A computational movement analysis approach for modelling interactions between pairs of moving objects

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Abstract

A better understanding of how individuals of an animal population interact is a fundamental aspect of a species' behavioural ecology and information on the frequency and duration of these interactions is an important component of their spatial ecology relating to mating and territorial behaviour, resource use, and the spread of epizootic diseases. There have been two main ways to quantify interactions in wildlife studies: 'static interactions', which involve measuring the degree of home range overlap (and are therefore just spatial), and 'dynamic interactions' which are defined as occurring within a spatial and temporal threshold. However, the amount of overlapping home ranges is not a reliable indicator of the degree of actual interaction between two individuals, therefore dynamic interactions are much more appropriate for assessing interaction behaviours such as attraction and avoidance of individuals that are in the same area at the same time and are far more useful for understanding how two individuals interact in the context of disease transmission and behavioural ecology. As they involve comparisons based on both space and time, dynamic interactions are more problematic to measure and recent studies have indicated a lack of congruence among dynamic interaction metrics when they have been compared with the same data (Miller, 2012; 2015, Long and Nelson, 2013; Long et al. 2014).

Dynamic interactions are measured using data representing an individual's location along with a time stamp (e.g., GPS, VHF) and the two main approaches involve comparing the point locations or the paths or trajectories that are inferred as connections between subsequent points. In this research I present results that compare existing dynamic interaction metrics and provide a new way to interpret them based on a null model approach. I also provide preliminary results that combine point-based interactions in order to explore path-based movement parameters in order to identify interaction movement behaviours such as following and avoiding.

Key words: movement pattern analysis, spatiotemporal, trajectories, null model, interaction, random walk

1. Introduction

High quality movement data are increasingly available for many different types of animals (ex. www.movebank.org), facilitating unprecedented access to insights about environmental influences on movement and how movement changes with different behaviours. In addition to increased spatial accuracy and temporal resolution of the locational information, technological advancements have facilitated the collection of ancillary behavioural and physiological information as well as photographs and video that can be used to annotate movement data (Rutz and Hays 2009). 'Computational movement analysis' (CMA) has recently emerged as an extension of time-geography that focuses on the development and application of computational techniques for collecting, managing, and analyzing movement data in order to better understand the processes that are associated with them (Gudmundssen et al. 2012). Animal telemetry studies have been used to collect location data for several decades, while CMA applications have focused more often on human movement, such as using travel diaries to better understand mobility and space use and studying potential exposures to environmental hazards. Concurrently, 'movement ecology' has become a rapidly growing subfield in ecology focused on understanding the "causes, mechanisms, and spatiotemporal patterns of (organismal) movement and their role in various ecological and evolutionary processes" (Nathan et al. 2008: 19052). In spite of the fact that both subfields deal with similar issues related to spatiotemporal representation and analysis, scale, uncertainty, and inferring process from pattern, there has been surprisingly little 'interaction' between researchers in different subfields.

The ability to measure interactions, or the degree to which the movement of an individual is dependent upon that of other individuals, is crucial to understanding behaviours related to territoriality and mating as well as resource use and infectious epizootic diseases. 'Dynamic interaction' (Doncaster 1990) between two individuals occurs within a spatial and temporal threshold and can provide information on possible attraction and avoidance of individuals that are in the same area at the same time, which is important in the context of investigating disease transmission and spatial ecology.

1.1. Modeling dynamic interactions

Dynamic interactions are measured based on either the point data or the paths or trajectories that are inferred as connecting subsequent points. When point data are used, an interaction is defined by using the distance between the two individuals (e.g., the mean distance of all pairs or the number of times a pair is within a critical distance) or their occurrence in the overlapping portion of their home range. While these point-based dynamic interaction metrics involve the concept of two individuals occurring "together", path-based interaction metrics use movement trajectories as the basic unit of analysis and compare similarity in movement parameters such as speed, direction, and mean displacement (Calenge et al. 2009). However, path-based metrics define interaction solely in terms of movement similarity based on simultaneous fixes (same time) and do not consider the distance between the two individuals or their location relative to designated spaces such as home range overlap.

Both point- and path-based dynamic interaction metrics have limitations that prevent robust and meaningful analysis of interactions. Point-based interaction metrics are often based on highly subjective factors such as home range delineation or a distance threshold. Distance thresholds can be based on previous research or observation, and there have been suggestions for ways to empirically derive them that have not been fully explored (Doncaster 1990; Haddidi et al., 2011). Temporal thresholds are also subjective but are often based on the resolution of the GPS data. Path-based metrics involve fewer subjective decisions, but what they are measuring in terms of 'interaction' is really path similarity irrespective of spatial proximity and may not be appropriate for some applications. Both point-based and path-based metrics lack a benchmarking framework that deals with expected values and allows for more meaningful interpretation of their values including the ability to quantify the degree of interaction relative to neutral interaction or independent movement.

In spite of the importance of measuring dynamic interactions, they have not been a main research focus in movement analysis. Few studies have tested different dynamic interaction metrics using the same data, and when they have been compared, the results have been quite incongruous (Long and Nelson 2013, Long et al. 2014; Miller, 2012; 2015). Some of the issues can be traced to the significant difference in spatial and temporal resolution of movement/location data when many of these dynamic interact metrics were developed (~1980-1990s). This research focuses on improving the interpretation of existing dynamic interact metrics as well as introducing a method that harnesses advantages from both point- and path-based dynamic interaction metrics.

2 Methodology

The research presented here borrows from the null model approach commonly used in community ecology to compare observed (empirical) dynamic interaction values with distributions of expected values generated by using different null models in order to interpret the interaction metrics, as well as limitations associated with their current implementation. Using GPS collar data from five brown hyena dyads in Northern Botswana (see Miller 2012) this research explores the use of four different types of null models with which to compare the existing dynamic interaction metrics:

- ***Random dates-*** refers to methods that involve using coordinate values of actual locations, but randomly shuffling them or measuring interactions for pairs of coordinates that did not actually occur at the same time.;
- ***Rotated trajectories-***involves randomly rotating and shifting actual movement trajectories so that a path is maintained but it is located randomly in the study area;
- ***Correlated random walk-*** involves simulating trajectories that are parametric, but include 'persistence' by specifying a turn angle concentration and a step length parameter;
- ***Bivariate Brownian movement-*** involves simulating a purely random trajectory that has only a dispersion parameter that is empirically estimated.

Observed dynamic interaction values for each of the five dyads are compared to the null distribution generated by the four methods described above. This facilitates improved interpretation of existing interaction metrics. For example, one of the DI metrics tested here, the half-weight association index (HAI) is calculated as

$$\boldsymbol{HAI} = \frac{n}{n+1/2(x+y)} \quad \text{(Equation 1)}$$

where *n* is the number of GPS fixes for two individuals that are within a temporal and spatial (distance) threshold and *x* and *y* are the number of times each of the individuals was located in the overlapping area of their home ranges without the other. ***HAI*** values range from 0, for pairs that are never located within the distance threshold to 1, for pairs that occur exclusively together. There is no inherent null model value (and therefore no test of statistical significance), and as the number of observations increases, the denominator is likely to increase making it difficult for an ***HAI*** value to be close to 1. Comparing observed ***HAI*** values to a null expectation can improve its ability to distinguish between no interaction and positive interaction (Miller 2015).

Additionally, a new hybrid method that incorporates both point-based and path-based concepts is tested. Movement trajectory parameters such as relative angle and step length are compared relative to a point-based interaction defined by a spatial and temporal threshold. Significant differences in these parameters can be used to identify potential movement behaviours such as attraction and avoidance.

2. Preliminary results

The new hybrid method introduced here uses GPS locations representing point-based dynamic interactions (two individuals within a spatial and temporal threshold) to compare path-based movement trajectories relative to the "interaction". Figure 1 shows the distribution of relative turning angles for two brown hyena individuals (Cyril and Honey) relative to when a spatio-temporal "interaction" occurred: the angles for the steps that occurred right before an interaction are in blue; all other angles are in red. These preliminary results suggest that both individuals use more tortuous movement (relative angles between 150-210 degrees) right before they are close in space and time compared to all of their other movements.

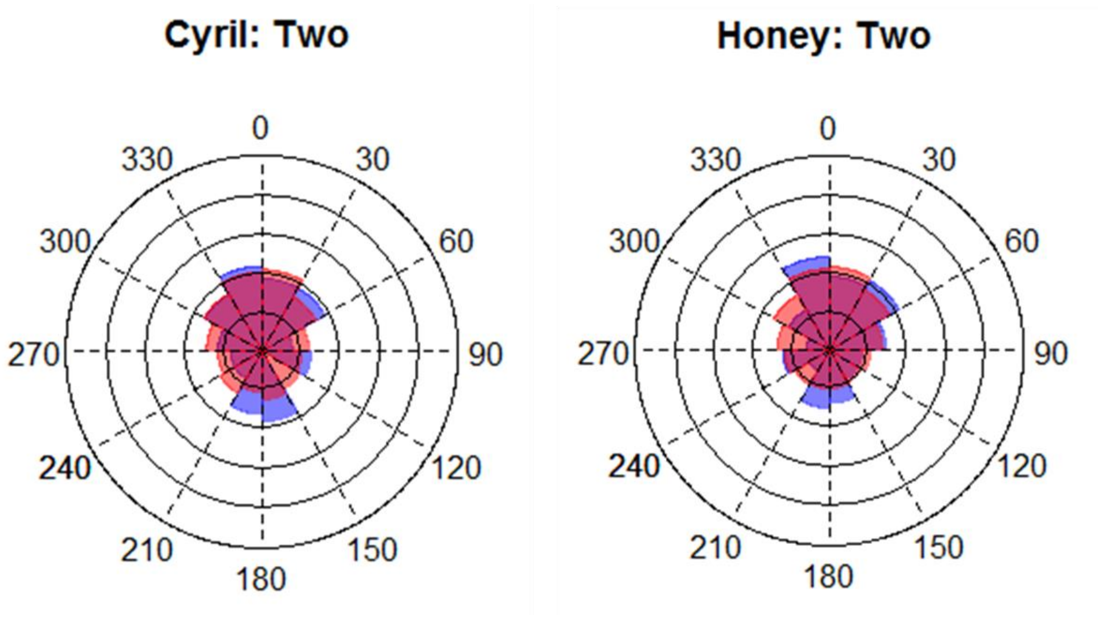

Figure 1: Distribution of relative turning angles for two hyenas (Cyril and Honey). Blue represents the angles one step before an "interaction" occurred and red represents the angles for all other steps.

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