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Context-sensitive spatiotemporal simulation model for movement

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Abstract

This paper presents a context-sensitive spatiotemporal model to simulate movement trajectories. The model incorporates both the correlated random walk and time-geography theories to generate a more realistic trajectory of an agent within its environment.

1. Introduction

Movement is an essential form of temporal change that is an integral characteristic of dynamic entities (e.g. humans, animals, vehicles, diseases). It is the focus of research in a range of application domains such as transportation, movement ecology, environmental studies, and human health. Movement models help us to better understand the characteristics of movement, enable us to simulate movement and predict its patterns (Dodge 2016). Examples of existing movement models include the random walk and its variations (Codling *et al.* 2008, Technitis *et al.* 2015), time-geography (Miller 2005, Song and Miller 2014), and Brownian Bridge (Horne *et al.* 2007) models. These models either generate trajectories using a set of geometric movement parameters (turn angle, distance), or they identify a visitation probability surface for an agent considering its speed and time budget. Existing models often disregard the characteristics of the environment or the context within which the movement takes place. Simulation of movement in relation to its embedding context is an essential problem that is applied to generate trajectories to fill gaps in low-resolution tracking datasets, or to examine behavioral responses of moving agents to environmental changes. This paper introduces a context-sensitive spatiotemporal simulation model based on a correlated random walk with external biases and is controlled by time-geography constraints of the moving agent. The novelty of the model is that at each step the simulation is driven by *behavior* and the *contextual factors* (i.e. environment, geography) that influence the local movement of the agent. As a case study, this research uses GPS observations of a tiger to parameterize the model and to simulate the tiger's movement between actual GPS observations.

2. Movement Simulation

The overall goal is to generate a trajectory (a sequence of spatiotemporal points) from a start location and time $S(x_s, y_s, t_s)$ to an end location and time $E(x_e, y_e, t_e)$. The simulation uses a correlated random walk from S with an external bias to move towards E (i.e. global constraints). The local movement at each *step* is driven by *agent's behavior* and *contextual factors*. The model specifications are: (1) the maximum movement speed is determined by behavior (e.g. patrolling, hunting, foraging, biking), (2) the global movement path and speed are controlled by the actual time-budget to reach the end-point, and (3) the path is influenced by agent's local choices based on context (environmental drivers and spatial constraints, -e.g. general movement direction, slope preferences, trail network).

The simulation algorithm runs on regular time intervals defined by the user, named *step time*, to ensure the global movement occurs within the time-budget ($tb = t_e - t_s$). The maximum speed of the agent (V_{max}) is determined based on expert knowledge or derived from GPS observations for the given behavior. At each simulation step, V_{max} is used to delimit a *possible terminal region (PTR)* as shown in Figure 1 (gray area). This is the area which the agent needs to move to by the end of the step to satisfy the time-budget and the global constraints of reaching the end-point. How the agent gets to that region is determined by the local choices it makes along the way. The model uses a raster (in this case a digital elevation model (DEM)) to integrate the influence of contextual factors (e.g. slope) on local movement choices (shown in Fig.1b).

As shown in Figure 1a, the step PTR (gray region) is calculated using the time-geography theory and V_{max} (Miller 2005) as the intersection of (1) the general *potential path area* (khaki ellipse) between the current point $I(x_i, y_i, t_i)$ and the end-point $E(x_e, y_e, t_e)$, (2) the farthest locations (d_{step}, red buffer) that can be reached at each step, and (3) the maximum possible distance (d_{left}) that can still remain to reach E and satisfy the time-budget (green buffer).

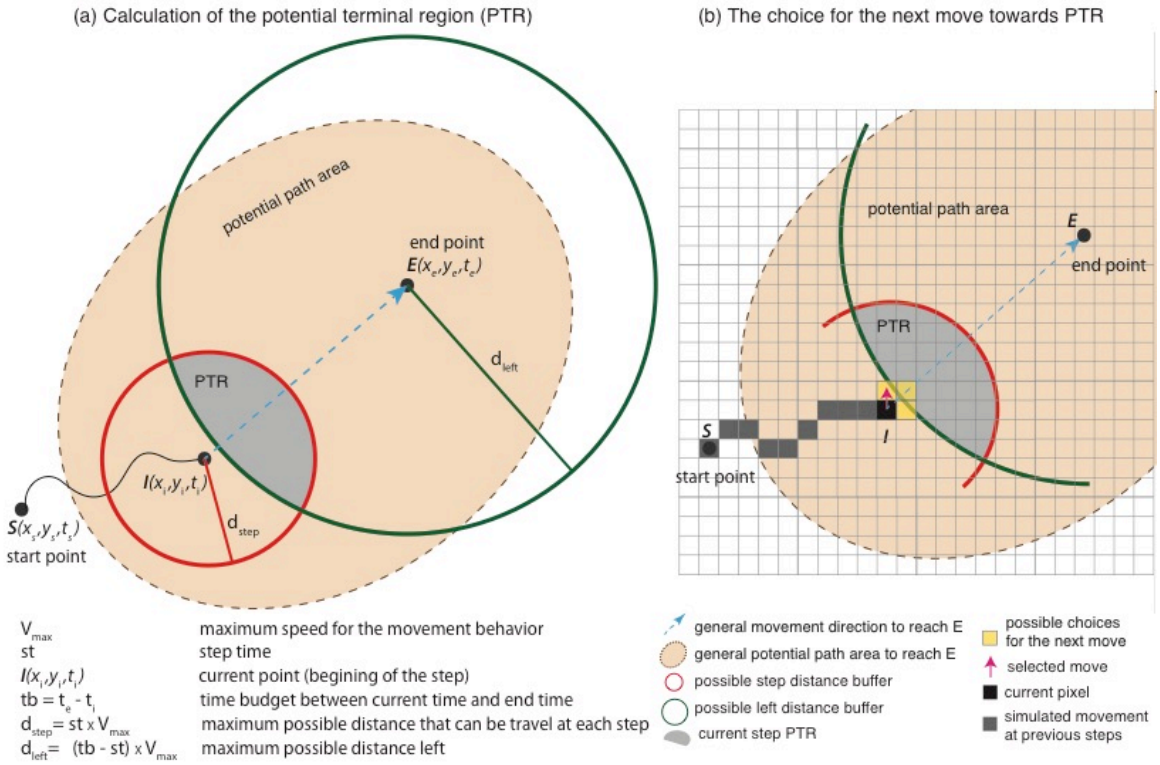

Figure 1. (a) Calculation of the potential terminal region (PTR) at each step, and (b) the choice for the next move towards PTR based on movement direction and context.

Following the calculation of the step PTR, the agent's movement proceeds from the current point I using a correlated random walk towards E. The deviation allowance from the general direction $\overrightarrow{IE}$ is drawn randomly from a normal distribution with a small δ (e.g. $X \sim N(0, 20°)$) to minimize backtracking. After the selection of movement direction, the associated pixel in that direction and its two neighboring pixels become possible choices for the next move (e.g. yellow pixels in Fig.1b). The move is then made based on the slopes of these three adjacent pixels calculated in the direction of movement. A random slope value is drawn from the χ^2 distribution of tiger slope use derived from actual GPS observations. From the three pixels the one with directional slope value closest to the random value is selected as the next move. The agent is moved to that pixel and the current simulation time is updated according to the speed and raster cell size. The simulation continues pixel-by-pixel until the agent reaches any location within the PTR. The simulation proceeds to the next step by calculating a new PTR from the terminal point of the previous step targeting E using the remaining time-budget. This process continues until the end-point E is reached at time t_e.

3. Results

The proposed model is implemented in Python using Numpy, GDAL, and Shapely libraries. The model is applied to actual observations of a tiger tracked over one year in Thailand Huai Kha Kaeng Wildlife Sanctuary with a sampling rate of 1 hour. The model was parameterized using the Kernel density plots of slope values used by the tiger and its speeds obtained from 4874 GPS observations (Fig.2). The maximum speed values for patrolling (1.8 km/h) and non-patrolling behaviors (0.7 km/h) are obtained using segmentation of the tiger trajectory.

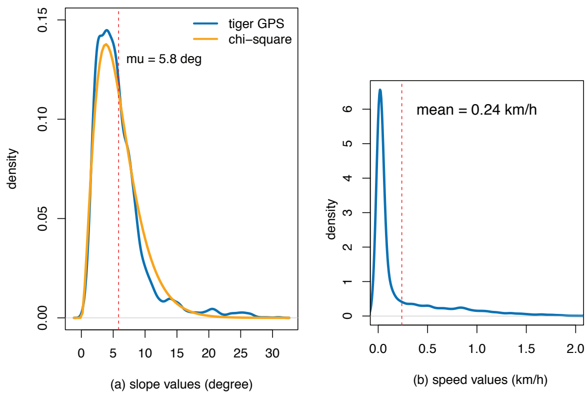

Figure 2. The Kernel density plots of slope values used by the tiger and tiger speed.

Figure 3 compares results of three simulations of 2-hour-long tiger trajectories with different behaviors: (a-b) non-patrolling and (c) patrolling, in different parts of the tiger's home-range. The simulations use two GPS observations, start-point (green) and end-point (red), and the DEM (30-meter) of the home-range. The simulation procedure (i.e. calculation of PTRs and local movement choices) at 10-minute *step times* is presented in Figure 3 (top row). Figure 3 (bottom rows) shows the resulted trajectories of three simulations. Although not used in the simulation, a control GPS mid-point (at hour 1) is marked (magenta) to test whether the simulated track hits the control point or not. Since the model follows a stochastic process, the three simulations result in different paths for each trajectory. The fact that the simulation often passes through or near the control point is promising.

4. Conclusions

This paper introduced a new context-sensitive spatiotemporal simulation model for movement. The model integrates behavior and contextual factors such as geography, spatial constraints, and environmental derivers of local movement choices in modeling trajectories. Although in this study only one environmental variable (i.e. slope) is considered, the model can be extended to include multiple contextual factors. The model can be used in a Monte Carlo approach to create a probability surface representing the probability of visitation of an area by the moving individual. And hence it can be compared to time-geography and Brownian Bridge models. Compared to similar approaches, the proposed simulation not only considers movement capacities of the moving individual and spatiotemporal constraints through time-geography, it also models the influence of the environment on local movement patterns. Future work will focus on the validation and extension of the model for simulating longer trajectories with different behavioral modes at multiple spatial and temporal scales.

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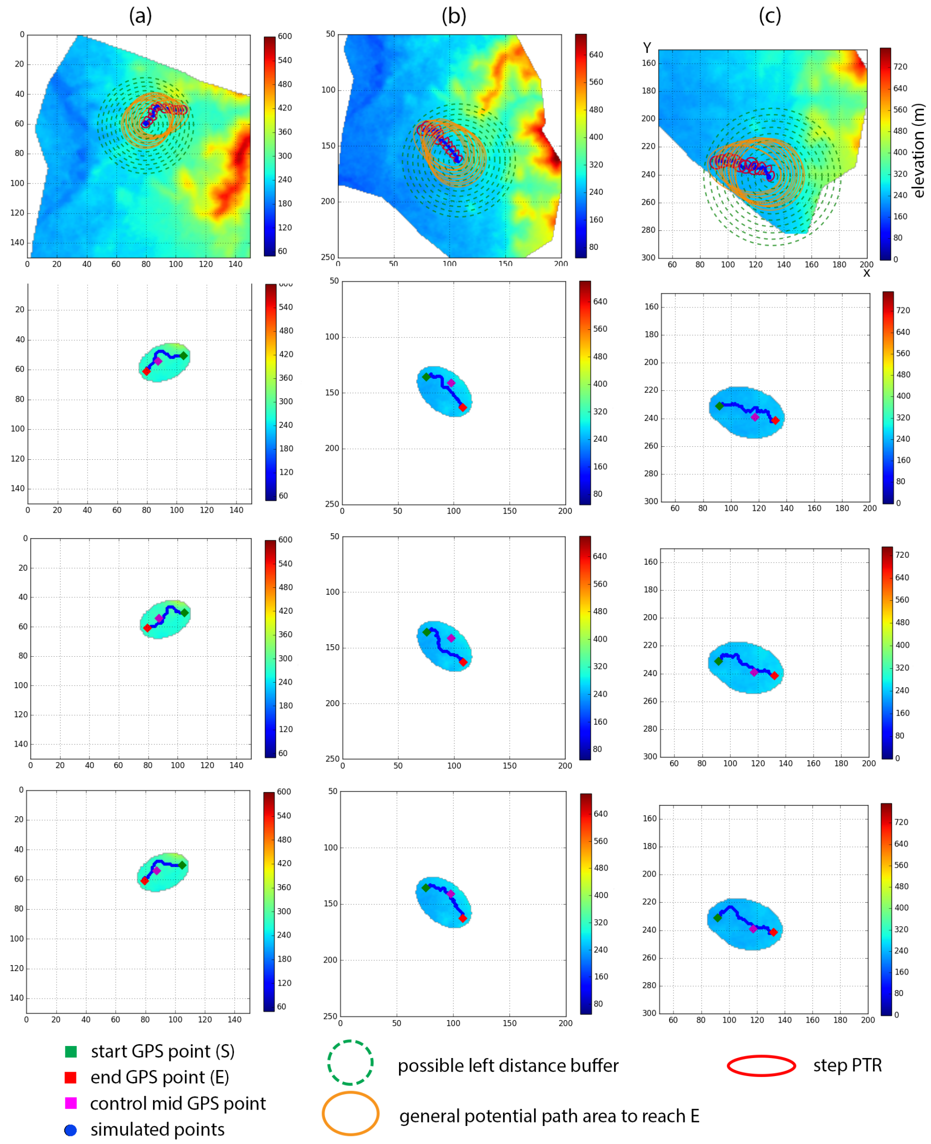

Figure 3. Three simulations for different start-end points and behaviors: the simulation process (top row), and resulted trajectories over the DEM of the potential path areas.

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