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Quantifying spatio-temporal interactions of animals using probabilistic space–time prisms

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ABSTRACT

Probabilistic space–time prisms are a recent development in time geography. They can be used to determine the probability of an object's location at any time given tracking data that record information about its whereabouts periodically. This paper extends this approach in order to quantify probabilities of interaction for two or more individuals that have tracking data for overlapping time periods. The method relies on using a voxel-based representation of the probabilistic space–time prism. Equations for computing interaction probabilities from the intersection of overlapping space–time prisms are formulated for single voxels, each time step, each raster cell, and for the tracking duration overall. The approach is illustrated using tracking data for three zebras. Probabilistic space–time prisms are mapped simultaneously for all three zebras, and the resulting interactions are summarized using probability clocks and maps. The results show when and where each pair of zebras, or all three zebras, were most likely to have physically interacted with one another. Implications of this research in GIScience, ecology, and other disciplines are also discussed.

Introduction

Quantifying interactions between mobile objects, such as animals or people, is a common task in GIScience, ecology, and a variety of related disciplines. In terms of animals, both intraspecies (among individuals of the same species) and interspecies (between individuals of different species) interactions are of interest (Lowrey & Longshore, 2013; Potts, Harris, & Giuggioli, 2013; Shemesh et al., 2013). Animal interactions are important for understanding the life history requirements of species, which are important to conservation efforts, as well as for explaining community dynamics and the evolutionary history of species (Bode et al., 2012; Eriksson, Nilsson Jacobi, Nyström, & Tunstrøm, 2010; Giuggioli, Potts, & Harris, 2011; Pettit, Perna, Biro, & Sumpter, 2013). Interactions are also well studied for people, as they are essential to understanding human behaviour, social networking, and accessibility patterns (Miller, 2005b). From a purely spatial perspective, interactions also present an interesting analytical problem, because two individuals must be located at the same place at the same time to physically interact.

There are numerous approaches to quantifying co-location and evaluating potential for physical interactions among individuals using tracking data. In ecology, two main approaches are used: home range overlap and frequency of co-location. Home ranges describe the physical area occupied by an individual animal and are typically estimated from tracking data using GIS-based techniques (Downs & Horner, 2008, 2009; Downs, Horner, & Tucker, 2011; Kernohan, Gitzen, & Millspaugh, 2001; Worton, 1987). Home range overlap measures the amount or percentage of space shared by two individuals (Olsen, Downs, Tucker, & Trost, 2011). As this measure does not factor in any temporal information, it only gives a measure of potential interaction because two animals can use the same places but at different times. However, if two animals are tracked simultaneously with the same temporal sampling scheme, then a more useful approach is to quantify how often they are located at the same place at the same time. Additionally, this frequency of co-location can be compared to the number expected under a correlated random walk model to determine if interaction occurs more often than expected by chance (Miller, 2012). The main limitation of this approach is that interactions are only evaluated if tracking points for individuals are collected at identical times, as interactions are not estimated at unsampled intervals.

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In GIScience, time geography serves as the cornerstone approach for quantifying potential interactions of objects, particularly people. Specifically, space–time prisms map the potential locations of an object over space and time within a “net” of spatial, temporal, and physical constraints that limit its movements (Hägerstrand, 1970; Miller, 2005a). Space–time prisms have been instrumental for analyzing movements of people and have contributed numerous insights into understanding human behaviour and interaction (Horner & Wood, 2014; Kwan, 1998, 1999; Miller, 1991, 2005b; Neutens, Witlox, De Weghe, & De Maeyer, 2007; Shaw, Yu, & Bombom, 2008). Even with the demonstrated applicability of space–time prisms, recent advancements have transformed time geography into an even more powerful methodological approach by enabling probabilities to be assigned to those potential locations within the prism. Probabilistic space–time prisms estimate the probability of an object's location in continuous time given tracking data that record information about its whereabouts at periodic, discrete times. The concept of a probabilistic space–time prism was introduced by Winter and Yin (2010a, 2010b), while Downs, Horner, Hyzer, Lamb, and Loraamm (2013) developed a voxel-based approach for its geocomputation. This paper extends the voxel-based approach to support the computation of interaction probabilities for two or more individuals that have tracking data for overlapping time periods but not necessarily the same temporal sampling scheme.

First, a procedure for computing voxel-based space–time prisms is reviewed, since the approach described in this paper relies on this representation. Second, equations for computing interaction probabilities from intersected probabilistic space–time prisms are presented. Third, the approach is demonstrated using tracking data for three individual zebras tracked over a 60-h period in the same study area. Then, the resulting probabilistic space–time prisms for all three zebras are intersected to compute interaction probabilities for single voxels, each time step, each raster cell, and for the tracking duration overall. Finally, implications of this research in GIScience, ecology, and related disciplines are also discussed.

Background

Time geography is a cornerstone approach for analyzing mobile objects in GIScience. Basic elements of time geography include control points, the space–time path, and the space–time prism (Miller, 2005a; Miller & Bridwell, 2009). Control points, or tracking data, record an object's location periodically over time. The space–time path traces the estimated trajectory of an object through space and time by connecting successive control points with straight lines. The space–time prism maps the potential movements of an object about the space–time path given its maximum velocity. The prism is composed of an infinite number of space–time disks which delineate the set of possible locations for an object at each time instance. The relative size of the disks reflects the uncertainty of the object's location. Recent advancements in time geography enable the computation of probabilistic space–time prisms which record locational probabilities within each space–time disk. This allows the probability of an object's location to be quantified at any instant in time. Winter and Yin (2010a, 2010b) first introduced probabilistic space–time prisms. Recent work by Song and Miller (2013) has provided an additional theoretical basis for probabilistic space–time prisms, while Downs et al. (2013) provided the voxel-based geocomputational procedure that is used in this paper.

A voxel-based representation of space–time prisms facilitates their geocomputation. In GIScience, voxels, or cubic volume elements, are commonly used to model three-dimensional data, such as terrain. Space–time prisms can be generalized using voxels in three-dimensional space–time. Here, each individual voxel represents a spatial area (*i.e.* a raster cell) at a specific time interval. Once voxels in a study area are defined based on the desired spatial and temporal resolution, a space–time prism is computed by determining which spatial locations are accessible to the object at each time given a set of control points and its maximum velocity. Traditional time geography equations are used to compute the prism, with the exception that all calculations are performed at the voxel centroids, with the resulting values generalized to the rest of the voxel. The voxel centroids correspond to the geometric centres of each raster cell and the midpoint of each temporal interval. In practice, each voxel is encoded with a 1 or 0 to indicate whether it is contained in the prism or not, and the prism is geovisualized using the voxel centroids. Mathematically, a space–time prism (*STP*) can be formulated for each voxel, denoted l_{ba} (Fig. 1), using the following equation, as per Downs et al. (2013):

$$STP_{l_{b,a}} = \begin{cases} 1, & \text{if } \|x_a - x_i\| \le (t_b - t_i)v \text{ and } \|x_j - x_a\| \le (t_j - t_b)v \\ 0, & \text{otherwise} \end{cases}, \tag{1}$$

where:

$C = \{c_1(t_1, x_1), \ldots, c_i(t_i, x_i), c_j(t_j, x_j), \ldots, c_n(t_n, x_n)\}$ denotes the set of n tracking data points, where each control point c is indexed as i with timestamp t_i and spatial location x_i. Control points immediately following c_i are denoted c_j with timestamp t_j and location x_j.

$R = \{r_1(x_1), \ldots, r_a(x_a), \ldots, r_m(x_m)\}$ denotes the set of m raster cells r in the study region, where each raster cell indexed as a, where raster cell r_a has spatial location x_a recorded from its centroid.

$K = \{k_1(t_1), \ldots, k_b(t_b), \ldots, k_q(t_q)\}$ denotes the set of q time intervals k indexed as b, where timestamp t_b is recorded at the midpoint of the time interval k_b. In other words, k defines the height of the voxel in units of time; the time (t_b) recorded for each voxel is derived from the midpoint of that interval.

$L = \{l_{11}(k_1, r_1), \ldots, l_{ba}(k_b, r_a), \ldots, l_{qm}(k_q, r_m)\}$ is the set of voxels l that contains the space–time prism indexed as ba, where voxel l_{ba} corresponds to raster cell r_a at time interval t_b. L_k is used to denote the subset of voxels for a particular time interval, or space–time disk. L_r is used to denote the subset of voxels for a spatial location or raster cell.

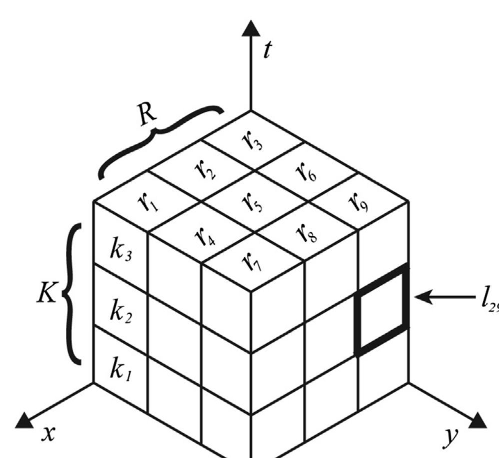

Fig. 1. Notation of raster cells (r) and time steps (k) in a space–time prism composed of voxels (l) arranged in space (x, y) and time (t).