing collar derived behaviors to GPS locations based on the time given in the collar output. Once we understood the complete scope of the problems and devised a correction procedure, we developed a manuscript. We expect that the resulting publication will be instructive for future collar users (Chapter 2). However, while the issues addressed in that manuscript are likely to be similar for most accelerometer-equipped collars currently being marketed, variation is likely among collars from different manufacturers and even among models from the same manufacturer. For example, the time shift procedure detailed in Chapter 2 and applied in Chapter 3 for Lotek 4400 GPS collars was effective for the work we did with Lotek 4500 GPS collars (Chapter 4) but durations of the necessary time shifts were more consistent, suggesting slightly different internal mechanisms between the two collar models. Users must work with manufacturers to assure that assumptions, sampling design, analysis, and conclusions align with the realities of the measurement tool (activity monitor).

We also discovered the critical importance of using full datasets (including pure and mixed intervals) for calibration of activity monitors (Chapter 3). Although most calibrations prior to ours relied entirely on pure interval datasets, and thus excluded mixed intervals, our work showed the potential bias resulting from such an approach. We showed that reliance on calibrations built solely with pure intervals can result in inaccurate classification models. Furthermore, because no quantification of the effect of excluding mixed intervals was performed prior to our work, users of pure-interval models were likely unaware of this potentially significant bias. Unaware of the problem, a user would likely develop inflated estimates and expectations of behavior classification accuracy. Based on our work, conclusions resulting from studies that relied on pure-interval classification models might need to be reexamined.

Selection of sampling interval duration is one of many decisions a researcher makes prior to deployment of activity-sensor GPS collars. Collar users must balance sampling frequency demands associated with specific research questions against the constraints of battery life. Many previous investigators and managers have selected 5-min sampling intervals. We explored whether use of shorter sampling intervals (64-sec and 152-sec) would result in greater classification accuracy, greater number of detectable behaviors, or both when sampling elk behavior (Chapter 4). We expected that shorter intervals might allow greater detection and classification of specific behaviors that are generally short in duration, such as running. We also explored whether supplemental feeding, such as when hay that is provided to some elk herds during extreme winters, would affect behavior of classification models. Somewhat surprisingly, models we constructed with data collected at 5-min intervals accurately classified a broader spectrum of a greater than or equal number of behaviors as 64-sec or 152-sec intervals. These results were consistent for datasets including and those excluding supplemental feeding. This work also revealed that animal motion associated with feeding on hay differs enough from grazing that the behaviors were distinguishable. Classification models constructed without the former for herds with access to hay, or using the former as a proxy for the latter, might need to be reexamined.

One additional (future) investigation became obvious as I concluded my work and reflected on past attempts to remotely record and classify behavior of ungulates. Previous investigations showed that movement rate (distance traveled during elapsed time) could be a valuable clue to classifying behavior. For example, work incorporating distance traveled by cattle helped distinguish feeding from travel behaviors (Ungar et al. 2005). Incorporating the distance traveled between successive GPS derived locations as an additional data input for our models could improve classification, especially for cattle. Although it is unclear whether such an approach will improve overall classification for elk and mule deer, I suspect it would help distinguish intervals dominated by walking from those dominated by feeding behaviors.

Despite the constraints and problems we encountered during this project, the most important point raised by our work is that accelerometer-based activity monitors have strong potential to be powerful tools for studying behavior provided that users understand the mechanisms, procedures, and limitations associated with their use. It is my hope that our work will help managers and researchers better use these devices and that manufacturers will consider our findings when designing future generations of activity monitor collars. With proper consideration and use, these tools will continue to illuminate animal behavior and lead to improved management for these ecologically and economically important species.

LITERATURE CITED

Ungar, E. D., Z. Henkin, M. Gutman, A. Dolev, A. Genizi, and D. Ganskopp. 2005. Inference of animal activity from GPS collar data on free-ranging cattle. Rangeland Ecology and Management 58:256-266.

BIBLIOGRAPHY

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

Aharoni, Y., Z. Henkin, A. Ezra, A. Dolev, A. Shabtay, A. Orlov, Y. Yehuda, and A. Brosh. 2009. Grazing behavior and energy costs of activity: A comparison between two types of cattle. Journal of Animal Science 87:2719-2731.

Beringer, J., J. J. Millspaugh, J. Sartwell, and R. Woeck. 2004. Real-time video recording of food selection by captive white-tailed deer. Wildlife Society Bulletin 32:648-654.

Bourgoin, G., M. Garel, B. Van Moorter, D. Dubray, D. Maillard, E. Marty, and J. M. Gaillard. 2008. Determinants of seasonal variation in activity patterns of mouflon. Canadian Journal of Zoology 86:1410-1418.

Cain III, J. W., P. R. Krausman, B. D. Jansen, and J. Morgart. 2005. Influence of topography and GPS fix interval on GPS collar performance. Wildlife Society Bulletin 33:926-934.

Carranza, J., J. H. d. T. Sebastian, M. Rosario, V. Juliana, D. Jose, and S. J. Hidalgo-de-Trucios. 1991. Space use by red deer in a mediterranean ecosystem as determined by radio-tracking. Applied Animal Behaviour Science 30:363-371.

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.

Craighead, F. C., Jr., J. J. Craighead, C. E. Cote, and H. K. Buechner. 1973. Satellite and ground radio tracking of elk. Pages 99-111 *in* S. R. Galler, editor. Animal orientation and navigation. University Press of the Pacific, Honolulu, Hawaii.

D'Eon, R. G., and D. Delparte. 2005. Effects of radio-collar position and orientation on GPS radio-collar performance, and the implications of PDOP in data screening. Journal of Applied Ecology 42:383-388.

Daniels, T. W. B. 1953. Winter at Blackrock...a big game report from a snowbound wilderness. Wyoming Wildlife 17:20-27.

Di Orio, A. P., R. Callas, and R. J. Schaefer. 2003. Performance of two GPS telemetry collars under different habitat conditions. Wildlife Society Bulletin 31:372-379.

Findholt, S. L., B. K. Johnson, D. Damiran, T. DelCurto, and J. G. Kie. 2005. Diet composition, dry matter intake, and diet overlap of mule deer, elk, and cattle. . Pages 159-169 *in* M. J. Wisdom, editor. The Starkey Project: a synthesis of long term studies of elk and mule deer. Lawrence, Kansas, USA, Alliance Communications Group.

Ganskopp, D. C., and D. D. Johnson. 2007. GPS error in studies addressing animal movements and activities. Rangeland Ecology and Management 60:350-358.

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

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: International Journal of the Systematics, Biology & Ecology of Mammals 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.

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

Hulbert, I. A. R., and J. French. 2001. The accuracy of GPS for wildlife telemetry and habitat mapping. Journal of Applied Ecology 38:869-878.

Janis, M. W., and J. D. Clark. 1999. Predicting mountain lion activity using radiocollars equipped with mercury tip-sensors. Wildlife Society Bulletin 27:19.

Jiang, Z., M. Sugita, M. Kitahara, S. Takatsuki, T. Goto, and Y. Yoshida. 2008. Effects of habitat feature, antenna position, movement, and fix interval on GPS radio collar performance in Mount Fuji, central Japan. Ecological Research 23:581-588.

Kie, J. G., C. J. Evans, E. R. Loft, and J. W. Menke. 1991. Foraging behavior by mule deer: The influence of cattle grazing. Journal of Wildlife Management 55:665.

Kilgour, R. J. 2012. In pursuit of “normal”: A review of the behaviour of cattle at pasture. Applied Animal Behaviour Science 138:1-11.

Kufeld, R. C., C. B. David, and L. S. Donald. 1988. Habitat selection and activity patterns of female mule deer in the front range, Colorado. Journal of Range Management 41:515-522.

Kuzyk, G. W., and R. J. Hudson. 2007. Twenty-four-hour activity budgets of mule deer, *Odocoileus hemionus*, in the Aspen Parkland of Eastcentral Alberta. Canadian Field-Naturalist 121:299-302.

Lindzey, F. G., and E. C. Meslow. 1977. Home range and habitat use by black bears in Southwestern Washington. Journal of Wildlife Management 41:413-425.

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.

MacKay, J. R. D., J. M. Deag, and M. J. Haskell. 2012. Establishing the extent of behavioural reactions in dairy cattle to a leg mounted activity monitor. Applied Animal Behaviour Science 139:35-41.

Martin, P., and P. Beteson. 2007. Measuring behavior: An introductory guide. 3rd edition. Cambridge University Press, Cambridge, UK.

Mattisson, J., H. Andrén, J. Persson, and P. Segerström. 2010. Effects of species behavior on global positioning system collar fix rates. Journal of Wildlife Management 74:557-563.

McCullough, D. R., and P. Beier. 1988. Motion-sensitive radio collars for estimation white-tailed deer activity. Journal of Wildlife Management 52:11-13.

Moen, R., J. Pastor, and Y. Cohen. 1996. Interpreting behavior from activity counters in GPS collars on moose. Alces 32:101-108.

Murie, O. J. 1944. Our big game in winter. Transactions of the North American Wildlife Conference 9:173-176.

Naylor, L. M., and J. G. Kie. 2004. Monitoring activity of Rocky Mountain elk using recording accelerometers. Wildlife Society Bulletin 32:1108-1113.

Nelson, M. E., and G. A. Sargeant. 2008. Spatial interactions of yarded white-tailed deer, *Odocoileus virginianus*. Canadian Field-Naturalist 122:221-225.

Proffitt, K. M., J. L. Grigg, R. A. Garrott, K. L. Hamlin, J. Cunningham, J. A. Gude, and C. Jourdonnais. 2010. Changes in elk resource selection and distributions associated with a late-season elk hunt. Journal of Wildlife Management 74:210-218.

Rencher, A. C. 2002. Methods of Multivariate Analysis. 2nd edition. John Wiley and Sons, Inc., New York.

Roth, H. U., and C. H. Meslow. 1983. Diel activity of a remnant population of European brown bears. Pages 223-229 *in* P. Zager, editor. Bears: Their biology and management. International Association for Bear Research and Management, Brookeville, MD.

Rouys, S., J. Theuerkauf, and M. Krasinska. 2001. Accuracy of radio-tracking to estimate activity and distances walked by European bison in the Bialowieza Forest, Poland. Acta Theriologica 46:319-326.

Rowland, M. M., L. D. Bryant, J. K. Johnson, J. H. Noyes, M. J. Wisdom, and J. W. Thomas. 1997. The Starkey project: History, facilities, and data collection methods for ungulate research. USDA Forest Service Technical Report PNW-GTR 396: 1-62.

Singer, F. J., A. R. Tipton, C. P. Hable, and D. K. Otto. 1981. Home ranges, movements, and habitat use of European wild boar in Tennessee. Journal of Wildlife Management 45:343-353.

Tabachnick, B., A., and L. S. Fidell. 2001. Using mulivariate statistics Allyn & Bacon, Needham Heights, MA.

Ungar, E. D., Z. Henkin, M. Gutman, A. Dolev, A. Genizi, and D. Ganskopp. 2005. Inference of animal activity from GPS collar data on free-ranging cattle. Rangeland Ecology and Management 58:256-266.

Walburger, K. J., T. DelCurto, and M. Vaura. 2007. Influence of forest management and previous herbivory on cattle diets. Rangeland Ecology & Management 60:172-178.

Wichrowski, M. W., D. S. Maehr, J. L. Larkin, J. J. Cox, and M. P. O. Olsson. 2005. Activity and movements of reintroduced elk in southeastern Kentucky. Southeastern Naturalist 4:365-374.

Wisdom, M. J., J. G. Cook, M. M. Rowland, and J. H. Noyes. 1993. Protocols for care and handling of deer and elk at the Starkey Experimental Forest and Range. General Technical Report PNW-GTR-311, Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

APPENDICES

APPENDIX A: FORMAL MODEL STRUCTURE

Our goal was to use GPS collar mounted accelerometers that remotely quantify animal movement to classify animal behavior. To assign a sampling interval from a novel dataset to a behavior category using its associated Activity Monitor Values (AMVs), we applied a linear discriminant function (LDA) or quadratic discriminant function (QDA) model structure calibrated with paired behavior observations and activity monitor data. For each new observation (interval) we calculated a classification value for each behavior category. We then assigned the interval to the behavior category with the highest classification value. This assignment represents the classification model's prediction of the most likely behavior category to which the new observation belongs.

To calculate the classification value for each behavior category, we used the following procedure:

<u>Linear Discriminant Function (LDA)</u>

1) Define a 3x1 vector consisting of the AMVs for the new interval:

$\mathbf{z} = \begin{bmatrix} \mathrm{X} \\ \mathrm{Y} \\ \mathrm{X} * \mathrm{Y} \end{bmatrix}$ or, if using the natural logarithm of the AMVs, $\mathbf{z} = \begin{bmatrix} \log\mathrm{X} \\ \log\mathrm{Y} \\ \log\mathrm{X} * \log\mathrm{Y} \end{bmatrix}$

Where: X = X-axis AMV
Y = Y-axis AMV

2) Use the linear classification function to calculate the linear classification value (L'_i) of each behavior category (i) for a new interval ($\mathbf{z}$) (Rencher 2002, equation 9.12).

$$L'_i(\mathbf{z}) = \ln p_i + \bar{\mathbf{z}}'_i \mathbf{S}_{pl}^{-1} \mathbf{z} - \frac{1}{2} \bar{\mathbf{z}}'_i \mathbf{S}_{pl}^{-1} \bar{\mathbf{z}}_i$$

Where an apostrophe denotes transpose and:
p_i = the prior probability of a behavior category's occurrence
$\mathbf{z}$ = vector of AMVs for the new interval (above)
$\bar{\mathbf{z}}_i$ = mean of $\mathbf{z}$ for behavior category i estimated from calibration dataset
$\mathbf{S}_{pl}^{-1}$ = inverse of the pooled covariance matrix

Where $\mathbf{S}_{pl}$ is calculated using:

$$\mathbf{S}_{pl} = \frac{1}{N-k}\sum_{i=1}^{k}(n_i - 1)\mathbf{S}_i$$

Where: n_i = sample size of the i th group
$\mathbf{S}_i$ = covariance matrix of the i th group estimated from the calibration dataset
N = total number of intervals from the calibration dataset
k = number of behavior categories an interval can be classified into

3) Assign the interval to the behavior category with the highest L'_i.

Quadratic Discriminant Function (QDA)

1) Use the quadratic classification function to calculate the quadratic classification value (Q'_i) of each behavior category (i) for a new interval (**z**) (Rencher 2002, equation 9.14).

$$Q'_i(\mathbf{z}) = \ln p_i - \frac{1}{2}\ln|\mathbf{S}_i| - \frac{1}{2}(\mathbf{z} - \overline{\mathbf{z}}_i)'\,\mathbf{S}_i^{-1}(\mathbf{z} - \overline{\mathbf{z}}_i)$$

Where: $\mathbf{S}_i^{-1}$ = inverse of the covariance matrix for behavior category i
$|\mathbf{S}_i|$ = determinant of covariance matrix for behavior category i

and the other variables are defined above.

2) Assign the interval to the behavior category with the highest Q'_i.

LITERATURE CITED

Rencher, A. C. 2002. Methods of Multivariate Analysis. 2nd edition. John Wiley and Sons, Inc., New York.

APPENDIX B: ACTIVTY MONITOR CALIBRATION PROCESS OUTLINE

To help users understand activity monitor calibration we offer the following outline of the calibration process including illustration using exerpts of an example dataset. We included references to locations within the thesis (chapter and page number) for specific details.

Procedure

1. Collar captive animals
    a. To minimize timing errors, activate collar GPS and set GPS fix rate to ≤ the duration of the sampling interval of the activity monitor (Chapter 2, p. 26)
    b. Use a 5-minute (actually 304-second) sampling interval (Chapter 4, p. 76)
        i. For Lotek model 4500 collars, this would be mode #4.

Example excerpts

ii. To minimize timing errors, activate the collar at the beginning of a 5-minute programmed sampling interval (e.g., 12:00:00, 12:05:00, etc., Chapter 2, p. 26)

2. Observe animals

   a. Formulate a list of mutually-exclusive behaviors or activity states for initial recording of directly observed behaviors (Chapter 3, p. 42)

   b. Captive animals

      i. Record type, start time, and duration of behaviors using a satellite-corrected hand-held data logger or other data collection tool (Figure B1)

Figure B1.

Date	**Elk**	**ETOA**	**Act**	**Dur**
5/1/2013	red	16:06:05	Graze	50
5/1/2013	red	16:06:16	Stand	11
5/1/2013	red	16:06:36	Graze	20
5/1/2013	red	16:06:40	Stand	4
5/1/2013	red	16:07:19	Graze	39
5/1/2013	red	16:07:26	Walk	7
5/1/2013	red	16:08:18	Graze	52
5/1/2013	red	16:36:18	Lay	1680
5/1/2013	red	16:36:21	Stand	2
5/1/2013	red	16:38:24	Graze	124
5/1/2013	red	16:38:35	Walk	11
5/1/2013	red	16:39:12	Graze	37
5/1/2013	red	16:39:14	Walk	2
5/1/2013	red	16:39:25	Walk	11
5/1/2013	red	16:41:31	Browse	126

An excerpt of behavior observations downloaded from a data logger including the date, individual animal name or number (Elk), end time of activity (ETOA), behavior (ACT), and duration of each behavior in seconds (Dur).

1. Periodically check the accuracy of the handheld's clock against an independent and reliable source such as a cell phone or the official US time available at www.time.gov

ii. Induce behaviors of interest that do not occur naturally, such as running (Chapter 3, p. 43)

c. Free-ranging animals

i. Record satellite-corrected time the animal is collared. As above (2bi), use data logger to record the type, start time, and duration of all behaviors while the animal is captive or immobilized

ii. Record the time the animal is released

    1. The transition from inactive (captive or immobile) to active (running away) can be used for time-shift procedure (step 4c below)

iii. Record the type, start time, and duration of all behaviors while the animal is in sight

iv. If possible, track the animal to observe additional behaviors

v. Future researchers should investigate the usefulness of video-enabled collars as a means of observing activity to calibrate collars without using captive animals (Beringer et al. 2004)

3. Remove and download collars (Figure B2)

    a. Note: some accelerometer collars are not capable of remote download of activity monitor data. Users who calibrate collars worn by free-ranging animals will need to use a drop-off mechanism or plan to recapture their animal(s)

Figure B2.

LMT_DATE	LMT_TIME	ACTIVITY_X	ACTIVITY_Y	TEMP
5/1/2013	16:10:00	19	19	16
5/1/2013	16:15:00	8	0	16
5/1/2013	16:20:00	0	0	15
5/1/2013	16:25:00	0	0	15
5/1/2013	16:30:00	0	0	15
5/1/2013	16:35:00	0	0	15
5/1/2013	16:40:00	32	29	15

Portion of unprocessed activity monitor data downloaded from Lotek 4400 collar including local date (LMT_DATE), time (LMT_TIME), X-axis activity monitor value (ACTIVITY X), Y-axis activity monitor value (ACTIVITY Y), and temperature (TEMP) for data record using a 5-minute sampling interval. Not shown: columns for Greenwich Mean Date (GMT_DATE) and Greenwich Mean Time (GMT_TIME).

4. Data processing

   a. Correct for brief bouts of observed behavior per Table 3.1 “May contain < 10 sec of other behavior” (Chapter 3, p. 42, Figure B3)

Figure B3.

Date	**Elk**	**ETOA**	**ETOA2**	**Act**	**Act2**	**Dur**	**Dur2**
5/1/2013	red	16:06:05	16:06:05	Graze	Graze	50	50
5/1/2013	red	16:06:16	16:06:16	Stand	Stand	11	11
5/1/2013	*red*	*16:06:36*		*Graze*		*20*	
5/1/2013	*red*	*16:06:40*		*Stand*		*4*	
5/1/2013	*red*	*16:07:19*		*Graze*		*39*	
5/1/2013	*red*	*16:07:26*		*Walk*		*7*	
5/1/2013	red	16:08:18	16:08:18	Graze	Graze	52	122
5/1/2013	red	16:36:18	16:36:18	Lay	Lay	1680	1680
5/1/2013	red	16:36:21	16:36:21	Stand	Stand	2	2
5/1/2013	red	16:38:24	16:38:24	Graze	Graze	124	124
5/1/2013	red	16:38:35	16:38:35	Walk	Walk	11	11
5/1/2013	red	16:39:12	16:39:12	Graze	Graze	37	37
5/1/2013	*red*	*16:39:14*		*Walk*		*2*	
5/1/2013	red	16:39:25	16:39:25	Walk	Walk	11	13
5/1/2013	red	16:41:31	16:41:31	Browse	Browse	126	126

Excerpt of direct observation data (see Figure B1) after correction for brief bouts of activity including the condensed behaviors (italics), corrected end time of activity (ETOA2), and corrected duration of each behavior (Dur2).

b. Perform initial pairing of observed behaviors to Activity Monitor Values (AMVs) using interval start times given in collar output (Figure B4)

   i. Note the pure interval (300 seconds) of lay associated with relatively high AMVs (Time 16:10:00) versus the pure intervals of lay associated with low AMVs (Times 16:15:00-16:30:00) versus the interval containing lay and a mix of active behaviors associated with low AMVs (Time 16:35:00). This is an example of mis-match due to timing errors.

Figure B4.

Date	**Time**	**Elk**	**ETOA**	**Act**	**Dur**	**X**	**Y**
5/1/2013	16:05:00	red	16:05:15	Stand	15	28	36
		red	16:06:05	Graze	50		
		red	16:06:16	Stand	11		
		red	16:08:18	Graze	122		
		red	16:15:54	Lay	102		
5/1/2013	16:10:00	red	16:15:54	Lay	300	19	19
5/1/2013	16:15:00	red	16:15:54	Lay	300	8	0
5/1/2013	16:20:00	red	16:15:54	Lay	300	0	0
5/1/2013	16:25:00	red	16:15:54	Lay	300	0	0
5/1/2013	16:30:00	red	16:15:54	Lay	300	0	0
5/1/2013	16:35:00	red	16:36:18	Lay	78	0	0
		red	16:36:21	Stand	2		
		red	16:38:24	Graze	124		
		red	16:38:35	Walk	11		
		red	16:39:12	Graze	37		
		red	16:39:25	Walk	13		
		red	16:41:31	Browse	35		

Portion of example behavior observations (see Figure B3) paired to collar data (see Figure B1) activity monitor values (X and Y) based on interval start times (Time) from collar output.

c. Correct timing errors using time-shift procedure (Chapter 2, Figure B5)

d. Re-pair observed behaviors and AMVs using shifted interval start times (Figure B5)

   i. Note the pure intervals of lay are now paired with very low AMVs (Time2s 16:11:00-16:31:00) and intervals containing mostly active behaviors associated with higher AMVs (Time2s 16:06:00 and 16:36:00)

Figure B5.

Date	**Time**	**Shift**	**Time2**	**Elk**	**ETOA**	**Act**	**Dur**	**X**	**Y**
5/1/2013	16:10:00	0:04:00	16:06:00	red	16:06:05	Graze	5	19	19
				red	16:06:16	Stand	11		
				red	16:08:18	Graze	122		
				red	16:15:54	Lay	162		
5/1/2013	16:15:00	0:04:00	16:11:00	red	16:15:54	Lay	300	8	0
5/1/2013	16:20:00	0:04:00	16:16:00	red	16:30:02	Lay	300	0	0
5/1/2013	16:25:00	0:04:00	16:21:00	red	16:30:02	Lay	300	0	0
5/1/2013	16:30:00	0:04:00	16:26:00	red	16:30:02	Lay	300	0	0
5/1/2013	16:35:00	0:04:00	16:31:00	red	16:36:18	Lay	300	0	0
5/1/2013	16:40:00	0:04:00	16:36:00	red	16:36:18	Lay	18	32	29
				red	16:36:21	Stand	2		
				red	16:38:24	Graze	124		
				red	16:38:35	Walk	11		
				red	16:39:12	Graze	37		
				red	16:39:25	Walk	13		
				red	16:41:31	Browse	95		

The same data (Figure B4) after application of the time shift procedure including the amount of time the interval start times (Time) were shifted (Shift). Note the correction of interval start times (Time2) that allow collar data and direct observations to align in an intuitive fashion.

e. Categorize all intervals based on the predominant behavior (greatest duration) within each interval (Chapter 4, p. 68, Figure B6)

Figure B6.

Date	***Time***	**Elk**	***ETOA***	***Act***	**Act2**	***Dur***	**X**	**Y**
5/1/2013	*16:06:00*	red	*16:06:05*	*Graze*	Lay	*5*	19	19
		red	*16:06:16*	*Stand*		*11*		
		red	*16:08:18*	*Graze*		*122*		
		red	*16:15:54*	*Lay*		*162*		
5/1/2013	*16:11:00*	red	*16:15:54*	*Lay*	Lay	*300*	8	0
5/1/2013	*16:16:00*	red	*16:30:02*	*Lay*	Lay	*300*	0	0
5/1/2013	*16:21:00*	red	*16:30:02*	*Lay*	Lay	*300*	0	0
5/1/2013	*16:26:00*	red	*16:30:02*	*Lay*	Lay	*300*	0	0
5/1/2013	*16:31:00*	red	*16:36:18*	*Lay*	Lay	*300*	0	0
5/1/2013	*16:36:00*	red	*16:36:18*	*Lay*	Graze	*18*	32	29
		red	*16:36:21*	*Stand*		*2*		
		red	*16:38:24*	*Graze*		*124*		
		red	*16:38:35*	*Walk*		*11*		
		red	*16:39:12*	*Graze*		*37*		
		red	*16:39:25*	*Walk*		*13*		
		red	*16:41:31*	*Browse*		*95*		

Portion of example calibration dataset with each sampling interval categorized based on the dominant behavior (Act 2), according to a priori rules. Italicized columns and rows are removed before data is uploaded into statistical software.

5. Construct classification models (Chapters 3, p. 45)

   a. Please note, a basic understanding of R statistical software is necessary for the remainder of this outline. There are many helpful free documents and tutorials available online. We recommend Quick-R at http://www.statmethods.net/

   b. We used the MASS package in R to construct 4 model structures: linear (LDA) and quadratic discriminant function (QDA) using both untransformed (X and Y) and log-transformed (logX and logY) AMVs (Figure B7)

(Right) R code used to build linear (LDA) and quadratic discriminant function (QDA) classification model structures using both untransformed (X and Y) and log-transformed (logX and logY) AMVs from the example calibration dataset (elk). Model accuracy is estimated using leave-one-out cross validation (CV=TRUE) and pre-assigned prior probabilities (prior) derived from prior activity and foraging studies.

Figure B7.

```
> elk<-read.csv("U:\\DataFolder\\Example.csv")
> library (MASS)
> elk $ logX <- log (elk $ X+1)
> elk $ logY <- log (elk $ Y+1)
> head (elk)
  Elk     Act    X   Y      logX       logY
1  P1   Browse 20   25  3.044522   3.258097
2  P1   Browse 19   22  2.995732   3.135494
3  P1   Browse 18   17  2.944439   2.890372
4  P1   Browse 18   25  2.944439   3.258097
5  P1   Browse 23   14  3.178054   2.708050
6  P1   Browse 33   43  3.526361   3.784190
> table (elk $ Act)
Browse    Hay  Graze    Lay   Run  Stand  Walk
    65    136   1018   1189    21    108   456
# LDA on Untransformed AMVs
> df.mod<-lda(Act~X*Y,data=elk, CV = TRUE,
                    prior = c(.12,.17,.18,.4,.02,.03,.08))
# LDA on log-transformed AMVs
> df.mod<-lda(Act~lX*lY,data=elk, CV = TRUE,
                    prior = c(.12,.17,.18,.4,.02,.03,.08))
# QDA on untransformed AMVs
> df.mod<-qda(Act~X*Y,data=elk, CV = TRUE,
                    prior = c(.12,.17,.18,.4,.02,.03,.08))
# QDA on log-transformed AMVs
> df.mod<-qda(Act~lX*lY,data=elk, CV = TRUE,
                    prior = c(.12,.17,.18,.4,.02,.03,.08))
```

i. We estimated the percentage of intervals that would be correctly classified if models were applied to a new dataset or the correct classification rates (CCRs) using leave-one-out cross validation (CV=TRUE, Figure B7)

ii. We assigned prior probabilities (prior, Figure B7) of behavior category occurrence based on activity pattern and foraging preference literature available for each species (Chapter 3, p. 45)

6.Group behaviors when necessary

(Chapter 4, p. 76, Figure B8)

1. We used the "car" package to group behaviors (recode) when their CCRs were < 70% (out1)
2. We considered models acceptable if CCRs for all behaviors were ≥ 70% (out2)

(Right) R code used to group behaviors (recode) with CCRs ≤ 70% (out1) after being classified using an LDA on log-transformed AMVs from the example calibration dataset (elk). Grouped behavior categories (Act 2) classify with CCRs ≥ 70% (out2).

Figure B8.

```
# LDA on log-transformed AMVs
> df.mod<-lda (Act ~ logX * logY, data = elk,  CV = TRUE,
                  prior = c(.12,.17,.18,.4,.02,.03,.08))
> error.matrix <- table (Act, df.mod $ class)
# CCRs for individual behaviors
> (out1<-diag (prop.table (error.matrix, 1)))
  Browse     Hay    Graze     Lay     Run    Stand    Walk
   0.831   0.735   0.661   0.921   0.667   0.000   0.603
#Total CCR of all intervals
> (tot<-sum(diag(prop.table(error.matrix))))
0.739
# Combine Stand, Graze, and Walk
 > library(car)
 > elk $ Act2 <- recode (elk $ Act,
            "c('Stand','Graze','Walk') = 'Grazing'")
 > table (elk $ Act2)
 Browse    Hay   Grazing    Lay    Run
     65    136      1582   1189     21
> # LDA on log-transformed AMVs
> df.mod <- lda (Act2 ~ logX * logY, data=elk, CV = TRUE,
                   prior = c(.12,.17,.29,.4,.02))
> error.matrix<- table(elk $ Act2, df.mod $ class)
# CCRs for grouped behaviors
> (out2 <-diag (prop.table (error.matrix, 1)))
  Browse     Hay   Grazing     Lay     Run
   0.831   0.750     0.832   0.913   0.810
#Total CCR of all intervals
> (tot <-sum (diag (prop.table (error.matrix))))
  0.861
```

ii. From the acceptable model structures (those which classified all behaviors with 70% CCRs, Figure B9) we chose the best model structure (mod2) based on the highest total classification rate (the percentage of all intervals correctly classified, tot1), the highest average classification rate among behaviors (avg2), and highest minimum classification rate among behaviors (Hay, both models)

(Right) R code showing CCRs for individual behaviors (out), all behaviors (tot), and average among behaviors (avg) used to choose the best classification model structure (mod2) based on the example calibration dataset (elk).

Figure B9

```
# LDA on untransformed AMVs
> df.mod1 <-lda (Act2 ~ X * Y, data = elk, CV = TRUE,
                    prior = c(.12,.17,.29,.4,.02))
> error.matrix <- table (elk $ Act2, df.mod1 $ class)
# CCRs for individual behaviors
> (out1<-diag (prop.table (error.matrix, 1)))
  Browse    Hay  Grazing     Lay      Run
    0.754  0.750   0.817   0.964   0.762
#Total CCR of all intervals
> (tot1<-sum(diag(prop.table(error.matrix))))
 0.871
# Average CCR among behaviors
> avg1 <-mean(out1)
 0.809

# LDA on log-transformed AMVs
> df.mod2 <-lda (Act2~logX*logY, data=elk, CV = TRUE,
                    prior = c(.12,.17,.29,.4,.02))
> error.matrix <- table (elk $ Act2, df.mod2 $ class)
# CCRs for individual behaviors
> (out2 <-diag(prop.table (error.matrix, 1)))
  Browse      Hay  Grazing      Lay     Run
    0.831   0.750    0.832    0.913   0.810
#Total CCR of all intervals
> (tot 2<-sum (diag (prop.table (error.matrix))))
[1] 0.861
# Average CCR among behaviors
> avg2 <- mean (out2)
 0.827
```

iii. Note, because total classification rates are greatly influenced by the number of intervals within each behavior category, we gave the highest average and minimum CCRs the greater weight in choosing a model structure

6. Apply model structure to novel data (Figure B10)

    a. To apply your chosen classification model (model) to collar data from a new animal (newdata), use the predict( ) function

    b. To view the predicted behaviors (predicted) aligned with your dataset (newdata), create a new data frame using dataframe( )

    c. To export your new data frame into an Excel spreadsheet (“new.collardata.csv”) for processing, use write.csv( )

Figure B10.

```
predicted <-predict(model, newdata = data, prior=myprior)

newdataframe  <- dataframe (newdata, predicted $ class)

write.csv (newdataframe, file = "new.collardata.csv",
row.names = FALSE)
```

R code for applying (predict) a classification model (model) to collar data from a new animal (newdata) and then aligning the predicted behavior classifications (predicted) with your dataset as a new data frame using dataframe( ) before then exporting it (write.csv) into an Excel spreadsheet (“new.collardata.csv”) for processing.
.

LITERATURE CITED

Beringer, J., J. J. Millspaugh, J. Sartwell, and R. Woeck. 2004. Real-time video recording of food selection by captive white-tailed deer. Wildlife Society Bulletin 32:648-654.