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# An Algorithm for Empirically Informed Random Trajectory Generation Between Two Endpoints

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## **Abstract**

We present a method for enabling the researcher to create empirically informed, and thus realistic, random trajectories between two endpoints. The method used relies on empirical distribution functions, which define a dynamic drift expressed in a stepwise joint probability surface. We create random discrete time-step trajectories that connect spatiotemporal points while maintaining a predefined geometry, often based on real observed trajectory. The resulting trajectories can be used a)to generate null models for hypotheses testing, b)as a basis for resource selection models, through the integration of spatial context and c)to quantify space use intensity.

### 1. Introduction

Random trajectories have been increasingly used in movement ecology since their introduction in the early 1980s (Kareiva and Shigesada 1983), gaining significant popularity in the last two decades (Turchin 1998). A wide range of case studies have used the concept, addressing multiple questions related to movement and space use. The majority of the examples found in the literature, however, share one characteristic: the movement has only one restrictive point, the start. Consequently, the simulation is forced to start at a specific location, but can then move according to the set conditions in the given space. In the real world however, this is not always useful: when studying migration patterns (Codling *et al.* 2010), nest borrowing (Waldeck *et al.* 2008), or fusion of high and low frequency GPS points, etc. the ability to specify the ending point is crucial. Technitis *et al.* (2015) introduced RTG, an algorithm that enables the user to create randomly varying, possible trajectories between endpoints, based on principles of Time Geography.

In this paper we substantially extend this algorithm. We present a methodology to connect two endpoints by generating empirically informed random trajectories, respecting characteristics of the moving object. Our approach is based on core theoretical concepts of Time Geography in combination with the Random Walk movement model, and most importantly, we use empirical data to inform our modelling process.

## 2. Background

Space-time prisms (STP) assist us in calculating the points accessible in space, given the time budget and the maximum speed of an agent (Kuijpers,  $et\ al.\ 2010$ ). The calculated path space (in three dimensions defined by x,y and t), and more specifically its 2-D spatial projection, also known as potential path area (PPA), is a homogenous area within which the trajectory lies. The concept of the STP is very intuitive, although it accounts only for the maximum speed of the mover, gives no information regarding the preference of the mover within the given boundaries, and the result is an area, not an individual trajectory.

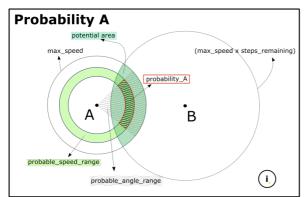
Bartumeus *et al.* (2005) highlighted the need for movement ecology to add directional persistence into movement modelling, in order to reproduce realistic animal movement, as noted previously by others (Kareiva and Shigesada 1983; Bovet and Benhamou 1988).

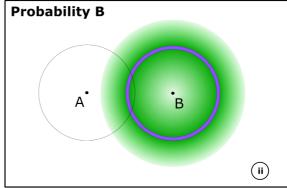
Aiming at this gap, Fleming et al. (2014) described a framework that supports the estimation of auto-correlated movement processes, which was later used in home range estimation. Finally, Technitis et al. (2015) presented an algorithm capable of efficiently generating random trajectories between a given origin and destination, with the least bias possible, within the bounds of the STP, honoring speed and time-budget limitations. The significant assumption of this algorithm is that for each step all space-time reachable points are equally probable to be selected. The trajectories derived from this algorithm are all possible, yet not all of them realistic, as they ignore typical movement characteristics of the moving object. In summary, the direction that movement modeling is taking in ecology seems clear: starting from random walk models, these were successively extended by STP principles and point-to-

In summary, the direction that movement modeling is taking in ecology seems clear: starting from random walk models, these were successively extended by STP principles and point-to-point constraints. However, what is still missing is the integration of empirically informed movement parameters that can lead to realistic trajectories.

## 3. Algorithm

Our algorithm generates trajectories with given set of movement characteristics between two points, in discrete time-steps. The main motivation for creating probable trajectories is that these points represent an arbitrary pair of consecutive fixes of a trajectory, typically placed at a significant distance due to coarse sampling rate. Both points exert an effect on the agent's movement, though of different nature: the probability based on the starting point(A) expresses the 'local' decisions of a moving individual, such as the step-length and direction used for each relocation, performing a correlated random walk with fixed starting point, that assumes no a priori knowledge about the context of the movement (e.g. resource distributions).





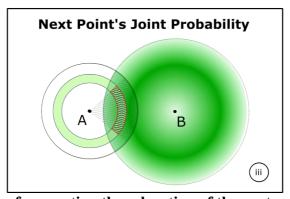


Figure 1. Workflow of generating the relocation of the next point of a trajectory.

On the other hand the probability based on the ending point(B), is a gravitational-type reminder, that the mover should head towards the desired endpoint. Depending on the time left and the current location this force is adjusted and acts as a dynamic drift parameter, applying the necessary bias towards the destination. The model can be described by a meanreverting Ornstein-Uhlenback process in which "individuals [are] drifting randomly but attracted to an average point" (Smouse et al. 2010). The intensity of the attraction becomes higher, as time is running out, ensuring that the mover is within reach of the destination at any point in time. The flow of the methodology has three steps. First we pre-process the recorded data and calculate the summary statistics of the movement characteristics. Next, starting from the origin, Figure 1.i, we calculate for each time step the probability surface based on the movement characteristics extracted. Then, we calculate the attraction to the destination for the entire study area (Figure 1.ii) given the remaining number of steps to the end point, resulting in a probability surface for each time step. The number of time-steps(n) is the quotient of the duration of the walk and the simulation time interval set by the user. The last step is to combine the two surfaces into a joint probability (Figure 1.iii) out of which we sample the next location of the individual. The procedure is repeated over all time-steps, generating in a new trajectory.

## 4. Results and Discussion

The proposed algorithm was evaluated in depth on both synthetic and real data. We show an example using synthetic data, where we created three template trajectories using a correlated random walk, out of which our algorithm derived the empirical distributions of movement characteristics.

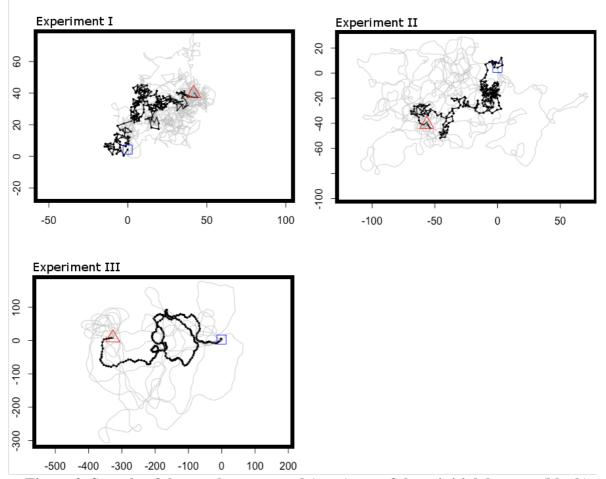


Figure 2. Sample of the results generated (gray) out of three initial datasets (black).

Each template resembles a different behavior of a potential animal, namely migration, foraging and opportunistic behavior. Figure 2 shows the simulated trajectories in gray and the created trajectories in black. While these illustrations suggest in a visual way that the simulated trajectories indeed resemble the original ones in their characteristics (though each takes a different path, as expected), we also conducted an in-depth statistical evaluation to establish that the empirical distributions of the generated trajectories on average match those of the original templates. The next step for this work is to optimize the algorithm's performance and incorporate the context's effect on the mover's behaviour.

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