THESIS

EVALUATION OF A NOVEL WILDLIFE TELEMETRY DEVICE WITH DATA TRANSFER CAPABILITIES

Submitted by

Melanie Davis

Graduate Degree Program in Ecology

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Spring 2012

Master's Committee:

Advisor: N. Thompson Hobbs

Michael W. Miller
Kevin Crooks
Daniel Massey

ABSTRACT

EVALUATION OF A NOVEL WILDLIFE TELEMETRY DEVICE WITH DATA TRANSFER CAPABILITIES

The construction of low-cost, advanced GPS telemetry systems for wildlife tracking is growing in popularity, especially systems that can communicate with each other to track contacts and, more recently, transfer data. This novel function represents a step forward from current technology because it allows researchers to retrieve data from collars that have been damaged or lost. It also elucidates broad networks of interactions between individuals to monitor disease spread and social preference. I tested the communication and data transfer capabilities of a low-cost, custom-built GPS telemetry collar with an on-board wireless sensor network. I performed several trials using captive bighorn sheep to measure how data transfer reliability is impacted by the bodily obstruction of an animal, and to determine the accuracy of logged contacts. I present the results of these trials, which show that data transfer is adversely affected by the placement of the collar around the sheeps' necks, but that the contact accuracy remains uncompromised. Once refined, this technology could represent a significant improvement over currently-available telemetry devices, and may offer novel insight into previously unobserved ecological phenomena.

ACKNOWLEDGEMENTS

I am grateful for the wisdom and support of my advisor, Tom Hobbs, and for the guidance of my committee members: Mike Miller, Kevin Crooks, and Dan Massey. I would also like to acknowledge our co-contributors at the University of Colorado at Boulder including Xinyu Xing, Sravan Thokala, Ming Lian, Rick Han, and Shivakaht Mishra. Special thanks to Dan Walsh, Katie Grashorn, Michael Sirochman, and Tracy Davis at the Colorado Division of Wildlife's Foothills Wildlife Research Facility for their assistance with animal handling and study support. Thanks to David Augustine with the United States Department of Agriculture, and all the technicians at the Central Plains Experimental Range. I also thank Pat Clark, Chris Geremia, and Chris Kochanny for their helpful suggestions concerning the construction of our collars.

This research was made possible through funding by the National Science Foundation (grant # DBI-0754606). It could not have been possible without the support of the Natural Resources Ecology Laboratory and the Colorado State University Graduate Degree Program in Ecology.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Advances in Telemetry for Observing Individual States and Interactions

RH: Davis et al. • State-Centric Telemetry

MELANIE J. DAVIS, Natural Resource Ecology Laboratory, and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO, 80523, USA

N. THOMPSON HOBBS, Natural Resource Ecology Laboratory, and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO, 80523, USA

KEY WORDS

activity logger, behavior, disease transfer, proximity logger, state-centric telemetry, wildlife telemetry

SUMMARY

Traditional, location-centric wildlife telemetry is useful for collecting spatial and temporal information on where animals spend their time. Recently, telemetry companies and independent developers have introduced a wide variety of non-location-centric telemetry devices, including biologgers, activity loggers, animal-mounted cameras, proximity loggers, and delay-tolerant data-relaying capabilities. We will refer to these devices as state-centric, because they allow observations of the state of individuals and their interactions with the environment and other individuals. State-centric devices can be used apart from, or in conjunction with location-centric telemetry to monitor physiological condition, to reveal social networks, and to observe fine-scale habitat choices. Here we review these new state-centric technologies, giving a brief explanation of how each device functions, for what it is used, and how it has contributed to the field of ecology. We discuss some sources of error in state-centric technology, propose possible improvements, and suggest future directions.

Wildlife telemetry is a rapidly-evolving field. Manufacturers frequently introduce devices with new functions and improvements in data-collecting capabilities. Traditional telemetry devices were generally location-centric, allowing for observation of an animal's spatial location at a specific time. Location-centric technology has benefited wildlife biologists and ecologists since the first very high frequency (VHF) devices were developed in the 1950s and 60s (LeMunyan et al. 1959, Cochran and Lord 1963). The introduction of radio telemetry allowed researchers to collect unprecedented amounts of data at a previously unattainable level of precision. It was the first time scientists could track the movements of individuals and populations across inaccessible tracts of land, locate feeding and breeding grounds, and determine home range without invasive behavioral observation or extrapolation from presence-absence data (Dunn and Gipson 1977, Craighead 1982, Wanless et al. 1988, Thompson and Miller 1990).

The commercial introduction of GPS technology in 1991 improved positional accuracy and eliminated several types of bias, especially after the dissolution of selective availability in 2000 (Rodgers et al. 1996, Lawler 2000). This technology allowed scientists to monitor animal locations within at least ±10m precision, at any time of day, without the need to take receivers into the field (Rodgers et al. 1996, Beyer and Haufler 2004, Cadahia et al. 2007, Hansen and Riggs 2008). Furthermore, combining GPS data with the Argos data collection and relay system (operated by the United States National Oceanic and Atmospheric Administration and the French Centre National d'Etudes Spatiales) provided scientists with the opportunity to match animal locations to specific habitat types and topographical information *in situ*(Schwartz and Arthur 1999, Jay and Garner 2002).

Hebblewhite and Haydon (2010) point out that while such location-centric data can elucidate broad-scale habitat choice and movement, it cannot easily be extrapolated to describe an animal’s condition or its feeding and social behaviors at a specific point in time. To do this, researchers need fine-scale, qualitative data to accompany spatial and temporal information. Telemetry companies and researchers have answered the call for such data by introducing a suite of non-location-centric telemetry devices including biotelemetry, activity loggers, and proximity loggers. These new technologies provide information about body condition, activity levels, feeding behavior, and social networks. Because these devices focus on the individual and its state, we will refer to this technology as state-centric. In this review, we briefly describe these devices, and explain how their use offers a unique insight into several recurring ecological themes.

ADVANCES IN STATE-CENTRIC TELEMETRY

State-centric telemetry has offered insight into the everyday behaviors and activities of a wide variety of species. Previously, this information was gathered by direct observation in the wild, observations on captive animals, or by remote camera traps. Now individuals can be fitted with telemetry collars and/or tags, which can be deployed for months or even years, and require little to no human interference post-deployment. Collecting fine-scale information on the health, activity, and social interactions of wildlife is necessary for scientists to determine not just where animals are spending their time, but why. State-centric telemetry allows researchers to gather information on individual condition, where animals are most and least active, what they are choosing to eat, with whom they are competing, from whom they are fleeing, and where they are coming into contact most or least often.

Monitoring Animal Condition

Knowledge of animal states originated with devices that could detect whether an animal was alive or was likely dead. The best example of this is the mortality logger available on most VHF and GPS devices. Mortality loggers were originally designed such that a thermistor would sense the body temperature of an individual, allowing scientists to determine if an animal’s lack of movement was behavioral or if it was dead (Stoddart 1970). Currently-available devices rely on movement to determine mortality (Steigers and Flinders 1980).Knowing the location of an animal carcass allows researchers to collect tissue samples from the deceased animal as soon as possible, thus increasing the probability that the cause of death can be determined (Houseknecht 1970).

Manufacturers expanded upon this idea by developing biotelemetry devices (or biologgers) that measured external temperature and pressure, body temperature, and heart rate (Kooyman et al. 1971, Weimerskirch et al. 1995, Woakes et al. 1995, Handrich et al. 1997). These devices can be used to gather information about an animal’s health and energy expenditure, its environment, or both (Fryer et al. 1966, Wilson et al. 2002, Brown-Brandl et al. 2003). For example, temperature-sensitive radio transmitters have long been used to monitor phenomena such as the sheltering behavior and resulting body temperature fluctuations of reptiles (Huey et al. 1989), the overwintering metabolic strategies of ungulates (Arnold et al. 2004), and the body temperature and foraging strategies of birds in response to ambient temperature (Krijgsveld et al. 2003). Biologgers have also been popular with aquatic ecologists, because they allow researchers to gather information about an ecosystem that is otherwise difficult to observe. This is especially true for arctic birds and mammals. Some of the first pressure-sensitive biologgers were used to observe the diving depths of seals (DeVries and Wohlschlag 1964) and penguins (Kooyman et al. 1971) as they moved beneath thick ice shelves.

Observing Animal Activities

A more recent development is the wildlife activity logger, which uses an accelerometer to track the 2- or 3-dimensional movements of individuals at a particular location (Wilson et al. 2006, Shepard et al. 2008).These devices are particularly useful for monitoring when animals are most and least active. They can also be used to signal for telemetry devices to enter a “sleep mode,” which saves battery life and storage space (Laerhoven et al. 2006). Activity loggers may exhibit some error in determining the specific type of movement based upon the level of activity (i.e. activity levels might be equal for feeding, running, or fighting), although recent technology and modeling techniques have demonstrated greater reliability (Scheibe et al. 1998, Naylor and Kie 2004, Shepard et al. 2008). On the other hand, animal-mounted cameras can accurately record specific behaviors, but do not have a 360 degree view, and are also limited by lack of light, memory space, and energy expenditure (Beringer et al. 2004, Zhihai et al. 2008,Moll et al. 2009).

Despite some shortcomings, which we expand upon later, both of these technologies have been especially helpful for elucidating previously unobserved behavioral phenomena, such as what time of day animals are most likely to forage, and how they manage their energetic budgets (Coulombe et al. 2006, Krone et al. 2009, Horn et al. 2011). Activity loggers are commonly used to track the diving angle, buoyancy, and acceleration of deep-diving sea birds, offering insight into energy expenditure and prey capture strategies (Yoda et al. 1999, Watanuki et al. 2003). Moe et al. (2007) used combination GPS and activity-logging technology to determine the diel behavior of bears, and to reveal which habitat types they preferred when foraging. Hetem et al. (2011) used activity loggers to determine how the activity levels of oryx and gazelles change seasonally. These types of studies have also been performed using smaller, more elusive species such as reptiles and birds as animal subjects (Kerr et al. 2004, Phalan et al. 2007, Kerr et al.

2008). They represent an especially important tool for monitoring the activity patterns of species in habitats with unpredictable climate, variable light-dark cycles, or high impact due to global climate change.

Animal-mounted cameras allow researchers to take snapshots or video footage of animals interacting with their habitat without invasive and biased observation. Most devices attach to the animal such that they offer a unique look into what animals are seeing in the field (Moll et al. 2007, Bluff and Rutz 2008). This is useful for determining exactly what an animal is eating, as well as which predators and competitors an animal most frequently faces. Arthur et al. (2007) used animal-borne imaging devices to monitor the foraging habits of green turtles, thus offering valuable insight into the risks of toxic cyanobacterium to aquatic animals. Beringer et al. (2004) used a wireless video camera to determine the exact food choices of captive deer (Figure 1.1). Not only were they able to detect some unexpected resources, but they were also able to capture mutual grooming, breeding, and bedding behavior that would go unobserved with traditional telemetry equipment. Researchers can also use this technology to pinpoint how species interact with each other to capture prey. Takahashi et al. (2004) used animal-mounted digital cameras with built-in pressure sensors to log the aquatic social behavior of penguins. Their devices took over 10,000 photographs, from which they were able to determine average swimming group size, and whether group size changed during foraging. Parrish et al. (2008) observed that aquatic predators such as sharks and snappers take advantage of the monk seal’s prey-flushing abilities, thus elucidating a previously unobserved competitive interaction. This has broad ecological applications, because for many species terrestrial behaviors have been well-studied, but aquatic behaviors remain a mystery.

Observing Animal Interactions

Some of the newest and most exciting technology focuses on monitoring wildlife social networks. Proximity loggers allow researchers to monitor the frequency and duration of contacts between two individuals using an ultra high frequency (UHF) radio signal along with a traditional VHF signal. These devices log the identification code of each individual, the time of the contact, and how long the two individuals were within contact range (Prange et al. 2006). Contact information is valuable for exposing the reproductive and social behaviors of elusive species, finding possible pathways for disease spread, and tracking possible predation events.

Proximity loggers have the potential to alter previous assertions about animal social groups. For example, Prange et al. (2011) used proximity loggers to determine the social structure of a suburban raccoon population, and found that social pairings were common, and that the proportion of male-female social groups and male-male social groups varied seasonally. This contrasts with previous assertions that raccoons are a solitary, territorial species. Similarly, Marsh et al. (2011) used proximity loggers to elucidate the social behaviors of invasive rabbits. They found high individual heterogeneity and weaker social bonds than would be expected from previous observational and genetic data. This technology will soon be available for aquatic applications. Guttridge et al. (2010) used sharks to test the functionality of ultrasonic proximity loggers. Although their prototype devices had a high failure rate (4/5 devices lost data in one trial), the data they did retrieve were able to accurately log contacts among their cohort of sharks. An improved version of these ultrasonic proximity loggers would provide valuable information about the group characteristics and social behaviors of aquatic animals.

Proximity loggers have also made recent contributions to the field of wildlife epidemiology. Traditional telemetry has always been useful in determining the broad-scale behaviors of potentially susceptible individuals. In recent years, state-centric telemetry has supplemented this spatial-temporal information, and provided deeper insight into the spread of disease across wildlife populations. Elucidating complex wildlife social networks is crucial for modeling pathways of disease spread. Proximity loggers have been useful for closely monitoring contacts between individuals that would otherwise be undetectable. For example, Hamede et al. (2009) used proximity loggers to determine the contact network structure in a population of Tasmanian devils. This information is vital, since Tasmanian devil facial tumor disease is a widespread, deadly cancer that is spread via direct contact, particularly biting. They found that, unlike human social networks, the Tasmanian devil social network is not particularly aggregated, although it does differ between mating and non-mating seasons. These data suggest that targeting a particular age or sex class of Tasmanian devil for culling or quarantine would be a limited strategy.

Proximity loggers have also offered insight into interspecific disease spread. Bohm et al. (2009) collared badgers and cattle in order to find high-risk individuals for the transmission of bovine tuberculosis. They found that several badgers were coming into contact with cattle, leading researchers to conclude that direct inter-species contacts are not as rare as previously thought. Meanwhile, Ji et al. (2005) offer a different theory for the indirect transmission of bovine tuberculosis based upon the proximity-logged contact rates of possum populations.

Proximity loggers are useful in determining the habitat use and territory overlap of one or more species. Joint habitat use, or the likelihood that two intra- or inter-specific individuals are occupying the same habitat, is one way to measure intraspecific interaction and possible competition or predation events. Joint habitat use is beneficial for knowing how social groups vary environmentally, where competition is most likely to occur, and which habitats are most likely to facilitate predation (Maitz and Dickman 2001, Kjær et al. 2008, Valeix et al. 2009). Previously, researchers would use mark-recapture techniques or combine traditional spatial-temporal telemetry data with remote sensing data to model the joint habitat use under varying seasonal or environmental conditions (Schauber et al. 2007). Proximity loggers now monitor when two or more tagged individuals come into contact without a significant temporal lag. When combined with traditional telemetry, this allows researchers to know when and where animals are most likely to come into contact with one another, without having to extrapolate or account for temporal staggering of data.

More sophisticated contact-logging technology combines proximity-logging technology with the data-transfer capabilities of a delay-tolerant network (DTN). A DTN is a type of intermittently connected network that is ideal for use in an ecological setting due to its disruption-tolerant structure (Zhang 2006). Although state-centric telemetry that incorporates this technology is not yet commercially available, it has been tested in a variety of scenarios, including zebras (Juang et al. 2002) and reindeer (Dopico et al. 2011). We tested our own in-house constructed system using captive bighorn sheep (Davis et al. 2012). This new technology functions similarly to proximity loggers, but offers a more complete data set due to its data-forwarding capabilities (Figure1.2). Furthermore, data-transfer enables data collection in the field and prevents data loss. In general, an accurate representation of a population's social network requires saturation with proximity-logging devices (Borgatti et al. 2006, Prange 2006). Since device failure and data loss are common technical problems (up to 33% of devices fail to log data in some cases), data sets can be compromised, even if the number of devices initially deployed does represent a statistically appropriate sample size (Ji et al. 2005, Prange et al. 2006). The incorporation of delay-tolerant networks with data-transferring capabilities remedies this problem by transferring data from one device to another, eventually funneling it to a target device or base station (Martonosi 2006). This means that even if a device stops working mid-study, the "lost" data can still be recovered from another source. If these devices were to be refined for commercial distribution, they would offer a clearer picture of wildlife social networks, which would benefit wildlife epidemiology, and the field of ecology as a whole.

LIMITS IN TECHNOLOGY

As would be expected, there are several limitations and inherent errors that may occur with the use of state-centric telemetry. Even if state-centric data are used in conjunction with accurate spatial-temporal information, an ecologist or manager may still need to use observational, experimental, or theoretic methods to understand the system of interest. It is the researcher's responsibility to omit erroneous data points, recognize sources of bias, and analyze and interpret data correctly. Furthermore, electronics are inherently error-prone, and telemetry devices are no exception. Each kind of device has its own limits to how much data can be collected, and how much information can be gleaned from these data.

Activity loggers are able to accurately determine when animals are moving or resting, but they often cannot discern between specific movements (Robert et al. 2009). Accuracy levels vary widely between (or even within) studies, but seem to have improved in recent years, with some studies able to correctly identify movements with up to 93% accuracy (Naylor and Kie 2004, Moreau et al. 2009, Heurich et al. 2011). This is most likely due to the calibration of accelerometers using captive individuals. Despite improvements in both accelerometer technology and behavior models, scientists should supplement telemetry data with behavioral observation whenever possible, or at least incorporate error into their behavioral analysis to account for the probability that specific behaviors will be incorrectly categorized. This is not always realistic, since researchers often do not have access to captive individuals to calibrate their devices. Another option is to attach an accelerometer to a specific body part of interest. For instance, Naito et al. (2010) used mandible accelerometers to monitor the feeding behavior of seals, although there was still some ambiguity in their data since they had to make assumptions about differences in movement between vocalization events and feeding events.

Another way to record behavior and resource selection is via animal-mounted cameras, which face inherent limitation in storage space and view-range. While cameras offer fine-scale insight into occurrences at specific locations, their lifespan does not match that of a traditional telemetry device. Video cameras can last in the field up to 2 weeks, and digital cameras are dependent upon the number of pictures that can be taken and the amount of time between photos (Beringer et al. 2004, Takahashi et al. 2004). This means that devices either need to be re-deployed, or deployments need to be staggered throughout the field season to obtain an unbiased data set. Events caught on camera are also dependent upon the view range of the camera. Such imperfect detection has been demonstrated in camera traps and remotely-controlled video surveillance equipment (MacNulty et al. 2008, Tobler et al. 2008).

Proximity loggers are some of the newest telemetry devices on the market, and as such, they have been prone to error. Earlier studies experienced high error rates due to faulty data storage, clock malfunction, false or un-marked contacts, and inconsistent data (Prange et al. 2006, Hamede et al. 2009). Recent devices have been more successful, with error rates as low as 3% (Marsh et al. 2010, Marsh et al. 2011). Data loss is harmful to the integrity of a contact network study, because contact networks are less reliable when a population is not saturated with proximity loggers (Prange et al. 2011). More specifically, the robustness of inference about the structure and centrality of a contact network decreases as the number of tagged individuals (or logged contacts between individuals) decreases (Borgatti et al. 2006, Figure1.3).

It is difficult to tag every individual in a target population due to financial constraints, rarity, trap-shyness, or underestimation of total population size, so it is essential that researchers collect viable data from as many devices as possible. Such instances of data loss can be remedied with the use of wireless sensor networks. Although this technology is not yet commercially available, several different devices have been developed and tested independently with varied success. One of the most extensively-tested devices is ZebraNet, a wildlife telemetry device using a delay-tolerant network structure, which was recently developed by electrical engineers at Princeton University, and deployed on Zebras in Kenya. Although there have been several successful deployments, the development team has experienced reduction in contact range due to environmental stochasticity and problems related to limited energy availability (Zhang et al. 2004. Martonosi et al. 2006). Early experiences with our own DTN-based system, WildSense, have offered similar challenges including data loss due to malfunctioning devices, limited data storage due to energy constraints, and muddled contact data during data transfer (Davis et al. *unpublished data*). These are issues that need to be addressed before such a system will be available on the market.

CONCLUSION

State-centric telemetry is rapidly increasing in popularity because it offers a unique insight into the reproductive, social, and feeding behaviors of wildlife at a fine scale. While using this technology offers clear advantages, scientists and managers must still be wary of several areas of concern. First, like any piece of electronics equipment, these telemetry devices are inherently subject to error. Ecologists need to be cautious of faulty or incomplete data. Some applications rely on specific movements or environmental conditions, so ecologists should be sure to choose a device that is particularly suited to the species of interest, or to calibrate the device (particularly activity loggers and proximity loggers) when possible. Second, even the best technology cannot make up for poor study design. Because some of these devices are newer on the market, they may be subject to unpredictable data loss. Ecologists should take this into account when planning sample size and study location. Finally, the use of sophisticated technology is not our only option as scientists, and an ecologist can never fully understand or appreciate an ecosystem with quantitative data alone. We agree with Hebblewhite and Haydon (2010), who assert that a true ecologist does not divorce him or herself from the field.

The information required to elucidate an ecological process depends on the subject and breadth of a study. State-centric telemetry could (and should) be used in conjunction with a variety of ecological methods to gather needed information. For example, video footage of herbivory events could be linked with measures of plant abundance and diversity to obtain a clearer picture of how food choice affects community structure. Proximity loggers could be used alongside laboratory tests to determine how social connectivity is related to disease transfer within and between social groups. Furthermore, state-centric data represents a valuable accompaniment to ecological models and theory. These systems have a wide variety of uses, and they play an important role in elucidating ecological processes.

Telemetry is continuously improving. Manufacturers are extending battery life and data storage, reducing the amount of data lost, and introducing novel functions. We believe that state-centric technology such as biologgers, activity loggers, and proximity loggers will continue to improve in reliability and their breadth of applications, and will offer exceptional insight into ecosystem processes, especially when used in conjunction with location-centric telemetry and other ecological methods.

Figure 1.1. Beringer et al. (2004) equipped a male white-tailed deer with an antler-mounted video system in order to observe fine-scale feeding, grooming, bedding, and reproductive behaviors.

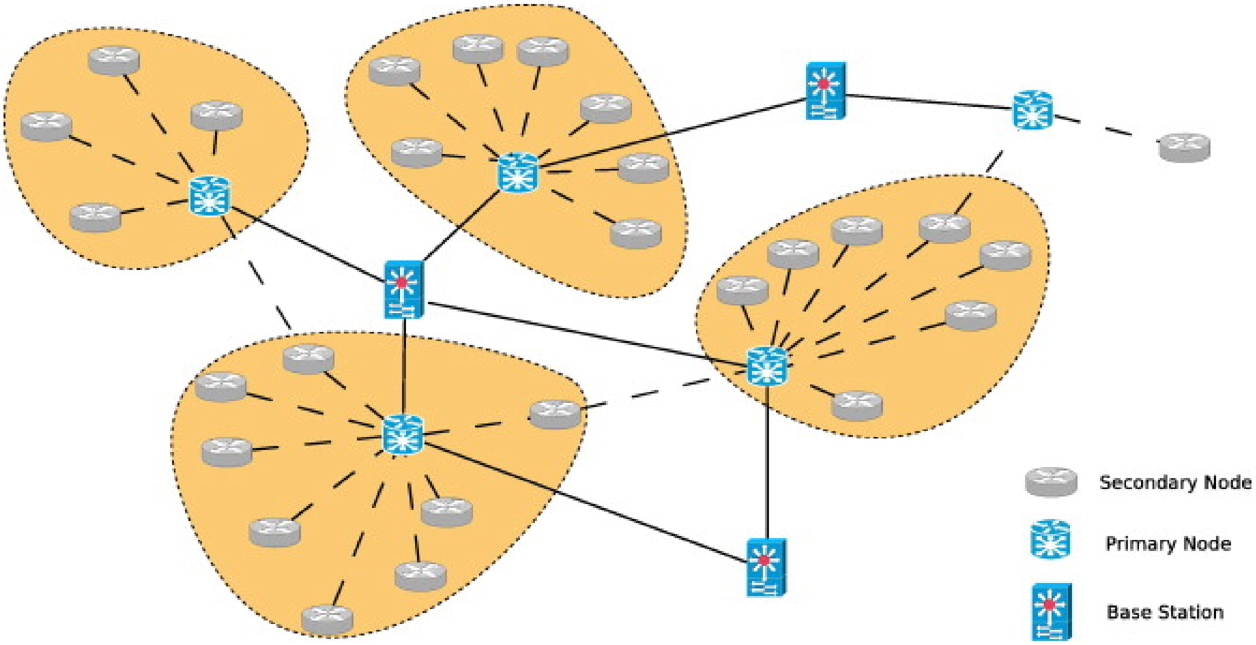

Figure 1.2. Dopico et al. (2011) tested a delay tolerant network incorporating GPS and proximity-logging capabilities. They chose to use a hierarchical architecture in which data were transferred to base stations, and only primary nodes were responsible for acquiring GPS data.

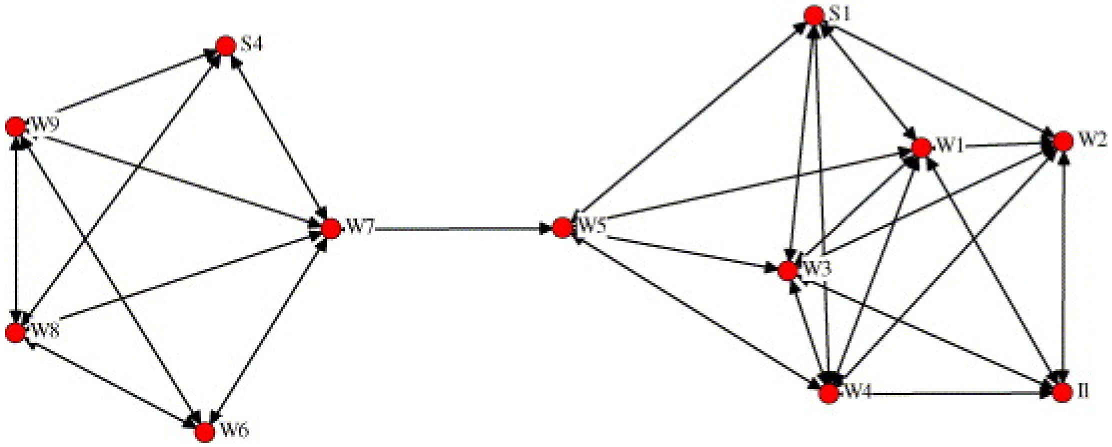

Figure 1.3. Network structure from the Hawthorne Bank Wiring Room study (Rothlisberger and Dickson 1939) used as an example by Borgatti et al. 2006. The network exhibits a single link between two otherwise separate networks. This fragile network structure demonstrates the need for saturation of an entire population with proximity-logging devices, and the need to collect as much data from these devices as possible in order to avoid an false “break” in the network.

LITERATURE CITED

Arnold, W, T Ruf, S Reimoser, F Tataruch, K Onderscheka, and F Schober. 2004. Nocturnal hypometabolism as an overwintering strategy of red deer (*Cervus elaphus*). American Journal of Physiology 286:R174-R181.

Arthur, KE, JM O'Neil, CJ Limpus, K Abernathy, and M Greg. 2007. Using animal-borne imaging to assess green turtle (*Chelonia mydas*) foraging ecology in Moreton Bay, Australia. Marine Technology Society Journal, 41:9-13.

Beringer, J, JJ 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.

Beyer, D.E., and J.B. Haufler. 1994. Diurnal versus 24-hour sampling of habitat use. Journal of Wildlife Management. 58: 178-180.

Bluff, LA, and C Rutz. 2008. A quick guide to video-tracking birds. Biology Letters 4:319-322.

Bohm, M, MR Hutchings, and PCL White. 2009. Contact networks in a wildlife-livestock host community: identifying high-risk individuals in the transmission of bovine TB among badgers and cattle. PLoS ONE 4:e5016.

Borgatti, SP, KM Carley, and D Krackhardt. 2006. On the robustness of centrality measures under conditions of imperfect data. Social Networks 28:124-136.

Brown-Brandl, TM, T Yanagi Jr., H Xin, RS Gates, RA Bucklin, and GS Ross. 2003. A new telemetry system for measuring core body temperature in livestock and poultry. Applied Engineering in Agriculture 19:583-589.

Cadahia, L., V. Urios, and J.J. Negro. 2007. Bonelli's eagle *Hieraaetusfasciatus* juvenile dispersal: hourly and daily movements tracked by GPS. Bird Study. 54: 271-274.

Cochran, WW, and RD Lord. 1963. A radio-tracking system for wild animals. Journal of Wildlife *Management* 27:9-24.

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

Craighead, FC. 1982. Track of the Grizzly. New York, NY. Random House.

Davis, MJ, S Thokala, X Xing, NT Hobbs, DP Walsh, RY Han, and S Mishra. 2012. Developing a data transfer model for a novel wildlife tracking network. Wildlife Society Bulletin *in press*.

DeVries, AL, and DE Wohlschlag. 1964. Diving depths of the Weddell seal. Science 45:292-293.

Dopico, NI, A Gutierrez, and S Zazo. 2011. Performance analysis of a delay tolerant application for herd localization. Computer Networks 55:1770-1783.

Dunn, JE, and PS Gipson. 1977. Analysis of radio telemetry data in studies of home range. Biometrics33:85-101.

Fryer, TB, GJ Deboo, and CM Winget. 1966. Miniature long-life temperature telemetry system. Journal of Applied Physiology 21:295-298.

Guttridge, TL, SH Gruber, J Krause, and DW Sims. 2010. Novel acoustic technology for studying free-range shark social behaviour by recording individuals' interactions. PLOS One 5:e9324.

Hamede, RK, J Bashford, H McCallum, and M Jones. 2009. Contact networks in a wild Tasmanian devil (*Sarcophilus harrisii*) population: using social network analysis to reveal seasonal variability in social behaviour and its implications for transmission of devil facial tumour disease. Ecology Letters 12:1147-1157.

Handrich, Y, RM Bevan, JB Charrassin, PJ Butler, K Putz, AJ Woakes, J Lage, and Y Le Maho. 1997. Hypothermia in foraging King Penguins. Nature 388:64-67.

Hansen, M.C., and R.A. Riggs. 2008. Accuracy, precision, and observation rates of global positioning system telemetry collars. Journal of Wildlife Management. 72: 518-526.

Hebblewhite, M, and DT Haydon. 2010. Distinguishing technology from biology: a critical review of the use of GPS telemetry data in ecology. Philosophical Transactions of the Royal Society B365:2303-2312.

Hetem, RS, WM Strauss, LG Fick, SK Maloney, LCR Meyer, M Shobrak, A Fuller, and D Mitchell. 2011. Does size matter? Comparison of body temperature and activity of free-living Arabian oryx (*Oryx leucoryx*) and the smaller Arabian sand gazelle (*Gazella subgutturosa marica*) in the Saudi desert. Journal of Comparative Physiology B pp. 1111-1119.

Heurich, M, M Traube, A Stache, P Lottker. 2011. Calibration of remotely collected acceleration data with behavioral observations of roe deer. Acta Theriologica*in press*.

Horn, JA, N Mateus-Pinilla, RE Warner, and EJ Heske. 2011. Home range, habitat use, and activity patterns of free-roaming domestic cats. Journal of Wildlife Management 75:1177-1185.

Houseknecht, CR. 1970. Biotelemetry as a technique in disease ecology studies. Journal of Wildlife Diseases 6:414-417.

Huey, RB, CR Peterson, SJ Arnold, and WP Porter. 1989. Hot rocks and not-so-hot rocks: retreat-site selection by garter snakes and its thermal consequences. Ecology 70:931-944.

Jay, CV, and GW Garner. 2002. Performance of satellite-linked GPS on Pacific walruses (*Odobenus rosmarus divergens*). Polar Biology 25:235-237.

Ji, W, PCL White, and MN Clout. 2005. Contact rates between possums revealed by proximity data loggers. Journal of Applied Ecology 42:595-604.

Juang, P, H Oki, Y Wang, M Maronosi, L Peh, and D Rubenstein. 2002. Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with ZebraNet. Proceedings of the 2003 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communications pp 27-34.

Kerr, GD, GR Cottrell, and CM Bull. 2004. Use of an ‘on board’ datalogger to determine lizard activity patterns, body temperature, and microhabitat use for extended periods in the field. Wildlife Research 31:171-176.

Kerr, GD, MJ Botterna, and CM Bull. 2008. Lizards with rhythm? Multi-day patterns in total daily movement. Journal of Zoology 275:79-88.

Kjær, LJ, EM Schauber, and CK Nielsen. 2008. Spatial and temporal analysis of contact rates in female white-tailed deer. Journal of Wildlife Management 72:1819-1825.

Kooyman, GL, CM Drabek, R Elsner, and WB Campbell. 1971. Diving behavior of the emperor penguin, *Aptenodytes forsteri*. Auk 88:775-795.

Krijgsveld, KL, JWH Reneerkens, GD McNett, and RE Ricklefs. 2003. Time budgets and body temperatures of American golden-plover chicks in relation to ambient temperature. The Condor 105:268-278.

Krone, O, A Berger, and R Schulte. 2009. Recording movement and activity pattern of a white-tailed sea eagle (*Haliaeetus albicilla*) by a GPS datalogger. Journal of Ornithology 150:273-280.

Laerhoven, KV, HW Gallersen, and YG Malliaris. 2006. Long-term activity monitoring with a wearable sensor node. Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks pp. 174-178.

Lawler, A. 2000. Scientists gain access to sharper GPS signal. Science 288:783.

Lemunyan, CD, W White, E Nyberg, and JJ Christian. 1959. Design of a miniature radio transmitter for use in animal studies. Journal of Wildlife Management 23:107-110.

MacNulty, DR, GE Plumb, and DW Smith. 2008. Validation of a new video and telemetry system for remotely monitoring wildlife. Journal of Wildlife Management 72:1834-1844.

Maitz, WE, and CR Dickman. 2001. Competition and habitat use in native Australian *Rattus*: is competition intense, or important? Oecologia 128:526-538.

Marsh, MK, SR McLeod, MR Jutchings, and PCL White. 2011. Use of proximity loggers and network analysis to quantify social interactions in free-ranging wild rabbit populations. Wildlife Research 38:1-12.

Martonosi, M. 2006. Embedded systems in the wild: Zebranet software, hardware, and deployment experiences. In: LCTES.

Moe, TF, J Kindberg, I Jansson, and JE Swenson. 2007. Importance of diel behaviour when studying habitat selection: examples from female Scandinavian brown bears (*Ursus arctos*). Canadian Journal of Zoology 85:518-525.

Moll, RJ, JJ Millspaugh, J Beringer, J Sartwell, and Z He. 2007. A new ‘view’ of ecology and conservation through animal-borne video systems. Trends in Ecology and Evolution 22:660-668.

Moll, RJ, JJ Millspaugh, J Beringer, J Sartwell, Z He, JA Eggert, and X Zhao. 2009. A terrestrial animal-borne video system for large mammals. Computers and Electronics in Agriculture 66:133-139.

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

Naito, Y, H Bornemann, A Takahashi, T McIntyre, and Joachim Plotz. 2010. Fine-scale feeding behavior of Weddell seals revealed by a mandible accelerometer. Polar Science 4:309-316.

Naylor, LM, and JG Kie. 2004. Monitoring activity of Rocky Mountain elk using recording accelerometers. Wildlife Society Bulletin 32:1108-1113.

Parrish, FA, GJ Marshall, B Buhleier, GA Antonelis. 2008. Foraging interaction between monk seals and large predatory fish in the Northwestern Hawaiian Islands. Endangered Species Research 4:299-308.

Phalan, B, RA Phillips, JRD Silk, V Afanasyev, A Fukuda, J Fox, P Catrym H Higuchi, and JP Croxall. 2007. Foraging behaviour of four albatross species by night and day. Marine Ecology Progress Series 340:271-286.

Prange, S, T Jordan, C Hunter, and SD Gehrt. 2006. New radiocollars for the detection of proximity among individuals. Wildlife Society Bulletin 34:1333-1344.

Prange, S, SD Gehrt, and S Hauver. 2011. Frequency and duration of contacts between free-ranging raccoons: uncovering a hidden social system. Journal of Mammalogy 92:1331-1342.

Robert, B, BJ White, DG Renter, and RL Larson. 2009. Evaluation of three-dimensional accelerometers to monitor and classify behavior patterns in cattle. Computers and Electronics in Agriculture 67:80-84.

Rodgers, AR, RS Rempel, and KF Abraham. 1996. A GPS-based telemetry system. Wildlife Society Bulletin 24:559-566.

Rothlisberger, F, and W Dickson. 1939. Management and the Worker. Cambridge University Press, Cambridge.

Schauber, EM, DJ Storm, and CK Nielsen. 2007. Effects of joint space use and group membership on contact rates among white-tailed deer. Journal of Wildlife Management 71:155-163.

Scheibe, KM, T Schleusner, A Berger, K Eichhorn, J Langbein, L Dal Zotto, and WJ Streich. 1998. ETHOSYS ® - new system for recording and analysis of behaviour of free-ranging domestic animals and wildlife. Applied Animal Behaviour Science 55:195-211.

Schwartz, CC, and SM Arthur. 1999. Radiotracking large wilderness mammals: integration of GPS and Argos technology. Ursus11:261-273.

Shepard, ELC, RP Wilson, F Quintana, AG Laich, N Liebsch, DA Albareda, LG Halsey, A Gleiss, DT Morgan, AE Myers, C Newman, and DW Macdonald. 2008. Identification of animal movement patterns using tri-axial accelerometry. Endangered Species Research 10:47-60.

Steigers, WD Jr, and JT Flinders. 1980. Mortality and movements of mule deer fawns in Washington. Journal of Wildlife Management 44:318-388.

Stoddart, LC. 1970. A telemetric method for detecting jackrabbit mortality. Journal of Wildlife Management. 34:501-507.

Takahashi, A, K Sato, Y Naito, MJ Dunn, PN Trathan, and JP Croxall. 2004. Penguin-mounted cameras glimpse underwater group behavior. Proceedings of the Royal Society B 271:281-282.

Thompson, PM, and D Miller. 1990. Summer foraging activity and movements of radio-tagged common seals (*Phoca vitulina l.*) in the Moray Firth, Scotland.Journal of Applied Ecology 27:492-501.

Tobler, MW, SE Carillo-Percastegui, R Leite Pitman, R Mares, and G Powell. 2008. An evaluation of camera traps for inventorying large and medium-sized terrestrial rainforest mammals. Animal Conservation 11:169-178.

Valeix, M, AJ Loveridge, S Chamaillé-Jammes, Z Davidsom, F Murindagoma, H Fritz, and DW Macdonald. 2009. Behavioural adjustments of African herbivores to predation risk by lions: spatiotemporal variations influence habitat use. Ecology 90:23-30.

Wanless, S, JA Morris, and MP Harris. 1988. Diving behaviour of guillemot (*Uria aalge*), puffin (*Fratercula arctica*), and razorbill (*Alca torda*) as shown by radio-telemetry. Journal of Zoology 216:73-81.

Watanuki, Y, Y Niizuma, WG Geir, K Sato, and Y Naito. 2003. Stroke and glide of wing-propelled divers: deep diving seabirds adjust surge frequency to buoyancy change with depth. Proceedings of the Royal Society B 270:483-488.

Weimerskirch, H, RP Wilson, C Guinet, and M Koudil. 1995. Use of seabirds to monitor sea-surface temperatures and to validate satellite remote-sensing measurements in the Southern Ocean. Marine Ecology Progress Series 126:299-303.

Wilson, RP, D Gremillet, J Snyder, MAM Kierspel, S Garthe, H Weimerskirch, C Schafer-Neth, JA Scolaro, CA Bost, J Plotz, and D Nel. 2002. Remote-sensing systems and seabirds:

their use, abuse, and potential for measuring marine environmental variables. Marine Ecology Progress Series 228:241-261.

Wilson, RP, CR White, F Quintana, LG Halsey, N Liebsch, GR Martin, and PJ Butler. 2006. Moving towards acceleration for estimates of activity-specific metabolic rate in free-living animals: the case of the cormorant. Journal of Animal Ecology 75:1081-1090.

Woakes, AJ, PJ Butler, and RM Bevan. 1995. Implantable data logging system for heart rate and body temperature: its application to the estimation of field metabolic rates in Antarctic predators. Medical and Biological Engineering and Computing 33:145-151.

Yoda, K, K Sato, Y Niizuma, M Kurita, C Bost, Y Le Maho, and Y Naito. 1999. Precise monitoring of porpoising behaviour of Adelie penguins determined using acceleration data loggers. Journal of Experimental Biology 202:3121-3126.

Zhang, P, CM Sadler, SA Lyon, and M Martonosi. 2004. Hardware design experiences in ZebraNet. Proceedings of the 2nd International Conference on Embedded Network Sensor Systems pp. 227-238.

Zhang, Z. 2006. Routing in intermittently connected mobile ad hoc networks and delay tolerant networks: overview and challenges. IEEE Communications Surveys Tutorials 8:24-37.

Zhihai, H., J Eggert, C Wenye, Z Xiwen, J Millspaugh, R Moll, J Beringer, and J Sartwell. 2008. Energy-aware portable video communication system design for wildlife activity monitoring. Circuits and Systems Magazine 8:25-37.

Developing a Data Transfer Model for WildSense: A Wildlife Tracking Network

RH: Davis et al. • Distance versus Data Transfer

MELANIE J. DAVIS,[1] *Natural Resource Ecology Laboratory, and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO, 80523, USA*

SRAVAN THOKALA, *Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA*

XINYU XING, *Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA*

N. THOMPSON HOBBS, *Natural Resource Ecology Laboratory, and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO, 80523, USA*

DANIEL P. WALSH, *Colorado Division of Wildlife, Fort Collins, CO, 80523, USA*

RICHARD Y. HAN, *Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA*

SHIVAKAHT MISHRA, *Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA*

[1] *E-mail: melanie.davis@colostate.edu*

KEY WORDS contact logging, data transfer, GPS telemetry, maximum likelihood estimation, *Ovis canadensis*, wireless sensor network.

SUMMARY

The construction of low-cost, advanced GPS telemetry systems for wildlife tracking is growing in popularity, especially systems that can communicate with each other to track contacts or transfer data. We tested the communication and data transfer capabilities of a low-cost, custom-built GPS telemetry system with an on-board wireless sensor network (i.e. WildSense) using

people and captive bighorn sheep as an experimental model. We tested data transfer capabilities at several transmission strengths and with several types of obstruction. Under conditions of high transmission strength and low obstruction, a log logistic decay curve was the best model for data transfer success. This is consistent with data transfer patterns previously found under controlled conditions. Contrastingly, under conditions of low transmission strength and high obstruction, data transfer was less reliable, and was best represented by a linear model. Obstruction resulting from animal position adversely affected the communication abilities of our system, with bighorn sheep lowering baseline data transfer success to less than 50% at low transmission strengths. Obstruction also affected the optimum distance of data transfer for each transmission strength, but bighorn sheep had less of an impact than did humans. Obstruction adversely affected maximum distance of data transfer for each transmission strength, but bighorn sheep and humans did not differ in their effects. Wireless sensor node manufacturers recommend an ideal communications distance for each possible transmission strength, but we suggest that scientists fine-tune the communications systems of their in-house constructed GPS telemetry systems using human or preferably animal subjects in order to ensure proper communications in the field.

Remote tracking systems and telemetry represent important pieces of technology for observing wildlife populations and communities with minimal human interference. Global Positioning System (GPS)-based technology has emerged as a particularly useful way to observe wildlife because location data can be obtained over a 24-hour period, in all weather conditions, and with a level of accuracy usually within ± 10 m (Beyer and Haufler 1994, Rodgers et al. 1996, Cadahia et al. 2007, Hansen and Riggs 2008). GPS telemetry has rapidly improved during the last decade. Positional accuracy increased immensely with the dissolution of selective availability in May, 2000 (Lawler 2000). Available functions have expanded to include activity-monitoring programs, and contact-monitoring capabilities (Coulombe et al. 2006, Prange et al. 2006). Unfortunately, commercially-produced GPS-tracking systems often cost thousands of dollars each, which can limit sample size, thereby compromising the ability of investigators to obtain reliable inferences (Girard et al. 2002). As a result of such limitations, low-cost systems produced in-house are becoming a favorable option (Clark et al. 2006). Manual assembly of GPS-tracking systems also allows for implementation of specific functions that are not yet available from commercial sources, such as data transfer components through use of wireless sensor networks (WSN).

WSNs use a collection of wireless sensor nodes to create an interconnected system for data transfer that can ferry data from source to target using two or more transfer events (Yick et al. 2008). WSNs for application in wildlife tracking use delay-tolerant networking, which relies on mobile nodes that do not communicate continuously, but rely on several discrete incidences of data transfer (Zhao and Guibas 2004, Shah et al. 2010). The primary benefit of this technology is that it prevents data loss due to damaged or dysfunctional equipment. In commercially-available communicating systems, contacts are logged but data is not transferred between collars.

Thus, if data from two or more collars are lost, entire contact networks can be broken. Wildlife tracking networks using a WSN prevent this loss because data can be recovered from another collar in the network. Communication between GPS units for tracking purposes via distributed WSNs is becoming a popular idea, and several of these mobile networks have already been implemented (Liu et al. 2004, Huang et al. 2005, Jiang et al. 2009).

The sensor nodes adapted for wildlife tracking mobile networks use radio and GPS devices that are not crafted specifically for wildlife research. In conditions of low movement, data (packet) transfer decreases in an erratic, but generally sigmoid fashion with increasing distance (Anastasi et al. 2007). This pattern holds true at lower transmission strengths, with the maximum transmission distance decreasing with transmission strength (Klingbeil and Wark 2008). When movement and physical obstruction are added as sources of stochasticity, as would be the case with wildlife applications, these patterns of packet loss can change substantially (Woo and Culler 2003, Ekici et al. 2006). As such, the mobile network should be adjusted to take into account obstruction caused by the body mass of a subject wild animal.

Due to fiscal constraints or the lack of animal subjects for testing, researchers constructing a network of GPS tracking units might opt to test their data transfer system using human subjects, or with an object mimicking the shape of the animal of interest (such as a hunting target). In terms of data transfer success, communications distance, and noise, such tests may not result in equivalent measurements to what would actually occur when the collar is placed on the animal. On the other hand, testing a WSN on a human subject before use in the field may still be a better option than not testing the system’s communications abilities at all. Previous research on sensor networks used for monitoring human subjects have found detrimental levels of data loss due to bodily obstruction (Zasowski et al. 2003); however a comparison of the varying effects of obstruction source on WSN data transfer systems with respect to wildlife telemetry has not yet been rigorously tested. This information is important, because it affects the quality of data obtained by researchers in the field. Maximizing the amount of data transfer and the quality of data obtained is necessary in order to paint a clearer picture of interactions between individuals and populations. We believe the results of this experiment will serve as an example for the testing of other in-house mobile networks.

The purpose of our study was to examine the success rate of data (packet) transfer when communication attempts were made between two sensor nodes in a WSN constructed specifically for wildlife tracking (i.e WildSense). We used maximum likelihood estimation and model averaging to model packet transfer versus distance for 5 different radio frequency (RF) transmission strengths. In order to determine how physical obstruction might affect the pattern of packet transfer, we also examined 3 separate obstruction treatments: unobstructed, human obstructed and bighorn sheep obstructed. We used these models to determine the maximum possible packet transfer, optimum transfer distance (distance of 90% data transfer), and maximum transfer distance (distance of 10% data transfer) for each of the 5 transmission strength and 3 obstruction treatments. These values were examined in order to determine if there were individual or interactive effects of treatment groups on the estimated parameters.

We hypothesized that the data for packet transfer success rate versus distance would follow a sigmoid pattern, which would be best represented by a 3-parameter log logistic model due to the proportional nature of the data. We predicted that a decrease in transmission strength would negatively impact optimum transfer distance and maximum transfer distance, but would not affect the maximum packet transfer success rate. We expected that obstruction, from either human or sheep, would significantly decrease the maximum packet transfer success rate, optimum transfer distance, and maximum transfer distance of packet transfer. We also hypothesized that, due to their greater mass and unpredictable movement, the sheep would result in greater depreciation of these three variables than humans.

STUDY AREA

We performed unobstructed and human obstructed trials at the University of Colorado Department of Electrical, Computer, and Energy Engineering in Boulder, Colorado, USA. We ran these tests outside in an academic quadrangle (40° 0’N, 105° 15’W) with little canopy cover. We performed sheep body-block trials at the Colorado Division of Wildlife’s Foothills Wildlife Research Facility (FWRF) in Fort Collins, Colorado, USA (40° 35’N, 105° 10’W). This facility is located on open, slightly rolling pasture, approximately 7 km west of the city of Fort Collins. There is little overhead interference due to canopy cover.

METHODS

Equipment

We assembled the prototype WildSense GPS devices used in this experiment from a MICAz MRP2400 2.4 GHz radio board and MTS420 sensor node. A MIB520mote interface board was the base station (Crossbow® Technology Inc., Milpitas, CA, USA). Sensor nodes measure approximately 6 x 3.5 x 2 cm, including two AA batteries. We used MOTE-VIEW client software to acquire communications data and MOTE-CONFIG client software to program RF transmission strengths into our sensor nodes. Our wireless sensor devices came with 8 pre-set RF power setting options. We chose to test 5 of these transmission strengths to estimate communication distances that would be most helpful for wildlife managers: -25 dBm, -15 dBm, -10 dBm, -5 dBm, and 0 dBm.

We used 2 sensor nodes for this experiment (node 11 and node 13), and 1 base station (base 2). Our base station was connected via USB port to a Dell™ laptop computer running MOTE-VIEW, which saved a running count of packets transferred. We tested sensor nodes in a protective casing consisting of a weatherproof polycarbonate electronics enclosure measuring approximately 11 x 8 x 6 cm. We lined the interior of the enclosure with foam padding to prevent damage to the sensor nodes due to shaking and bumping. The enclosure was attached to a prototype collar made from two sheets of leather strapping sewn together. The collar could be adjusted to fit the sheeps' necks via 2 rows of holes punched along the length of the strapping. Collars were fastened with a double-bolt closure. The complete product weighed approximately 0.450 kg.

Data Collection

For each of the 5 different power levels, we tested 3 different obstruction types: unobstructed, human obstructed and bighorn sheep obstructed. We performed unobstructed and human obstructed trials at the University of Colorado Department of Electrical, Computer, and Energy Engineering on 23 July 2010 from 1000 to 1500 MST and 30 July 2010 from 1000 to 1500 MST. For testing without obstruction, we placed the base station and laptop computer on a stool. This represented the receiving station. We then set the two sensor nodes within their protective enclosures on a separate stool at a set distance from the receiving station. We set both nodes to the same transmission strength, and we made sure to leave enough space in between nodes to prevent interference. We turned on each sensor node and allowed both nodes to transfer approximately 300 packets, after which we switched off the node, stored the data as a *.csv file, and moved the nodes to the next distance. We performed trials at 4-6 different distances for each transmission strength (-25 dBm: 1 m, 1.5 m, 2 m, 2.5 m, 3 m, 4 m; -15 dBm: 10 m, 15 m, 20 m, 25 m; -10 dBm: 9 m, 18 m, 24 m, 30 m; -5 dBm: 9 m, 18 m, 24 m, 30 m, 39 m, 41 m; 0 dBm: 9 m, 18 m, 27 m, 36 m, 45 m).

For testing with human obstruction, we set up the receiving station as described above. Instead of placing the sensor nodes on a stool, we created a physical barrier by holding the sensor nodes to our necks. This was meant to imitate the positioning of the enclosure on a wildlife tracking collar. We staggered our positions at different distances to help prevent double obstruction. We turned on each sensor node, and allowed both nodes to transfer approximately 300 packets, after which we switched off the node, stored the data as a *.csv file, and repeated the packet transfer at different distances. Similarly to the unobstructed trials, we tested 4-6 different distances for each transmission strength (-25 dBm: 1 m, 1.5 m, 2 m, 2.5 m, 3 m, 4 m; -15 dBm: 1.5 m, 3 m, 3.5 m, 4 m; -10 dBm: 1.5 m, 3 m, 6 m, 9 m; -5 dBm: 3 m, 4.5 m, 7.5 m, 9 m; 0 dBm: 6 m, 9 m, 10.5 m, 12 m, 13.5 m, 15 m).

We performed obstruction trials with tame bighorn sheep at the Colorado Division of Wildlife’s Foothills Wildlife Research Facility on 6 August 2010 and 13 August 2010 from 800 to 1000 MST. We attached the enclosures to the sheep with a collar similar to one that might be used in a field study with free-range bighorn sheep. We tethered sheep at set distances facing away from the receiving station, allowing the nodes to transfer approximately 200 packets before moving the sheep to a different distance. We minimized the amount of time sheep had to sit still, and did not switch the nodes on and off between separate distance trials in order to prevent stress from handling. We used two sheep at a time, each with a node set to a different transmission setting, in order to minimize handling time. We tested 4-5 distances for each transmission strength (-25 dBm: 1.5 m, 3 m, 4.5 m, 6 m; -15 dBm: 3 m, 4.5 m, 6 m, 9 m, 12 m; -10 dBm: 1.5 m, 3 m, 4.5 m, 6 m; -5 dBm: 6 m, 12 m, 18 m, 24 m; 0 dBm: 7.5 m , 15 m, 22.5 m, 27.5 m, 30 m). All testing using live animals was approved by Colorado Division of Wildlife ACUC protocol #04-2010.

To ensure that there were no functional differences between our two sensor nodes, we ran a one-way analysis of variance (ANOVA) to test whether the packet transfer success rate differed between the two nodes and an analysis of covariance (ANCOVA) with distance as a covariate. We ran a separate one-way ANOVA to examine packet transfer success rate through time (up to 7 data splits with split 1 representing the earliest time period) in order to determine if the sensor nodes had a "warm up" period after being switched on. These analyses were performed using SAS version 9.2 (SAS Institute, Inc., Cary, NC, USA).

Model Selection and Parameter Optimization

We compared five candidate models as a framework for examining the relationship between distance and transmission strength. Three of these models are commonly-used, sigmoid growth functions that exhibit a wide range of flexibility.

The Gompertz function is a sigmoid function with the formula:

$$f(x) = ae^{be^{cx}} \tag{1}$$

Where *a* represents the upper asymptote (maximum packet transfer success rate), *b* determines displacement along the x axis (location of maximum signal deterioration), and *c* represents the growth rate (rate of signal deterioration).

The generalized logistic function, or Richards function, is an asymmetric sigmoid function similar to the Gompertz equation, except it introduces a fourth parameter for curve lopsidedness:

$$f(x) = \frac{A}{(1+Qe^{-B(x-M)})^{1/Q}} \tag{2}$$

In this equation, *A* represents the maximum packet transfer success rate, *B* represents the rate of signal deterioration, *M* represents the location of maximum signal deterioration, and *Q* represents curve lopsidedness. By adding this fourth parameter, the model goes beyond the assumption that the amount of signal deterioration is linear with distance.

The log logistic function is characterized by the equation:

$$f(x) = \frac{Kx^{\beta}}{\alpha^{\beta} + x^{\beta}} \tag{3}$$

It is a form of the simple logistic equation in which the random variable (in this case, packet transfer success rate) must be non-negative. As such, it is useful for evaluating proportion data. *K* represents the maximum packet transfer success rate, α represents the scale of the curve along the x axis, and β represents the shape parameter of the curve.

We also chose to examine the reliability of two simpler, parametric equations in predicting the distribution of the data.

A linear model:

$$f(x) = \gamma_{0+}\, \gamma_1 x \tag{4}$$

Where γ_0 represents the maximum packet transfer success rate and γ_1 represents the rate of signal deterioration.

A parabolic model:

$$f(x) = \gamma_0 + \gamma_1 x + \gamma_2 x^2 \tag{5}$$

Where γ_0 represents the maximum packet transfer success rate, γ_1 determines the location of maximum signal deterioration, and γ_2 determines the rate of signal deterioration.

Choosing the appropriate model for each of the 15 treatment groups was important for increasing our understanding of how data are transferred within our particular network, and for estimating correct values for three network quality parameters: maximum possible data transfer, optimum distance of data transfer, and maximum distance of data transfer. We performed maximum likelihood estimation and model selection in R version 2.10.1 (R development core team, 2006) to optimize parameters and determine the best fit candidate model for each of our 15 treatment groups. Likelihood is the probability of observing the data conditional on the values of the model parameters. For our maximum likelihood estimation process, we chose to use the sum of negative log likelihoods, where models with more negative log likelihood values exhibit greater lack of fit. We obtained the sum of log likelihoods using a normally distributed maximum likelihood estimator. The results obtained using this type of estimator were comparable to those obtained using a lognormal likelihood estimator, so we found no reason to use a distribution other than the normal.

We ran a maximum likelihood analysis for each of the 5 models using data organized as the proportion of successful packet transfers out of the number of attempted packet transfers. Proportion values were calculated for splits of 50 packets each. We used Akaike's Information Criterion (AIC) to determine the best fit model for each of the 15 treatment groups based on the maximized likelihood values (Akaike 1973). We used a second order derivative, AIC_c, with a bias correction term for small sample size (Burnham and Anderson 2002). The model with the lowest AIC_c value was the best fit model out of our set of 5 candidate models.

We used model averaging (Burnham and Anderson 2002) to find the maximum possible packet transfer, optimum transfer distance, and maximum transfer distance for each treatment group. We organized data into 3 randomized testing sets containing approximately 75% of the data for each treatment group. We ran each testing set through the model selection process as described above. From AIC_c values of each of the 5 models, we derived the ΔAIC, which we used to derive the Akaike weight. We then found the weighted average of the parameter estimates. The end result was three estimates of the model averaged parameters for each of the 15 treatment groups.

Evaluating Treatment Effects

To determine how transmission strength and obstruction affected maximum possible packet transfer, optimum transfer distance, and maximum transfer distance, we ran a two-way ANOVA in SAS. We tested transmission strength and obstruction as individual factors. We also examined a transmission-by-obstruction interaction model in order to determine if the effects of obstruction varied with transmission strength.

RESULTS

The two sensor nodes did not differ in their ability to transfer packets, even when taking into account distance as a covariate ($F_{1,402} = 2.07$, $P = 0.1508$; $F_{3,400} = 0.37$, $P = 0.5426$). We did find a “warm up” effect, with packet transfer success increasing through time ($F_{6,397} = 5.75$, $P < 0.0001$, Table 2.1). This pattern of increasing packet transfer success through time did not differ between nodes ($F_{13,390} = 0.30$, $P = 0.9376$).

When taking into account all data points and all 15 interactive treatment groups, the log logistic model was the best fit candidate model for 8/15 treatment groups, the linear model best represented 6/15 treatment groups, and the parabolic model best represented 1/15 treatment groups (Table 2.2). The Gompertz model and Richards function were not the best-fit models for any of the treatment groups. For obstruction treatments averaged over transmission strength, the log logistic model was the best fit candidate model for the unobstructed treatment group, while the linear model best represented the human and sheep obstructed treatment groups (Figure2.1).

Both transmission strength and obstruction affected maximum possible packet transfer. Transmission strength had an effect on maximum possible packet transfer, with transmission strengths -15 and -25 dBm being lower than transmission strengths 0 and -5, but neither treatment group within each pair differing from one another ($F_{14,30} = 11.44$, $P< 0.0001$, means ± SE: 0 dBm, 84.18 ± 2.69 %; -5 dBm, 85.33 ± 2.69 %; -10 dBm, 62.89 ± 2.69 %; -15 dBm, 75.26 ± 2.69 %; -25 dBm, 73.94 ± 2.69 %). Transmission strength -10 had the lowest possible packet transfer success out of all other transmission strengths. Obstruction also affected maximum possible packet transfer ($F_{14,30} = 103.25$, $P < 0.0001$, means ± SE: unobstructed, 97.16 ± 2.08 %; human obstructed, 76.93 ± 2.08 %; sheep obstructed 54.88 ± 2.08 %). Unobstructed treatments had a maximum success rate of roughly 100%. Treatments with human obstruction were lower, followed by sheep obstruction. There was an interaction effect such that obstruction affected maximum possible packet transfer differently at different transmission strengths ($F_{14,30} = 14.09$, $P< 0.0001$; Figure2.2).

Optimum transfer distance generally decreased with transmission strength, except from 0 to -5 dBm, where it increased ($F_{14,30} = 254.16$, $P< 0.0001$, means ± SE: 0 dBm, 11.79 ± 0.39 m; -5 dBm, 19.11 ± 0.39 m; -10 dBm, 13.02 ± 0.39 m; -15 dBm, 9.01 ± 0.39 m; -25 dBm, 2.16 ± 0.39 m). Unobstructed treatments had the highest optimum transfer distance, followed by treatments with sheep obstruction and human obstruction ($F_{14,30} = 1692.08$, $P< 0.0001$, means ± SE: unobstructed, 24.96 ± 0.30 m; human obstructed, 1.54 ± 0.30 m; sheep obstructed 6.56 ± 0.30 m). There was an interaction effect in that obstruction affected optimum transfer distance differently at different transmission strengths ($F_{14,30} = 116.16$, $P< 0.0001$; Figure2.3).

Maximum transfer distance decreased steadily with transmission strength ($F_{14,30} = 364.18$, $P< 0.0001$, means ± SE: 0 dBm, 37.12 ± 0.65 m; -5 dBm, 24.28 ± 0.65 m; -10 dBm, 20.94 ± 0.65 m; -15 dBm, 11.40 ± 0.65 m; -25 dBm, 5.03 ± 0.65 m). There was an obstruction effect such that both human and sheep obstruction lowered the maximum transfer distance, but the human and sheep obstructed groups did not differ from one another ($F_{14,30} = 544.66$, $P < 0.0001$, means ± SE: unobstructed, 33.26 ± 0.50 m; human obstructed, 12.72 ± 0.50 m; sheep obstructed 13.28 ± 0.50 m; $P = 0.4293$). There was an interaction effect such that without obstruction, the amount of decrease in maximum transfer distance with decreasing transmission strength was greater than with obstruction ($F_{14,30} = 42.44$, $P < 0.0001$; Figure2.4).

DISCUSSION

Our first goal in testing the communications system of WildSense was to determine if a general model could elucidate patterns of packet transfer success rate by distance under varying transmission strength and obstruction conditions. As predicted, the log logistic function best represented the sigmoid distribution of the data for the majority of treatment groups, especially unobstructed treatment groups. However, in sub-optimum conditions of physical obstruction, data exhibited greater variation (i.e. did not follow a clear sigmoid distribution), and a linear model offered a more appropriate fit. These results indicate that packet transfer is less predictable under sub-optimum conditions, such as those presented by an animal body.

Both transmissions strength and obstruction had a substantial impact on the ability of WildSense to transfer data between nodes. Maximum possible packet transfer (as estimated by weighted averaging of model parameters) was almost 100% for all transmission strengths in situations of minimal physical obstruction. This is consistent with the expectation that WSNs be constructed to achieve 100% packet transfer success under optimum conditions (Lal et al. 2004). Human and sheep obstruction did not have the same effect on maximum possible packet transfer. Nodes that were obstructed by sheep body mass had consistently lower estimated maximum possible packet transfer than nodes that were obstructed by human body mass. Nodes that experienced human obstruction experienced a dip in packet transfer at -10 dBm, but then returned to higher packet transfer success at -15 and -25 dBm. The reason for this dip in packet transfer is unclear, although this data set exhibited higher variance, which may have contributed to error in parameter estimation. For bighorn sheep, our results indicate that choosing a higher power level of 0 or -5 dBm would be optimal, as these power levels offer the greatest potential for packet transfer success.

The estimated optimum distance of packet transfer, or the distance at which 90% packet transfer occurred, decreased with decreasing transmission strength, except from 0 to -5 dBm, where it increased significantly. This unexpected increase held true for both unobstructed and sheep obstructed treatment groups. We could find no explanation in the literature for why the optimum distance of packet transfer would be greater for a lower transmission strength, unless the answer lies in an unmeasured source of stochasticity such as wind or interference from other physical sources. Unobstructed treatment groups had the greatest optimum distance of packet transfer, followed by sheep and human obstructed groups. This is consistent with the available literature, which shows that physical blocking by biomass from plants and animals can cause unpredictable dampening of packet transfer success at shorter distances (Darr and Zhao 2008, Li et al. 2010).Even while restrained by a tether, the sheep still moved unpredictably, while our human subjects consistently stood still. Accidental pivoting of the sheep towards the receiving station would result in a less obstructed communication path, which could have contributed to the greater distance at which data could be reliably transferred.

Estimated maximum distance of data transfer, or the distance at which 10% packet transfer occurred, decreased consistently with decreasing transmission strength across all obstruction treatment groups. This, along with the shortening of optimum distance of data transfer with decreasing transmission strength (described above), is consistent with findings presented by Son et al. (2004). Unobstructed groups could transmit data the furthest, but human obstructed and sheep obstructed treatment groups did not differ from one another. These results indicate that, even when obstructed by the body of an animal, our mobile network still has the potential to transfer data at distances of 5-30 m.

Choice of which transmission strength to use depends on the territory size of the population of interest and the scale of the study. In a closed environment, such as a paddock, a lower transmission strength might be appropriate, while in a large-scale study taking place across several square kilometers, a higher transmission strength might be necessary. The type of study also plays a clear role in tuning a WSN for wildlife tracking. Researchers who are interested in close contact (as for disease transfer) might choose to limit sensor node communication to a couple of meters, but researchers studying home range overlap might need to allow communication across much higher distances. What our testing clearly shows is that tuning a WSN to transfer data based on a manufacturer's estimated communications distances could result in significant miscalculation of wireless data transfer capabilities, thereby compromising the integrity of a study. Wherever possible, scientists who are building their own WSN for use in a wildlife tracking setting should fine tune their devices, ideally with the subject animal of interest. If such an opportunity is unavailable, tests using human subjects may suffice, but are not guaranteed to yield the same calculated contact distances.

Our research brings to light the importance of testing the functionality of a WSN before deployment in a field setting, but our results should not be extrapolated to other low-cost systems. Variance in equipment, such as the brand of the GPS and communications devices, the actual configuration and materials of the collar, battery power, link quality, and deployment environment will affect packet transfer in various ways (Fanimokun and Frolik 2003, Lal et al.

2004, Park et al. 2005). Researchers who plan to construct their own low-cost WSNs should take these differences into account when performing their own testing, and should choose a transmission strength based on the needs of their research interests. To date, a fully functional, long-term GPS tracking system that incorporates a data transfer network has not been successfully deployed, but we believe a system such as WildSense is the next logical step in the advancement of wildlife telemetry.

MANAGEMENT IMPLICATIONS

In-house construction of low-cost telemetry systems is now common, despite the advancement of GPS technology into more sophisticated realms. The results of our study should serve as an example for scientists who plan to construct their own mobile networks for use in a wildlife tracking scenario. The effects of physical obstruction on the functioning of our sensor nodes clearly altered the effectiveness of data transfer. This demonstrates the importance of fine-tuning equipment, preferably using animal subjects if it is an available option.

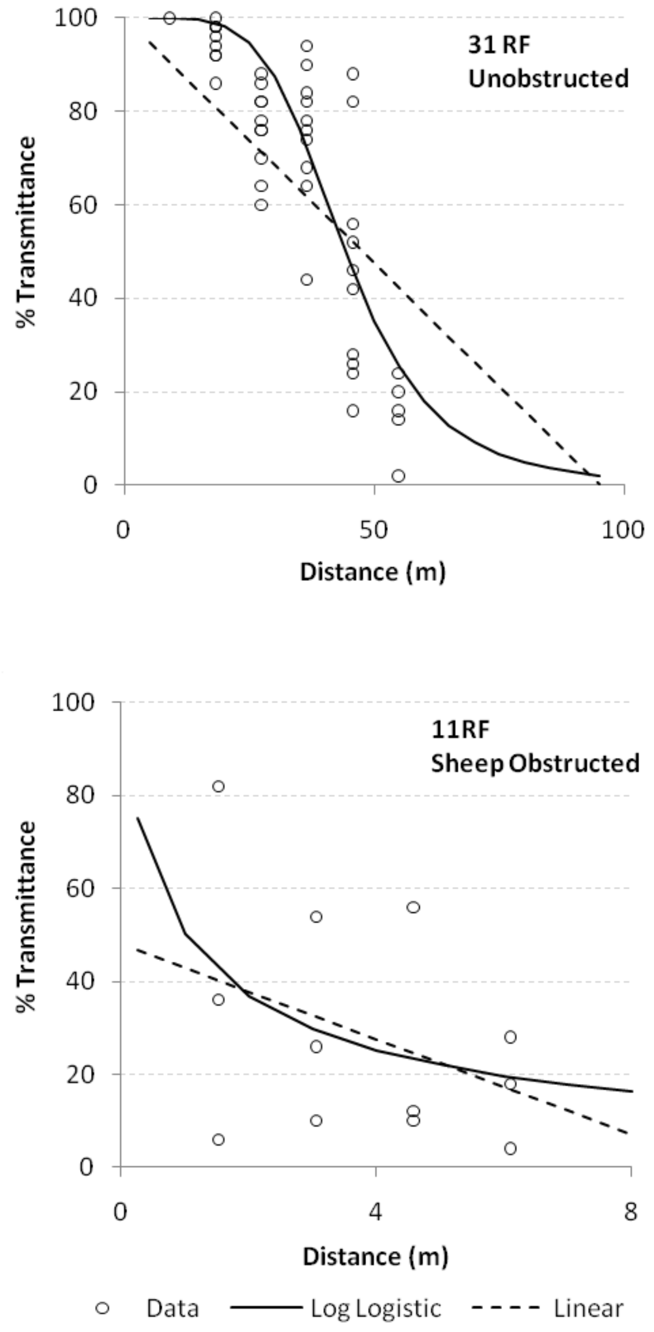

Figure 2.1. A comparison of data distribution between two treatment groups. The top data set is from a high-strength treatment group with no physical interference, and is best represented by the log logistic model. The bottom data set is from a lower-strength treatment group with obstruction, and is best represented by a linear model.

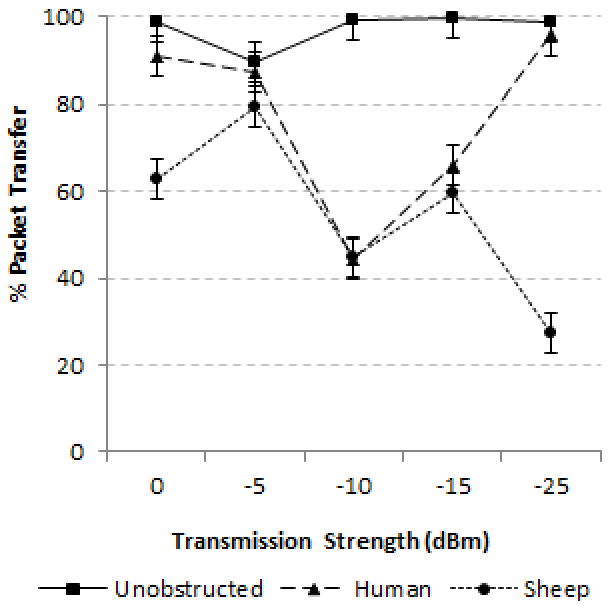

Figure 2.2. Transmission strength-by-obstruction interaction effect for mean maximum possible % packet transfer. Error bars represent one standard error.

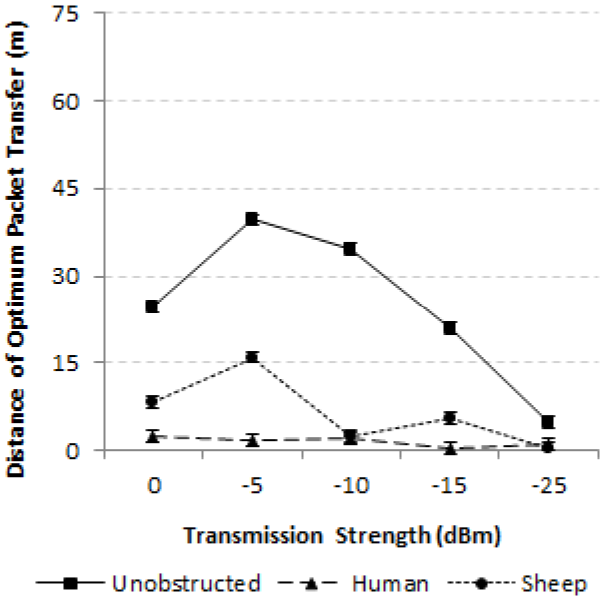

Figure 2.3. Transmission strength-by-obstruction interaction effect for mean optimum distance of data transfer. Error bars represent one standard error.

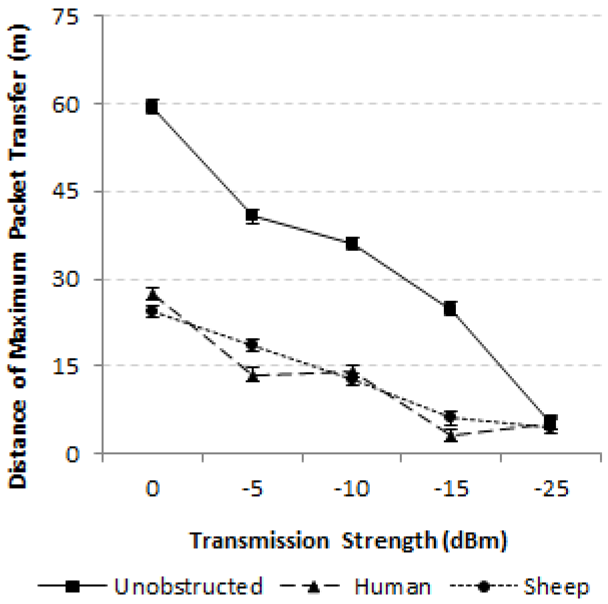

Figure 2.4. Transmission strength-by-obstruction interaction effect for mean maximum distance of data transfer. Error bars represent one standard error.

Table 2.1. Least squares means and standard errors of packet transfer success rates through time, where split 1 represents the earliest set of 50 attempted packet transfers and split 7 represents the latest.

Split	LS Mean	Standard Error
1	59.63	3.46
2	64.19	3.67
3	70.05	3.88
4	79.04	4.34
5	86.50	4.78
6	81.00	8.61
7	100.00	13.01

Table 2.2. Number of data points (n), best candidate model, number of free parameters (*K*), model variance (*Var*), log likelihood (*LL*), and AIC values (AIC_c), for all 15 treatment groups.

Treatment	n	Model	K	Var	LL	AIC_c
0 dBm Unobstructed	58	**Parametric**	**3**	**12.89**	**230.56**	**467.56**
0 dBm Human	22	**Linear**	**2**	**17.34**	**93.98**	**192.98**
0 dBm Sheep	13	**Linear**	**2**	**15.04**	**53.69**	**112.58**
-5 dBm Unobstructed	65	**Log Logistic**	**3**	**8.99**	**234.99**	**476.38**
-5 dBm Human	16	**Linear**	**2**	**21.80**	**72.01**	**148.95**
-5 dBm Sheep	10	**Log Logistic**	**3**	**13.23**	**40.01**	**90.03**
-10 dBm Unobstructed	44	**Log Logistic**	**3**	**1.55**	**81.67**	**169.95**
-10 dBm Human	10	**Log Logistic**	**3**	**17.47**	**42.80**	**95.59**
-10 dBm Sheep	12	**Linear**	**2**	**21.59**	**53.89**	**113.12**
-15 dBm Unobstructed	30	**Log Logistic**	**3**	**3.63**	**81.26**	**169.44**
-15 dBm Human	8	**Linear**	**2**	**15.60**	**33.33**	**73.06**
-15 dBm Sheep	14	**Log Logistic**	**3**	**3.86**	**38.79**	**85.98**
-25 dBm Unobstructed	89	**Log Logistic**	**3**	**9.98**	**330.99**	**668.27**
-25 dBm Human	8	**Log Logistic**	**3**	**12.22**	**27.46**	**68.91**
-25 dBm Sheep	6	**Linear**	**2**	**9.37**	**18.28**	**46.56**

LITERATURE CITED

Akaike, H. 1973. Information theory as an extension of the maximum likelihood principle. Pages 267-281 *in* Proceedings 2nd international symposium on information theory. Petrov, B.N., and Csaki, F., eds. Akademiai Kiado, Budapest.

Anastasi, G., M. Conti, E. Gregori, C. Spagoni, and G. Valente. 2007. Motes sensor networks in dynamic scenarios: an experimental study for pervasive applications in urban environments. Journal of Ubiquitous Computing and Intelligence. 1: 9-16.

Beyer, D.E., and J.B. Haufler. 1994. Diurnal versus 24-hour sampling of habitat use. Journal of Wildlife Management. 58: 178-180.

Burnham, K.P., and D.R. Anderson. 2002. Model Selection and Multi-model Inference: A Practical Information-Theoretic Approach, Springer.

Cadahia, L., V. Urios, and J.J. Negro. 2007. Bonelli's eagle *Hieraaetus fasciatus* juvenile dispersal: hourly and daily movements tracked by GPS. Bird Study. 54: 271-274.

Clark, P.E., D.E. Johnson, M.A. Kniep, P. Jermann, B. Huttash, A. Wood, M. Johnson, C. McGillivan, and K. Titus. 2006. An advanced, low-cost, GPS-based animal tracking system. Rangeland Ecology and Management. 59: 334-340.

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.

Darr, M., and L. Zhao 2008.A model for predicting signal transmission performance of wireless sensor networks in poultry layer facilities. Transactions of the ASABE. 51: 1817-1827.

Ekici, E., Y. Gu, and D. Bozdag. 2006. Mobility-based communication in wireless sensor networks. IEEE Communications Magazine. 44: 56-62.

Fanimokun, A., and J. Frolik. 2003. Effects of natural propagation environments on wireless sensor network coverage area. *Pages 16-20 in* proceedings of the 35th southeastern symposium on system theory.

Girard, I., J. Ouellet, R. Courtois, C. Dussault, and L. Breton. 2002. Effects of sampling effort based on GPS telemetry on home-range size estimations. Journal of Wildlife Management. 66: 1290-1300.

Hansen, M.C., and R.A. Riggs. 2008. Accuracy, precision, and observation rates of global positioning system telemetry collars. Journal of Wildlife Management. 72: 518-526.

Huang, J.H., S. Amjad, and S. Mishra. 2005. Cenwits: a sensor-based loosely coupled search and rescue system using witnesses. In ACM SenSys, 2005.

Jiang, L., J.H. Huang, A. Kamthe, T. Liu, I. Freeman, J. Ledbetter, S. Mishra, R. Han, and A. Cerpa. 2009. SenSearch: delay-tolerant GPS and witness-assisted tracking for delay-tolerant sensor networks. Lecture Notes in Computer Science. 2009: 255-269.

Klingbeil, L., and T. Wark. 2008. A wireless sensor network for real-time indoor localisation and motion monitoring. Pages 39-50 *in* Proceedings 2008 international conference on information processing in sensor networks. Washington, DC, USA.

Lal, D., A. Manjeshwar, F. Herrmann, E. Uysal-Biyikoglu, and A. Keshavarzian. 2004. Measurement and characterization of link quality metrics in energy constrained wireless sensor networks. Globecom. 1: 446-452.

Lawler, A. 2000. Scientists gain access to sharper GPS signal. Science. 288:783.

Li, Z., N. Wang, and T. Hong. 2010. Radio path-loss modeling for a 2.4 GHz in-field wireless sensor network. Transactions of the ASABE. 53: 615-624.

Liu, T., C.M. Sadler, P. Zhang, and M. Martonosi. 2004. Implementing software on resource-constrained mobile sensors: experiences with Impala and ZebraNet. Pages 256-269 *in* Proceedings of the 2nd international conference on mobile systems, applications, and services. June 2004. Boston, MA, USA.

Park, C., K. Lahiri, and A. Raghunathan. 2005. Battery discharge characteristics of wireless sensor nodes: an experimental analysis. Pages 430-440 *in* Sensor and Ad Hoc Communications and Networks. Proceedings 2nd Annual IEEE Communications Society Conference.

R Core Development Team. 2006. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available from: <http://www.R-project.org>.

Rodgers, A.R., R.S. Rempel, and K.F. Abraham. 1996. A GPS-based telemetry system. Wildlife Society Bulletin. 24: 559-566.

Shah, H., and Y.P. Kosta. 2010. Evolution or routing techniques, routing protocols, and routing efficiencies for delay tolerant network. International Journal of Computer Applications. Special issue on MANETs: 46-53.

Son, D., B. Krishnamachari, and J. Heidemann. 2004. Experimental study of the effects of transmission power control and black-listing in wireless sensor networks. Pages 289-298 *in* IEEE Secon.

Woo, A., and D. Culler. 2003. Evaluation of efficient link reliability estimators for low-power wireless networks. Technical report UCB//CSD-03-1270, University of California Berkeley, Computer Science Division. Berkeley, CA, USA.

Yick, J., B. Mukherjee, and D. Ghosal. 2008.Wireless sensor network survey. Computer Networks. 52: 2292-2330.

Zasowski, T., F. Althaus, M. Stager, A. Wittneben, and G. Troster. 2003. UWB for noninvasive wireless body area networks: channel measurements and results. Pages 285-289 *in* IEEE Conference on Ultra Wideband Systems and Technologies.

Zhao, F., and L. Guibas. 2004. Wireless sensor networks: an information processing approach. Morgan Kaufman Publishers, San Francisco, CA, USA.

Testing the Functionality and Contact Error of a GPS-Based Wildlife Tracking Network

RH: Davis et al. • Functionality and Contact Error

MELANIE J. DAVIS, Natural Resource Ecology Laboratory, and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO, 80523, USA

SRAVAN THOKALA, Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA

XINYU XING,Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA

N. THOMPSON HOBBS, Natural Resource Ecology Laboratory, and Graduate Degree Program in Ecology, Colorado State University, Fort Collins, CO, 80523, USA

DANIEL P. WALSH, Colorado Division of Wildlife, Fort Collins, CO, 80523, USA

RICHARD Y. HAN, Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA

SHIVAKANT MISHRA, Department of Computer Science, University of Colorado, Boulder, CO, 80309, USA

KEY WORDS contact logging, contact error, data transfer, delay tolerant network, GPS telemetry, *Ovis canadensis*, WildSense

SUMMARY

Telemetry has become a fundamentally important tool for studying animal movements. Traditional telemetry systems have provided time-specific information on locations of individuals; however, recent deployments in instruments allow for the tracking of networks of interactions among individuals, providing some insight into who is contacting whom and when. Currently, these devices rely on very high frequency (VHF) radio technology, and cannot

precisely gauge where contacts occurred and how far apart they occurred within the pre-set contact threshold. The high rate of data loss from contact-logging devices, and even traditional telemetry devices that are lost or damaged in the field, poses another obstacle to monitoring wildlife social networks. We have developed a prototype contact-logging GPS collar that offers greater spatial resolution of contact data, and reduces probability of data loss. In this study, we used captive bighorn sheep (*Ovis canadensis*) to test the GPS capabilities, contact rates, and contact distance error of our prototype collars. The GPS fix success rate of our collars was greater than 95%. The collars were communicating with each other about 98% of the time, and communication was reciprocated 9% of the time because the animals were observed in small paddocks. Contact distance error was 9.5 m, which is what would be expected taking into account a baseline GPS spatial error of ±5 m in open environment. The high GPS fix success, low GPS error, and ability to log accurate contacts with low contact distance error by our prototype collars suggest that the implementation of GPS with contact-logging technology has the potential to improve upon currently-available contact network data.

Wildlife telemetry has become the tool of choice for monitoring the spatial and temporal locations of individuals in their environment. Technology based on global positioning systems (GPS) is particularly popular because data are obtained non-invasively and provide a continuous record of locations at all times of day and in all weather conditions (Beyer and Haufler 1994, Rodgers et al. 1996, Cadahia et al. 2007). Since the dissolution of selective availability in May, 2000, the positional accuracy of GPS telemetry systems has also improved (Lawler 2000). Individuals can now be tracked with a positional accuracy generally within ± 10 m depending on environment (D’Eon et al. 2002, Hansen and Riggs 2008). These attributes make GPS devices particularly sought-after, despite the expensive per-unit costs of utilizing such technology.

Although GPS can be easily used to elucidate individual movements through landscapes, using raw GPS data (i.e. latitude, longitude, and GMT date/time) to observe interactions among individuals is more difficult. Kjær et al. (2007) plotted GPS points using ArcView 3.2 and used a joint utilization distribution and compositional analysis to estimate contact rates of white-tailed deer in different land-cover types. Similarly, Schauber et al. (2007) estimated direct and indirect contact rates among white-tailed deer using pairwise measures of proximity. These methods yield valuable insight, but they depend on complicated mathematics, recently updated remote sensing data, a designated overlap zone that is subject to the positional accuracy of GPS data, and GPS data that are temporally in-sync between individuals. This dependence limits their utility.

Commercial manufacturers have recently developed proximity data loggers that can record contacts between individuals. These data loggers use a pulse-controlled ultra high frequency (UHF) transmitter with a specific pulse rate to transmit a communications beacon. When two loggers come within a user-defined detection distance, each logger records the date, time, and duration of the contact. These devices are valuable tools for determining which individuals are contacting each other, but they cannot log the locations of all contacts because they rely on very high frequency (VHF) rather than GPS technology (Ji et al. 2005, Prange et al. 2006, Hamede et al. 2009). Researchers can only verify location data of those contacts that are triangulated in the field.

To date, there is little data in the scientific literature on the success rate, contact error, and contact distance accuracy of these commercially available devices. Ji et al. (2005) put proximity loggers on possums, and were able to retrieve data off of 66% of their loggers. As would be expected, some of these data were confounded by damage, limited battery life, or memory constraints. Hamede et al. (2009) were able to recover complete data sets from 27 out of 46 devices when they used proximity loggers on Tasmanian devils, with much of the lost data occurring due to damage and memory constraints. Due to the elusive nature of the species of interest, neither study could visually verify contact error (whether or not contacts were actually occurring). Prange et al. (2006) ran extensive laboratory and field tests using raccoons, and found that their commercial collars recorded accurate contacts and contact durations, but logged false or “phantom” contacts in group-contact situations. These studies demonstrate that currently available technology can obtain contact data at a high temporal resolution, but stands to benefit from improved spatial resolution. Adding location data using GPS technology would be particularly useful, because it would allow researchers to determine the environment in which the contact occurred, and would enable a more accurate estimation of contact distance. Elevated rates of data loss (>30%) also suggest the need for improved data retrieval capabilities.

To address the need for increased spatial resolution and hardier data storage in contact-logging telemetry, we propose the use of next-generation GPS technology with the integration of a delay-tolerant network (DTN). DTNs are a type of wireless sensor network that rely on a "store-and-forward" message transfer system. Data are ferried between individual "nodes", which eliminates the need for constant connectivity (Fall 2003, Shah and Kosta 2010). This type of data transfer is ideal for wildlife telemetry, because contact between individuals may happen intermittently and asymmetrically, and field conditions are often too harsh to support continuously-connected wireless internet. Incorporating a DTN with currently-available GPS technology will improve wildlife telemetry in several ways. 1) Data can be ferried to a set destination such as a base station or "listening" node. 2) Data redundancy in the on-board storage systems allows researchers to retrieve data from a lost or damaged node off of a node that is still intact. 3) Networks of data transfer can be analyzed in conjunction with single contact logs to elucidate contact networks.

We have developed a prototype wildlife telemetry collar (called "WildSense") that incorporates DTN-based technology, GPS, and contact-logging capabilities, which we intend to use in the field. Each collar is comprised of a GPS chip, which is connected to a wireless sensor node. The sensor node can act as either a communicating (sending) or recipient (receiving) device in the data transfer process (Fig. 3.1). We expect that our experiences with this prototype will demonstrate how such next-generation technology can elucidate contact networks for vital applications in disease transfer, territory overlap, competition, and predation events. As such, it is crucial that our system can accurately portray contact distances between two individuals, and maintain levels of data redundancy that allow researchers to obtain at least some of the data logged by lost or damaged collars.

The purpose of this study was to test the GPS functioning, data transfer capabilities, and contact error of our prototype WildSense GPS devices in a simulated field setting. To accomplish this, we ran several trials using captive bighorn sheep in an enclosed pen. We analyzed the means and standard errors for each measure of functionality, and compared these values between different power levels and duty cycles. We expected that the GPS fix success rate of our collars would be high (greater than 95%) given the open environment in which we tested, and the results of past experimentation. We also expected that unintentional data duplication from repeated satellite fixes would be low (less than 5%) based on how we initially thought the GPS devices were programmed to communicate with the satellites. For communication capabilities, we expected that the sheep would be in contact most of the time due to the social nature of the bighorn sheep and the communications range of the devices as compared to the size of the pen. We predicted that the higher power nodes would communicate more often than the lower power nodes due to their broader communications range. Finally, we predicted that contact distance error would be a function of both spatial and temporal imprecision, but would ideally be less than ± 10 m.

STUDY AREA

We performed simulated field testing at the Colorado Division of Wildlife's Foothills Wildlife Research Facility (FWRF) in Fort Collins, Colorado, USA (40°35'N, 105°10'W). This facility is located on open, slightly rolling pasture, approximately 7 km west of the city of Fort Collins. There is little overhead interference due to canopy cover.

METHODS

Equipment

We assembled the prototype WildSense GPS devices used in this experiment from a MICAz MRP2400 2.4 GHz radio board and MTS420 sensor node (Crossbow® Technology Inc., Milpitas, CA, USA). Sensor nodes measure approximately 6 x 3.5 x 2 cm, including two AA batteries. We used MOTE-VIEWclient software (Crossbow® Technology Inc., Milpitas, CA, USA)to acquire communications data and MOTE-CONFIG client software to program RF transmission strengths into our sensor nodes.

We tested sensor nodes in a protective casing consisting of a weatherproof polycarbonate electronics enclosure measuring approximately 11 x 8 x 6 cm. We lined the interior of the enclosure with foam padding to prevent damage to the sensor nodes due to shaking and bumping. We attached the enclosure to a prototype collar made from two sheets of leather strapping sewn together. The collar could be adjusted to fit the sheeps' necks via 2 rows of holes punched along the length of the strapping. Collars were fastened with a double-bolt closure. The complete product weighed approximately 0.450 kg.

Data Collection

We put GPS devices on 4 separate captive bighorn sheep to test collar functioning. The study area was a 25 x 75 m pen at the FWRF, in which we marked a 5 m grid system using bright orange spray paint. We mounted Panasonic® SDR-H85 video camcorders on the north and south ends of the pen in order to visually record contacts. Sheep were allowed to roam freely within the pen, and did not leave the study area during the course of the experiment.

We performed three study trials: a 1-day trial, a 2-day trial, and a 4-day trial. The first day of each trial began at 800 MST, and the last day of each trial ended at 1600 MST. For the 1-day trial, we used a 30 minute writing interval, during which 10 minutes were spent communicating with the GPS satellites and transferring data (awake), and the other 20 minutes were devoted to transferring data only (sleep). For the 2-day and 4-day trials, we used a 1 hour writing interval in which 10 minutes were spent awake and the other 50 minutes were spent in the sleep cycle. While in awake mode, nodes made GPS fix attempts roughly once a minute, and sent out communications beacons roughly once every two seconds.

During each trial, we set two devices to a (high) power level of 0 dBm, and the other two were set to a (medium) power level of -5 dBm. Our choice of power level was based on previous testing, which showed that the -5 dBm power level was optimum for use in a wildlife setting (Davis et al., unpublished data). Preliminary models of communications distance by power level under conditions of bodily obstruction found a maximum communications distance of roughly 30 m for the 0 dBm power level and 15 m for the -5 dBm power level, so these were the communications distances we expected to see during all trials.

We did not enable multi-hop data transfer capabilities for this experiment, opting to focus only on single-hop data transfer. This means that data were only transferred from the communicating node to the recipient node (a single data transfer event) rather than across all available nodes over the course of the experiment (multiple data transfer events). Each collar recorded the communicating node ID, the recipient node ID, the contact “count,” the time and date of the contact, the latitude, and the longitude of the individual wearing the device. For visual observations, we took roughly four hours of video footage per day during each trial. These occurred either in the morning (roughly 800 MST to 1200 MST) or the afternoon (roughly 1200 MST to 1600 MST).

Statistical Analysis

We used GPS fix success rate and duplicated data points from unintentional, simultaneous GPS fixes as a measure of GPS functioning. We calculated the GPS fix success rate as the percentage of GPS logs with successful satellite fixes out of the total number of data points. We calculated the percentage of duplicated data points as the number of duplicated GPS logs (identical date, time, and location) out of the total number of GPS logs. We calculated the means and standard deviations averaged over the entire experiment. We also ran a logistic regression model to test whether there were differences in GPS functioning between trials or power levels.

To test the contact marking and data transfer capabilities, we measured the average percentage of time in contact, the average percentage of reciprocated data transfer, the distance of reciprocated versus non-reciprocated data transfer, and the contact error. The percentage of time in contact was calculated as the number of contact logs with a valid recipient node ID out of the total number of contact logs. We defined an instance of reciprocated data transfer as a contact log for which the recipient node ID and communicating node ID were identical on both collars. Reciprocal data transfer events were necessary to determine an accurate contact distance. For each contact log, we calculated the distance between the communicating and recipient node using the Haversine formula:

$$a = sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_1) * \cos(lat_2) * sin^2\left(\frac{\Delta long}{2}\right) \tag{1}$$

$$c = 2 * arctan^2(\sqrt{a}, \sqrt{(1-a)}) \tag{2}$$

$$d = R * c \tag{3}$$

We used these distances to analyze the difference between reciprocated and non-reciprocated data transfer. We calculated the means and standard deviations of these variables averaged over the entire experiment, and ran a logistic regression model to test whether there were differences in percent time in contact or percent reciprocated data transfer between trials or power levels. We used a one-way ANOVA with Tukey’s HSD post-hoc analysis to test whether distance of reciprocated data transfer and non-reciprocated data transfer differed between trials or power levels.

Finally, we used these distance calculations to estimate contact error, or the difference between a GPS-logged distance and a visually-observed distance. After sorting contacts, we randomly selected 200 reciprocal contacts that occurred within the timespan for which we had video footage. We ran a paired Student's t-test to determine whether the observed distances between individuals differed from GPS-recorded distances between individuals. All statistical analyses were performed using R version 2.10.1 (R development core team, 2006).

RESULTS

The mean GPS fix success rate over all trials and power levels was 95.46 ± 10.25%. Fix success differed between trials (X^2= 1726.1, df=2, P<0.001; Fig. 3.2), with 2 and 4-day trials having greater fix success than the 1-day trial (P<0.01). Fix success also differed between power levels (X^2=1365.9, df=1, P<0.001; Fig. 3.2), with the 0 dBm power level having lower fix success than the -5 dBm power level.

The mean percentage of unintentionally duplicated data was 98.03 ± 2.03%. Duplicated data differed between trials (X^2= 58.2, df=2, P<0.001), with the 4-day trial having more duplicates than the 1-day trial (P<0.01). Duplicated data transfer also differed between power levels (X^2=45.7, df=1, P<0.001). Nodes set to 0 dBm had slightly less data duplication than nodes set to -5 dBm. These differences were biologically meaningless, since data duplication was unacceptably high in all trials and for all power levels.

Overall, the average percentage of time individuals were in contact with at least one other individual was 98.05 ± 2.46%. This contact rate differed between trials (X^2= 24.5, df=2, P<0.001, means ± SE: 1-day, 98.7 ± 2.3%; 2-day, 98.5 ± 0.6%; 4-day, 97.1 ± 3.8%), with the sheep making less contact during the 4-day trial than the 1-day trial (P<0.01). Time in contact also differed between communicating node power levels (X^2= 24.5, df=2, P<0.001, means ± SE:

0 dBm, 97.5 ± 3.0% ; -5 dBm, 98.8 ± 1.7%). Recipient node power level had an effect on how likely a node was to be contacted, but this effect differed between trials. During the 1-day trial, the higher power 0 dBm nodes were less likely to be contacted (X^2= 897.2, df=1, *P*<0.001; Fig. 3.3); however, during the 2-day and 4-day trials, the higher power 0 dBm nodes were more likely to be contacted (X^2= 714.2, df=1, *P*<0.001; X^2= 317.1, df=1, *P*<0.001; Fig. 3.3).

The mean percentage of reciprocated communication was 9.20 ± 9.07%. Reciprocated communication differed between trials (X^2= 549.8, df=2, *P*<0.001; Fig. 3.4), with reciprocal contacts occurring less frequently during the 2-day trial (*P*<0.01), but power level did not have an effect on the amount of reciprocal contacts. Reciprocated communication occurred at an average distance of 8.42 ± 14.01 m, with higher power nodes generally having a greater distance of reciprocated communication ($F_{1,1118}$=53.573, *P*<0.001; means ± SE: 0 dBm, 11.8 ± 18.8 m; -5 dBm, 5.75 ±7.43 m). The distance between reciprocal contacts did not differ from the distance between non-reciprocal contacts.

On average, visual contact distances differed 5.10 ± 13.74 m from GPS-recorded contact distances, or 9.44 ± 11.16 m when absolute differences were taken into account (Fig. 3.5). While this value is significantly different from 0 (t = 2.922, df = 61, *P* = 0.005), our expected contact error of ±5 m was well within the calculated confidence intervals (95% CI: 1.61, 8.59).

DISCUSSION

The basic functioning of our GPS devices met or exceeded requirements for use in the field. The GPS fix success rate for our collars was over 95%, which is comparable to commercially available systems under conditions of minimal habitat complexity (Frair et al. 2004, Hansen and Riggs 2008). We found a slightly decreased fix success for the 1-day trial and the 0 dBm power level, but this was due to an outlier node that had less than 60% communications success with the satellites. We were able to remedy this with reprogramming, and had no further issues with this node during later trials.

Duplicated data was over 98%, but we were expecting data duplication levels of less than 5%. Data duplication statistically differed between trials and power levels, but these differences were not substantial enough to improve the functioning of the collars. After further investigation, we found that the GPS nodes had been programmed to make four communications attempts for each GPS data point, so most GPS points were quadrupled. This programming error has been remedied for ongoing studies, and it will be necessary to reanalyze data duplication with further testing.

The contact logging and data transfer capabilities of our collars also met the standards we set according to the functionality of proximity-logging devices that are already on the market. For all trials, bighorn sheep were in contact with each other almost 100% of the time. Bighorn sheep exhibit herding behavior, especially among family groups (Geist 1971, Festa-Bianchet 1991), and the potential contact area of the nodes covered much of the 25m x 75m pen. The furthest distance that -5 dBm nodes have been observed to communicate under conditions of animal obstruction is roughly 15 m (Davis et al. unpublished data). This 30 m diameter accounts for almost half of the study area (707 m^2 out of 1875 m^2), so even if our captive bighorn sheep were moving randomly within the pen, we would expect nodes to be in contact with at least one other node for the majority of the time. Likewise, the broader communications range of the 0 dBm nodes as compared to the -5 dBm nodes most likely explains why the higher power nodes were contacted more frequently on the 2 and 4-day trials (Klingbeil and Wark 2008).

Because the bighorn sheep were in contact with at least one other individual for the majority of the trial time, we had ample data to analyze the accuracy of GPS-logged contact distances, but we could not effectively analyze contact error *per se* due to lack of un-logged, "true" contacts. In order to determine where, when, and how far apart contacts occurred within the study area, we needed to evaluate reciprocal contacts, as these were the only logged contacts for which the GPS data of both communicating nodes were available. Given that we deployed 4 nodes, node A had a 1/3 probability of contacting node B at any given time (P(A)=0.33) and vice versa (P(B)=0.33). If we assume that each node was always in contact with one other node, then the probability that both node A was contacting node B and node B was contacting node A is P(A and B) = P(A)*P(B), or 0.11. The expected 11% reciprocal communication rate is well within the confidence intervals of our 9.2% reciprocal communication rate.

Reciprocal contact distances averaged about 8.5 m apart, but differed between power levels. Because the higher power levels have a broader communications range (Klingbeil and Wark 2008), reciprocal contacts between 0 dBm nodes averaged roughly 6 m greater distance than reciprocal contacts between -5 dBm nodes (11.8 vs. 5.75 m). Reciprocal contact distances did not differ from non-reciprocal contact distances, which suggests that contact "preference" between nodes is regulated by who requests to transfer data first, not who is closer in Euclidian distance. This is consistent with the use of a collision avoidance protocol in DTNs, which determines how nodes interact to avoid data collisions mid-transfer (Veres et al. 2001). When two nodes first come into contact in an idle network, one node sends a Request To Send (RTS) message, to which the receiving node will respond with a Clear To Send (CTS) response. If nodes A and B both send an RTS to node C at the same time, a data collision may occur. In this situation, nodes A and B use a random countdown timer to determine how long until the next RTS can be sent. If node A randomly selects a shorter countdown time, node A will be more likely to receive the CTS from node C. Therefore, communication between nodes is determined by who can send the fastest RTS (i.e., who comes into contact range first), or who randomly selects the shorter countdown timer.

After sorting and randomly selecting 200 reciprocal contacts, we were able to match GPS date and time to compare GPS-logged contacts to visually observed contacts for 62 time stamps. We calculated the difference between GPS and visually-observed contacts, and found a 9.44 m contact distance error. This is remarkably close to the baseline GPS location error (at least ± 5 m) that would be expected in an open environment (D'Eon et al. 2002, Cain et al. 2005). This suggests that, even with a time lapse of 30 seconds-1 minute between two collars' GPS data, our contact distance error is contingent upon baseline GPS location error rather than other sources of uncertainty.

Overall, the GPS component of our prototype is functioning at the same level as commercial systems, as has been illustrated by our high fix success rate and low contact distance error. These positive results, along with our devices' consistent contact-logging capabilities, imply that WildSense will soon be ready to test in the field. Nevertheless, there are still some challenges that must be overcome before field deployment is feasible. In order to simplify our analysis of the contact error, we did not use the multihop data transfer (data ferrying) function in this study. We have yet to test these capabilities in a simulated field setting, and expect that the data redundancy offered by the multihop data transfer will add further complexity to the accuracy of the data and the data structure. Furthermore, in a field setting our GPS fix schedule will be much more intermittent, which may introduce temporal error into our measurements of contact distance. It still remains unclear how much data loss can actually be prevented when the multihop DTN function is turned on. More field testing needs to be completed before we can confidently claim that prototype devices such as ours represent a marked improvement over currently available technology, but the results of this study indicate that we are headed in the right direction.

Wildlife telemetry has made great strides in technological advancement in the last few decades. Our prototype WildSense collars have demonstrated that scientists now have the option to incorporate spatially-accurate GPS data into preexisting contact-logging devices, and that this technology may offer deeper insight into the spatial *and* temporal properties of wildlife contact networks. Furthermore, we expect that by adding DTN capabilities, we will be able to prevent the loss of valuable contact data. Contact-logging telemetry devices represent an important piece of the puzzle in deciphering population and community dynamics, and by adding GPS and DTN technology to currently-existing equipment, we surmise that scientists will be able to analyze wildlife contact networks with greater breadth and clarity.

MANAGEMENT IMPLICATIONS

Contact-logging telemetry devices are gaining popularity because they offer deeper insight into wildlife social networks. Although commercially-available devices can capture accurate snapshots of who is contacting whom and when, they cannot precisely gauge where these contacts occurred and how far apart they occurred within the pre-set contact threshold. Commercially available collars also seem to have a high rate of data loss – in some cases more than 33%. We have developed a prototype contact-logging GPS collar with DTN capabilities, which we believe offers greater spatial resolution of contact data, and may prevent data loss. The results of our preliminary testing show that our devices have high GPS fix success, low GPS error, and the capacity to log accurate contacts with low contact distance error. While there is still room for improvement, these results suggest that such next generation technology has great potential for improving upon currently available contact network data.

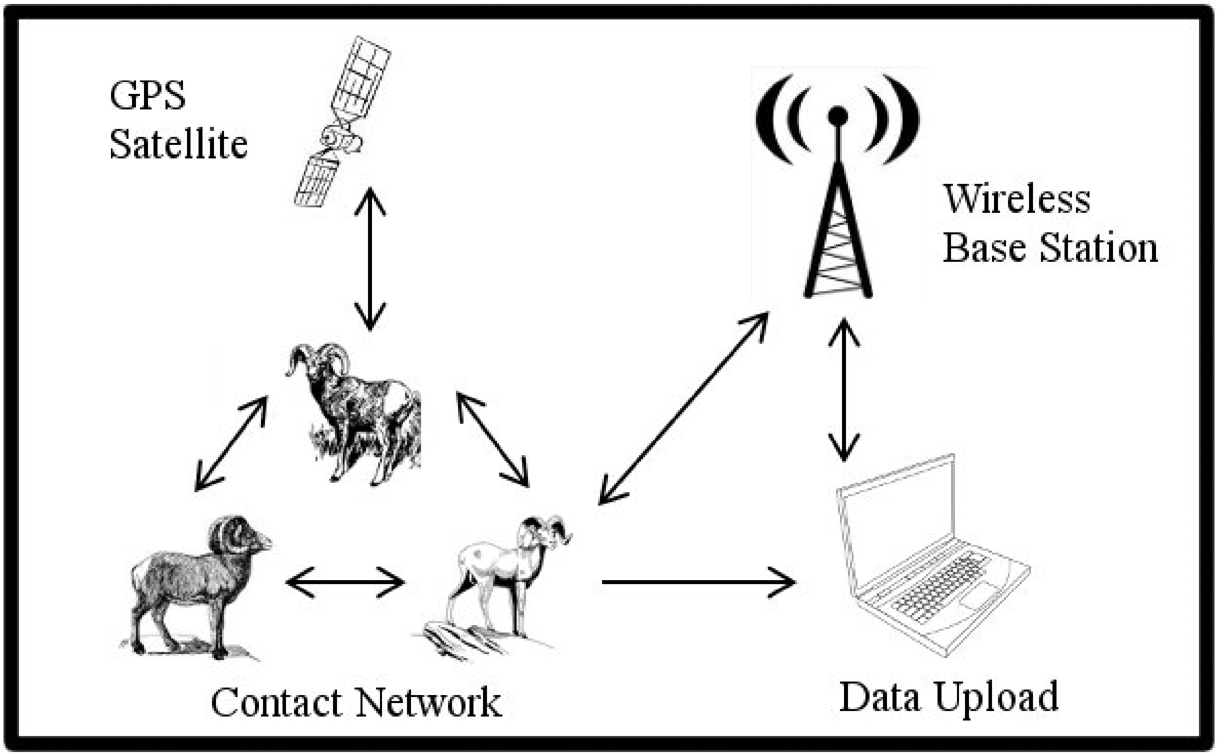

Figure 3.1. Network architecture of “WildSense”, including collars with GPS and wireless sensor nodes, base stations, and direct data upload.

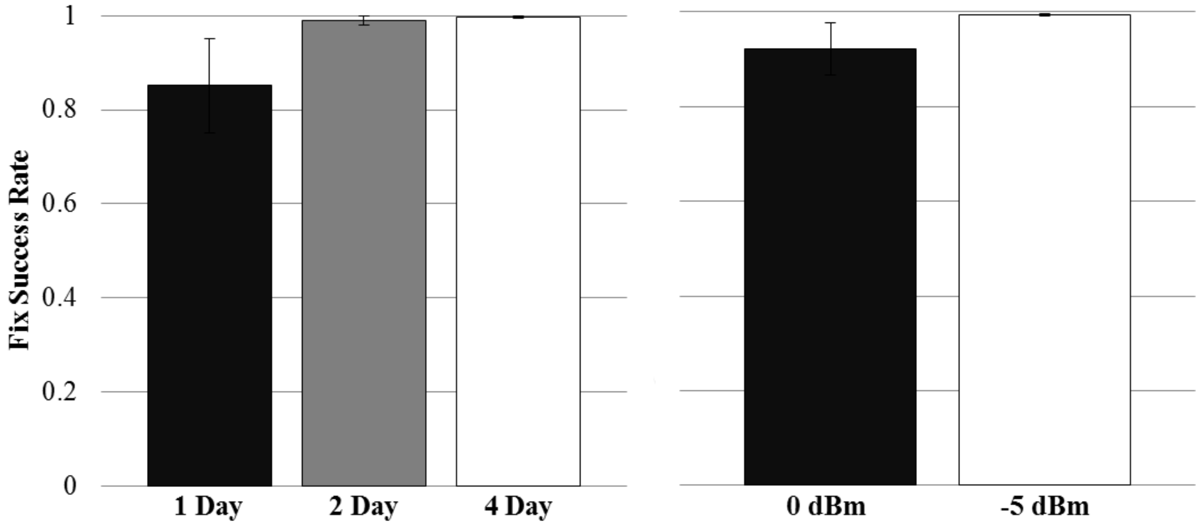

Figure 3.2. The nodes' ability to communicate with GPS satellites differed between trials (left) and power levels (right). Bars represent standard errors.

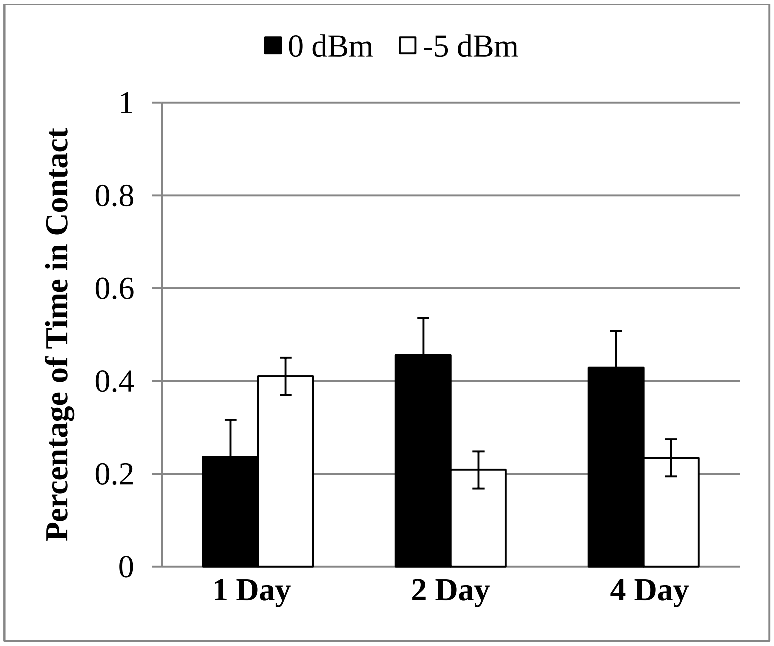

Figure 3.3. A node’s likelihood of being contacted depended on its power level setting, with high-power nodes being contacted more often. This was not the case during the 1-day trial, where lower-power nodes were contacted more often. Bars represent standard errors.

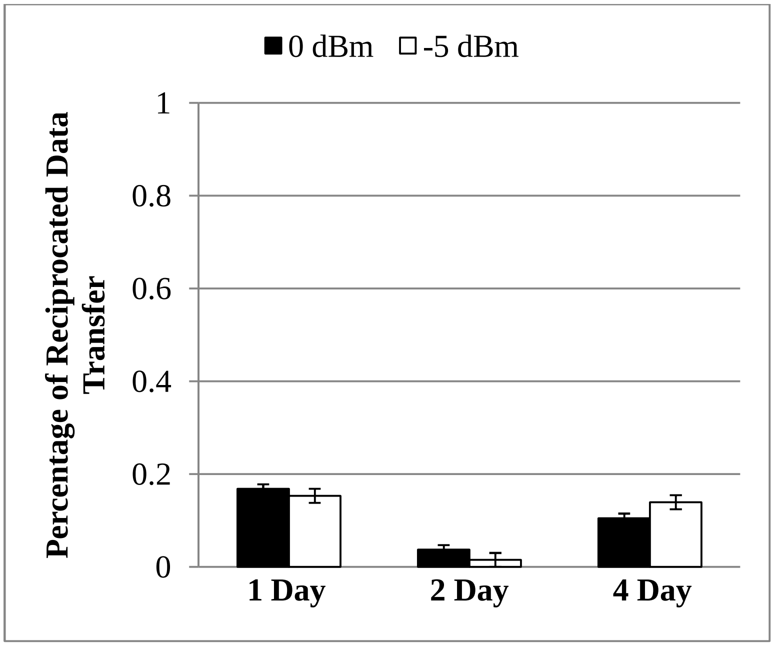

Figure 3.4. Percentage of reciprocal contacts by trial and power level. Reciprocal contacts occurred less frequently during the 2 day trial, but were not affected by power level. Bars represent standard errors.

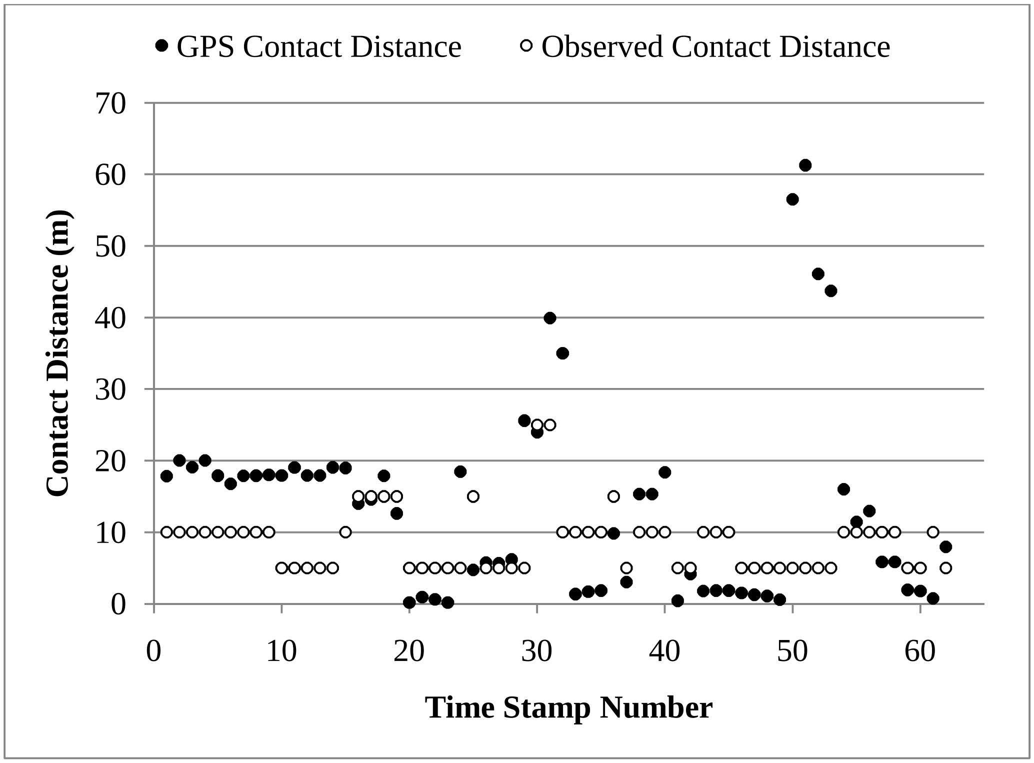

Figure 3.5. Contact distance error is represented as the distance between GPS contact distance (closed circles) and observed or "true" contact distance (open circles). This figure demonstrates several types of contact error, including GPS malfunction (~50 m difference), GPS rounding error (~10 m difference), and observational error (~5 m difference).

LITERATURE CITED

Beyer, D.E., and J.B. Haufler. 1994. Diurnal versus 24-hour sampling of habitat use. Journal of Wildlife Management. 58: 178-180.

Cadahia, L., V. Urios, and J.J. Negro. 2007. Bonelli’s eagle *Hieraaetus fasciatus* juvenile dispersal: hourly and daily movements tracked by GPS. Bird Study. 54: 271-274.

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

D’Eon, R.G., R. Serrouya, G. Smith, and C.O. Kochanny. 2002. GPS radiotelemetry error and bias in mountainous terrain. Wildlife Society Bulletin 30:430-439.

Fall, K. 2003. A delay-tolerant network architecture for challenged internets. Intel Research Technical. Report IRB-TR003-003, February 2003.

Festa-Bianchet, M. 1991. The social system of bighorn sheep: grouping patterns, kinship and female dominance rank. Animal Behavior42:71-82.

Frair, J.L., S.E. Nielsen, E.H. Merrill, S.R. Lele, M.S. Boyce, R.H.M. Munro, G.B. Stenhouse, and H.L. Beyer. 2004. Removing GPS collar bias in habitat selection studies. Journal of Applied Ecology 41:201-212. Geist, V. 1971. *Mountain Sheep: a Study in Behaviour and Evolution.* Chicago: Chicago University Press.

Hamede, R.K., J. Bashford, H. McCallum, and M. Jones. 2009. Contact networks in a wild Tasmanian devil (*Sarcophilus harrisii*) population: using social network analysis to reveal seasonal variability in social behaviour and its implications for transmission of devil facial tumour disease. Ecology Letters 12:1147-1157.

Hansen, M.C., and R.A. Riggs. 2008. Accuracy, precision, and observation rates of global positioning system telemetry collars. The Journal of Wildlife Management 72:518-526.Ji, W., P.C.L. White, and M.N. Clout. 2005. Contact rates between possums revealed by proximity data loggers. Journal of Applied Ecology 42:595-604.

Kjær, L.J., E.M. Schauber, and C.K. Nielsen. 2007. Spatial and temporal analysis of contact rates in female white-tailed deer. The Journal of Wildlife Management 72:1819-1825.

Klingbeil, L., and T. Wark. 2008. A wireless sensor network for real-time indoor localisation and motion monitoring. Pages 39-50 *in* Proceedings 2008 international conference on information processing in sensor networks. Washington, DC, USA.

Lawler, A. 2000. Scientists gain access to sharper GPS signal. Science. 288:783.

Prange, S., T. Jordan, C. Hunger, S.D. Gehrt. 2006. New radiocollars for the detection of proximity among individuals. Wildlife Society Bulletin 34:1333-1344.

R Core Development Team. 2006. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available from: <http://www.R-project.org>.

Rodgers, A.R., R.S. Rempel, and K.F. Abraham. 1996. A GPS-based telemetry system. Wildlife Society Bulletin. 24: 559-566.

Schauber, E.M., D.J. Storm, and C.K. Nielsen. 2007. Effects of joint space use and group membership on contact rates among white-tailed deer. The Journal of Wildlife Management 71:155-163.

Shah, H., and Y.P. Kosta. 2010. Evolution or routing techniques, routing protocols, and routing efficiencies for delay tolerant network. International Journal of Computer Applications. Special issue on MANETs: 46-53.

Veres, A., A.T. Campbell, and M. Barry. 2001. Supporting service differentiation in wireless packet networks using distributed control. IEEE Journal on Selected Areas in Communications 19:2081-2093. *Associate Editor*

GLOSSARY

Activity Logger: A wildlife telemetry device uses an accelerometer to track the 2- or 3-dimensional movements of individuals at a particular location.

Biologger: A wildlife telemetry device used to gather information about an animal's health and energy expenditure, and/or its environment.

Base Station: A wireless node installed at a fixed location to collect data in the field.

Communicating Node: The node requesting to send data in a reciprocally communicating pair.

Contact Distance Error: The difference between the true contact distance and the GPS-logged contact distance of a communicating pair of nodes.

Contact Error:Includes erroneously-logged contacts, or true contacts that are not picked up by the delay tolerant network. See also *Contact Distance Error*.

Delay Tolerant Network:A wireless network that uses "store-and-forward" architecture to transfer data under conditions of interrupted connectivity.

Fix Success Rate:The likelihood of obtaining a GPS fix with 3 or more satellites.

General Positioning System (GPS):A satellite-based navigation system that provides location and time information.

Maximum Distance of Data Transfer: The maximum distance that data can be transferred between two nodes for a given power level. See also *Power Level*.

Maximum Possible Data Transfer: The maximum amount of data that can be transferred between two nodes, assuming some level of packet loss. See also *Packet Loss*.

Multihop Data Transfer:Data transfer across multiple nodes to enable data redundancy, or to funnel data to a specific node or base station.

Optimum Distance of Data Transfer:The furthest distance apart two nodes can communicate at a specific power level before more than 10% of packets are lost. See also *Packet Loss, Power Level*.

Packet Loss: The amount of data (packets) lost during a data transfer event.

Power Level:See *Transmission Strength*.

Proximity Logger: A wildlife telemetry device used to monitor the frequency and duration of contacts between two or more individuals.

Recipient Node: The node receiving data in a reciprocally communicating pair.

Reciprocal Contact: A contact in which two nodes are transferring data to each other at the same time.

Sensor Node: A piece of a wireless sensor network used to gather information and communicate with other nodes in the network.

State-Centric Telemetry: Wildlife telemetry that can be used to monitor physiological condition, to reveal social networks, and to observe fine-scale habitat choices. Includes biologgers, activity loggers, animal-mounted cameras, and proximity loggers.

Telemetry:Technology that allows measurements to be made at a distance.

Transmission Strength: The magnitude of the electric field generated by a wireless antenna.

Wireless Sensor Network:A type of delay tolerant network that consists of communicating sensor nodes used to monitor physical or environmental conditions.