Modeling the relationships between patterns of movement of Panthera tigris and its behavioral states

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Introduction

The availability of high-resolution spatial and temporal information from GPS collars on animals provides us with a new source of spatio-temporal data and enables us to better understand the relationship between an animal's behavioral state (e.g. hunting, mating, home range protection) and its patterns of movement at different spatial and temporal scales (Ahearn and Smith, 2005). There have been a number of studies that have used GPS to examine the pattern of habitat use (Merrill 2000, Blake et al. 2001) and a limited number that have used it to quantify the nature of movement and its relationship to behavioral states (Brillinger et al. 2004, Franke, Caelli, and Hudson 2004, Franke et al. 2006; Jonsen et al. 2003). A key question with respect to these models is: how well do they capture the complexity of the movement and behavior of individuals as they relate to the environment in which they move, the other individuals with whom they interact and their own geographic strategies for resource usage (Ahearn and Smith, 2005). For this discussion, we will concern ourselves with the Hidden Markov Model (HMM), as this type of model has the interesting properties of imputing behavior and movement characteristics from a spatio-temporal signal. We will also examine ten spatial-temporal tiger data sets that represent a range of behavioral states and environmental conditions (e.g. females with different aged cubs, dispersing females, and male movement in relation to territorial boundaries) in the context of what constitutes a benchmark data set.

Data

Our data sets are composed of 2 elements: 1) the location and time of successive GPS locations and 2) the behavior of individuals at times when a particular movement pattern is observed.

Nine tigers were collared with GPS over the period of 6 years. These included six females and three males. Three females had young ranging from new born up to 10 months old. A forth female was a non-breading disperser and appeared to avoid prime habitat where encounters with resident females was more likely. The three males had home ranges encompassing 3 and 4 females and spent more time near territorial boundaries than in the interior of their territories. GPS locations were obtained at one hour intervals for six tigers, two of the three other tigers were collared twice and locations on these three tigers were attempted at 1, 2, 4 and 6 hour intervals. The number of samples ranged from 533 to 2939 for each tiger. Durations of collection ranged from 4 months to over a year (Table 1).

Our first behavior associated with a movement pattern is an obvious one, feeding. We infer feeding by going to a location where a tiger has been stationary for > 8 hours. If we find a kill we infer that the kill was made at the time the tiger arrived at that location. GPS/Iridium collars provide us with the opportunity to investigate the spoor of tiger (e.g. tracks, scrapes, scent marks, kills, mating sites and dens) from which we can infer behavior. For example, we have observed along a sandy stream bed 22 locations where tigers copulated. To obtain a large data set of identified behaviors associated with movement data requires traditional natural history skills. We are also developing visualization tools that will assist us in labeling patterns of movement with behavior based on expert opinion and these ground observations.

Animal id	Name	Date collared	Date last location	Location interval	Location number	% successful locations	Collar type
TF4		2/15/2005	8/16/2005	2 hr	603	n/a	ATS
TF5-1		7/1/2005	12/6/2005	2 hr	533	n/a	ATS
TM1-1	Bart	5/28/2005	8/15/2005	1 hr	614	49.7	ATS
TF5-2		11/21/2006	3/1/2008	6 hr	760	49.3	Telonics
TM1-2	Bart			4 hr			Telonics
F7204		9/30/2009	3/12/2010	1 hr	2679	90.3	Vectonic
F7203		12/8/2009	active	1 hr	2536	96.4	Vectonic
F7823		2/11/2010	active	1 hr	1471	94.5	Vectonic
F7835			active	1 hr	960	94.4	Vectonic
M6090	Mike	4/10/2009	8/6/2009	1 hr	2939	76.6	Vectonic
M6089	Mark	4/5/2009	6/21/2009	1 hr	1235	80.8	Vectonic

Table 1. Tigers radio collared in Thailand. Six data sets from Vectronic collars attempt locations at 1 hour intervals and 76-96% success rate allows fine grained daily to monthly analysis of movement patterns.

Environmental variation and relation to resource use

Tiger home range size is hypothesized to be primarily a function of abundance and accessibility of prey 50% to greater than 100% the size of a tiger. Prey abundance is in turn related to ecological variables including vegetation type, soil quality, ruggedness and distance from water as well as anthropogenic factors such as forest degradation, subsistence hunting and poaching of tigers. For females home range sizes ranged from

26 to 93 km^2. For males the range was from 191 to 278 km^2. Home range size and physiographic configuration impact patterns of movement and these factors need to be considered when establishing benchmark data sets. For example, one female had a donut shaped home range as a consequence of a large steep hill with low prey abundance in the middle of her home range. Another young tigress' movements were constrained by the locations of 11 caves where she repeatedly sought refuge during the day.

Quantitative Models for relating patterns of movement with behavioral states

Hidden Markov Models (HMM) are in a class of stochastic signal models that characterize the statistical properties of a signal. They are an extension to the idea of discrete Markov chains, which estimate the probabilities of state transition sequences. In Markov chains, each state relates to an observable, physical event. In contrast, in HHM the observation is a probabilistic function of the state, which results in a doubly stochastic process where one process is observable and one is hidden. The ergodic HMM assumes that every state can be reach from all other states (Rabiner et al. 1989).

HMMs are characterized by a number of parameters: N, the number of states in the model; M, the number of distinct observations; A, a state transition matrix; B, the observation probability distribution; and, the initial state distribution. HMM is often described by ($\lambda = \pi$, A, B).

For theoretical reasons, good initial estimates of state transitions are necessary to ensure optimal model parameterization, with particular importance given to good initial estimations of B. There are various techniques for making estimates, including manual segmentation of observation sequences, maximum-likelihood segmentation with averaging, and segmentation with k-means clustering (for a definitive review of HMM, see Rabiner et al. 1989). As we discuss below, selecting the number of states for the A matrix often requires significant information on the state and associated behavior of the animal being modeled. Selection of what constitutes the hidden "signal" is another critical aspect of development of the HMM.

HMM FOR TIGER MODELING

The conceptual model for the tiger reveals the complexity of the relationship between the tiger's state and its behavior (Ahearn and Smith, 2005). In considering the use of HMM for imputing tiger behavior from movement and in generating movement a number of issues arise: Can a tiger's movement be described by a first-order Markov process? How are different temporal scales accommodated? Are there state changes that result in the generation of different movement rates and patterns for the same behavior (i.e. female hunting patterns with and without cubs)? Are certain behaviors and therefore movement patterns dependent on the state of other entities? Some answers to these questions will be part of our presentation as well as our methodology for implementation of an HMM based analysis.

Conclusion

We will present data from nine tigers in a variety of biological states and environmental conditions to try to understand what might constitute a benchmark data set. We will also discuss a quantitative model for relating patterns of movement to behavior based on an HMM and explore its strengths and weakness.

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