1. Introduction

Mobile object analysis continues to be well-studied in GIScience (Hornsby and Egenhofer 2002; Laube et al. 2005; Neutens et al. 2011). Time geography remains the key theoretical framework for understanding mobile objects’ movement possibilities (Miller 2005). Within time geography, recent efforts have sought to enhance its ‘probabilistic’ potential through exploring questions of data uncertainty, spatial representation, and limitations of classical approaches (Kuijpers et al. 2010; Neutens et al. 2011; Winter and Lin 2011). Along these lines, Downs (2010) fused time geography and kernel density estimation in developing time-geographic density estimation (TGDE), which may be used to estimate mobile objects’ probable locations in continuous space, given a time budget between control points (Downs 2010). Downs and Horner (2012) extend TGDE to discrete network space, demonstrating its application with GPS-based vehicle tracking data (Downs and Horner 2012) and using it in searches for travellers’ destinations missing in travel surveys (Horner et al. 2012).

The present paper explores a new direction for TGDE, namely the creation of a density-based accessibility measure for mobile objects. Related to time geography, accessibility measures have also garnered widespread attention in the literature (Kwan 1998; Miller 1999; O’Sullivan et al. 2000; Yu and Shaw 2008; Delafontaine et al. 2012). Our new metrics gauge how accessible a moving object is to particular opportunities of interest, given the constraints inherent to its movement plan. Thus, we are able not only visualize where the object most likely could have been (Downs and Horner 2012), but we also capture the configuration and magnitude of activities relative to its travel path from both a visual and analytic perspective.

2. Metric Development

Recent work by Downs and Horner (2012) adapted TGDE to work with mobile objects in network space, computed as:

$$\hat{f}(x) = (N-1)^{-1} \sum_{i=1}^{N-1} PPT^s \left( \frac{t_p(i,x) + t_p(x,j)}{t(i,j) - t_a(i,j)} \right) s_{ij}^{-1}$$

where:

- $\hat{f}(x)$ = time-geographic estimate at location $x$ on a network,
- $N$ = number of control points in dataset; consecutive points are denoted $i$ and $j$,
- $PPT^s$ = distance weighting function of the potential path tree,
- $t(\cdot)$ = time elapsed between control points,
- $t_a(\cdot)$ = time spent for a stationary activity between control points,
- $t_p(\cdot)$ = minimum travel time between two network locations, as estimated from maximum velocities along shortest path $p$, and
- $s_{ij}$ = dimension of potential path tree for control points $i$ and $j$. 
Equation (1) assumes that the intensity at a given location $x$ is a function of evaluating a series of control points ($i$-$j$ pairs) for a mobile object. Locations $x$ are places on a network where intensity is to be estimated; these could be network links, evenly spaced segments along links, or network nodes. Given a bounded distance-weighting function $PPT^*$, such as a linear or exponential decay function (Horner et al. 2012), only locations $x$ that occur on the potential path tree will receive positive intensity values. Terms in the large parentheses track the ratio of time it takes to reach a given $x$ from the two control points to the total travel budget available for these two control points. $s_{ij}$ denotes a correction factor applied to adjust the intensity estimates downward for each $i$-$j$ pair controlling for the pairs’ different spatial structures, based on the number of unique connection paths (Downs and Horner 2012).

Horner et al. (2012) seek to reconstruct travelers’ destinations missing from survey data. In the process, they reduce equation (1) to focus on a single $i$-$j$ point pair for one individual:

$$j'_i(x) = PPT^*\left(\frac{t_p(i,x) + t_p(x,j)}{t(i,j) - t_p(i,j)}\right).$$

In equation (2), summations and the dimensionality adjustment $s_{ij}$ are omitted. The result of (2) if mapped for all $x$ in an $i$-$j$ pair’s potential path tree would show locations the object most likely traversed. Here, we adapt (2) and (1) to visualize an object’s accessibility levels along the tree relative to specific opportunities or activities.

3. Computational Example
We implemented a series of metrics based on a dataset containing simulated travel diary items for vehicular trips for a series of households in Tallahassee FL (see Horner et al. 2012). We worked with ‘traveler 1,’ who makes three stops after leaving the home location and then returns home. The red route structure linking stops in the figures represents the shortest path between known stops, but not the path the traveller necessarily took.

![Figure 1. Intensity Values for Traveller 1 (eq. 1).](image)
Figure 1 shows the vehicle stops, and intensity values based on a linear weighting function using standard network-based TGDE (Downs and Horner 2012). Darker areas correspond to locations where the vehicle was more likely to have travelled given its time budget.

![Figure 1](image1.jpg)

Figure 2. Activities distribution ($O_k$).

Figure 2 displays synthetic opportunity data $O_k$, where $O$ is the attractiveness of the opportunity at node $k$. Traveller 1’s composite potential path tree consisted of 3,145 network nodes. We randomly selected 300 of these 3,145 nodes, and then randomly assigned each a ‘high’, ‘medium’, or ‘low’ level of attractiveness (scored 3, 2, and 1, respectively). These were converted to node-based opportunity levels such that $\sum_k O_k = 1$.

![Figure 2](image2.jpg)

Figure 3. Accessibility for Traveller 1

We utilize the opportunities data in an extension of TGDE to produce an accessibility assessment for Traveller 1. Figure 3 shows node-based accessibility values for Traveller 1 (scaled by a constant to reduce excess decimals). Larger/darker nodes are places where they were more likely to be travelling and encounter higher-attractiveness activities.

![Figure 3](image3.jpg)
4. Summary
We introduce a density-based accessibility measure for moving point objects. We will implement the measure with vehicle movement tracks and discuss spatial database design and computational complexity concerns. Design issues include questions of node vs. arc-based estimation and possible computational efficiencies achievable through particular TGDE implementation approaches. Finally, we place our work in broader discussions of accessibility and place vs. people-based analyses (Kwan 1998; Miller 2007; Delafontaine et al. 2012) as our efforts combine both individual-level movement with location-based visualization and summarization.

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References


