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Time-geographic relationships between vector fields of activity patterns and transport systems

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ABSTRACT

The rise of urban Big Data has made it possible to use demand data at an operational level, which is necessary to directly measure the economic welfare of operational strategies and events. GIS is the primary visualization tool in this regard, but most current methods are based on scalar objects that lack directionality and rate of change – key attributes of travel. The few studies that do consider field-based time geography have largely looked at vector fields for individuals, not populations. A population-based vector field is proposed for visualizing time-geographic demand momentum. The field is estimated using a vector kernel density generated from observed trajectories of a sample population. By representing transport systems as vector fields that share the same time–space domain, demand can be projected onto the systems to visualize relationships between them. This visualization tool offers a powerful approach to visually correlate changes in the systems with changes in demand, as demonstrated in a case study of the Greater Toronto Area using data from the 2006 and 2011 Transportation Tomorrow Surveys. As a result, it is now possible to measure in real time the effects of disasters on the economic welfare of a population, or quantify the effects of operational strategies and designs on the behavioural activity patterns of the population.

1. Introduction

Recent advances in Big Data ubiquity (see LaValle et al., 2013) have resulted in many new opportunities in urban transportation operations and planning, particularly in understanding how people travel (Schönfelder et al., 2002). Understanding travel behaviour is important for urban policymakers because sustainable cities depend on healthy mobility patterns, which in turn depend on a host of complex factors. In the past, lack of abundant data sources of travel patterns confined analysts to rely on periodic travel surveys conducted every few years (see Stopher and Greaves, 2007), which limited the use of travel data primarily to planning purposes. As a consequence, traffic and transit operations conducted on a day-to-day basis largely relied on only trip data, which led to disconnects between operations and long term planning. For one, operational measures that depend only on trip data (travel times, volumes, delay at particular corridors, etc.) provide policymakers with information on trip characteristics, but not on the underlying economic demand from which travel is derived (Pinjari and Bhat, 2011). As a result, operational decisions often cannot be related directly to travel demand patterns, but only to trip characteristics: for example, the cost of a hurricane or a planned event quantified in terms of trip measures falls short as only proxies of direct measures of economic welfare. This lack of direct connection between travel demand patterns and operational factors due to lack of data is one reason why policymakers often cannot get a clear picture of trade-offs between operational alternatives with respect to mobility and economic efficiency. With the rise of Big Data, there is an opportunity to provide a much clearer and data-driven (instead of model-driven) connection between the two for policymakers because travel patterns can now be observed from many different sources at a day-to-day operational level.

However, the opportunity cannot yet be realized because there is no adequate methodology to visualize and quantify the travel pattern data observed on a day-to-day basis. In other words, Big Data is available for us to form "scatter plots" of travel demand patterns (as more direct indicators of economic activity) against operational factors, but we still lack the "scatter plot" device. Visualization and measurement of spatial–temporal patterns can be done using geographical information systems (GIS), and time geography is the specific field of visualizing and measuring societal spatial–temporal activity patterns throughout the day (Hägerstrand, 1970). However, there is no purely data-driven means of evaluating *population-level*

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time-geographic effects due to changes in a transportation system. For example, policy-makers currently have no tool to adequately visualize and quantify the real-time effects that a major blizzard or flood has on a population's travel patterns and subsequent economic welfare, *even if that data were available*. There are two reasons for this gap.

The first reason is related to the lack of consideration for travel disutility in GIS methods used for time geography. Individuals' activity patterns are often captured using activity trajectories under the framework of 3D time-geography where time of day is a third dimension. However, the shapes in those spaces are still only static lines (and prisms) that do not include direction or rate of change. Since travel is inherently a rate of change with directionality, impacts measured using changes in static points or lines do not provide a full picture, as argued by Miller and Bridwell (2009). As a result, more recent developments in GIS have considered vector fields, where each point of a space is associated with a vector that includes both magnitude and direction. Miller and Bridwell (2009) discuss "anisotropic cost fields" as direction-specific costs—the closest to addressing this first gap—but it leads to the second major gap: the vector fields have only been used to construct space–time prisms for individuals.

We propose a novel GIS methodology for time geography, under a ubiquitous data setting where travel trajectories can be continuously collected from a sample population. Miller and Bridwell's (2009) theory of anisotropic cost fields for individuals is extended to a demand vector field theory for a population to represent population space–time travel patterns. We propose "vector kernel densities" as estimates of this field from observed activity trajectories. We show how these vector kernel densities can be used for time geography, particularly in (1) visualizing and monitoring the relationship between transportation systems and daily activity patterns that are streamed from a population, or (2) on the effect of changes to those systems on the patterns. As a result, we can inform policy-makers and the public on operational welfare effects (even in real-time, if the data was available) on a region based on events measured purely from Big Data and time-geographic urban informatics.

The study is organized as follows. Section 2 provides a literature review of vector fields in GIS, particularly on Miller and Bridwell's (2009) methodology. Section 3 presents our proposed density-based methodology for representation population aggregations of vectors in space–time and applications in visualizing relationships with transport systems. Section 4 is an illustration of the methodology using survey data from the Greater Toronto Area. Section 5 concludes.

2. Literature review

The review is broken down into (1) an overview of time geography and the need for vector-based visualization tools, and (2) a survey of recent developments in vector field-based GIS techniques.

2.1. Time geography and modelling of activity patterns

Time geography was introduced by Hägerstrand (1970) to measure individuals' allocation of space and time (for time allocation, see Becker, 1965) throughout a day. Central to this theory is the conflict that arises from individuals seeking to maximize their utilities while constrained in time and space. Researchers have long realized the direct connection between time geography and travel behaviour, and have developed activity-based travel forecast models that align with the theory (e.g. Jones, 1979; Recker et al., 1986a,b; Ettema et al., 1993; Gärling et al., 1994; Recker, 1995; Kitamura et al., 1996; Miller and Roorda, 2003; Arentze and Timmermans, 2004; Bhat et al., 2004; Chow and Recker, 2012; Chow, 2014).

A number of studies have considered GIS tools to visualize and measure activity patterns of travellers, e.g. Miller (1991), Golledge et al. (1994), Kwan (2000), Pendyala et al. (2002), Kwan and Lee (2004), Buliung and Kanaroglou (2006), Neutens et al. (2008), Miller and Bridwell (2009), Demšar and Virrantaus (2010), Chen et al. (2011), Goodchild (2013), Chen et al. (2013). Techniques of visualizing the behavioural aspects of travel have primarily fallen into two groups: the first is the use of activity prisms introduced by Hägerstrand (1970) and implemented in a GIS environment by Miller (1991). While this visual representation conveniently captures the constraint-based nature of time–space allocation decisions, Pendyala et al. (2002) demonstrated the challenges of estimating such a prism from travel data. These challenges include the lack of identification of the vertices (anchors) of the prism for an individual, and the uniqueness of the prism to each individual making it difficult to extrapolate to other individuals in a population. As a result, while activity prisms are helpful in understanding space–time trade-offs for an individual, it is less meaningful when trying to depict the patterns of a population and relate that to factors from the built environment.

A second approach focuses on population aggregations of travel patterns as density patterns in space and time, e.g. Kwan and Lee (2004), Chen et al. (2011), Demšar and Virrantaus (2010), Downs (2010), Goodchild (2013). In these studies, population-based static attributes or travel paths are used to form kernel functions to obtain densities for a population. In effect, these studies look at densities of trajectories using 3D kernel functions as opposed to 2D kernel functions. These studies nonetheless treat the shapes as static magnitudes without any directionality (note that Chen et al. (2011) do provide directionality information with rose diagrams, although such information is not integrated with the kernel density visualizations). A GIS visualization that includes both magnitude and direction can more effectively describe the patterns within the region. For example, a cross section of the kernel densities in Chen et al. (2011) for a particular time would reveal a time-dependent density map of locations in space. If this visualization included direction, then the same cross-section would not only reveal locations in space but also the momentum of the densities.

Despite the number of studies on visualizing activity patterns, there are also very few time–space GIS methods to visualize the impacts of different transport system designs on the time–space patterns of a population. State of the art methods in transit system visualization and evaluation (e.g. O'Sullivan et al., 2000; Lei and Church, 2010; Langford et al., 2012) do not yet consider their explicit interaction with travellers' time–space paths or prisms.

2.2. Vector field-based GIS

The study of velocity fields in an urban setting began in the early 1970s. Such efforts recognized the variability of travel velocities and the need to map distances to travel times using densities of scalar velocities (velocity fields). Angel and Hyman (1970, 1976) and Hyman and Mayhew (2004) exemplify this research. As opposed to the research in time geography to monitor people's trajectories in space and time, the focus of urban field theory has been on more accurate quantification of accessibility in an urban setting, and did not consider velocity vectors in a time geographic context.

Miller and Bridwell (2009) propose a time geographic field theory as a more generalized form: conventional GIS assume isotropic cost fields that use scalar values that depend only on location, $k(x)$, while a vector cost field is anisotropic with a direction-specific cost function, $k(x, x')$. The term x' is the velocity vector. This continuous, vector-based cost function is analogous to a flow or a current (e.g. electromagnetic fields). Miller and Bridwell (2009) introduced the