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Monitoring city wide patterns of cycling safety

Darren Boss[a,*], Trisalyn Nelson[b], Meghan Winters[c]

[a] University of Victoria, 3800 Finnerty Road, Victoria, BC, V8P 5C2, Canada
[b] Arizona State University, 975 S. Myrtle Avenue, Tempe, AZ, 85287, United States
[c] Faculty of Health Sciences, Simon Fraser University, Burnaby, BC, V5A 1S6, Canada

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ABSTRACT

Many cities are making significant financial investments in cycling infrastructure with the aim of making cycling safer for riders of all ages and abilities. Methods for evaluating cycling safety tend to summarize average change for a city or emphasize change on a single road segment. Few spatially explicit approaches are available to evaluate how patterns of safety change throughout a city due to cycling infrastructure investments or other changes. Our goal is to demonstrate a method for monitoring changes in the spatial-temporal distribution of cycling incidents across a city. Using cycling incident data provided by the Insurance Corporation of British Columbia, we first compare planar versus network constrained kernel density estimation for visualizing incident intensity across the street network of Vancouver, Canada. Second, we apply a change detection algorithm explicitly designed for detecting statistically significant change in kernel density estimates. The utility of network kernel density change detection is demonstrated through the comparison of cycling incident densities following the construction of two cycle tracks in the downtown core of Vancouver. The methods developed and demonstrated for this study provide city planners, transportation engineers and researchers a means of monitoring city-wide change in the intensity of cycling incidents following enhancements to cycling infrastructure or other significant changes to the transportation network.

1. Introduction

Many cities are seeking ways to increase the number of people who cycle for transport by making cycling safer for riders of all ages and abilities. While cycling has numerous physical, environmental and social benefits, ridership levels remain low in North America (Gordon-Larsen et al., 2005; Pucher and Buehler, 2008; Teschke et al., 2012). In Canada and the United States, approximately one to two percent of all trips are taken by bike (Pucher and Buehler, 2008; Teschke et al., 2012). Cyclists and potential cyclists frequently cite concern for personal safety as a significant deterrent to bicycling (Winters et al., 2011a). Research has shown that infrastructure safety improvements, such as the installation of bike lanes, bike specific pathways and cycle tracks, lead to increased bicycle use for transportation (Buehler and Dill, 2015). Additionally, increased bicycle use results in the ‘safety in numbers’ effect; as more people cycle, incident rates decrease (Jacobsen, 2015).

To overcome barriers to increased ridership, cities are making significant investments in cycling infrastructure, with many cities making investments in connected networks of bicycle infrastructure. To be accountable to the public and encourage political will for cycling infrastructure projects, it is essential that cities monitor and report the impact of infrastructure on citizens. Safety impacts can bring both health and economic benefits (Krizec, 2007; Mueller et al., 2015). Standard approaches to monitoring safety quantify change in incidents for an entire city (Pedroso et al., 2016) or on a single street segment or intersection (Chen et al., 2012; Dill et al., 2011). However, approaches to characterize changes to safety across a city’s transportation network are limited. Mapping change in safety across the network can show where increases and decreases in incidents are occurring, and account for shifts from one street to the next as cyclists alter routes to use bicycling infrastructure.

A challenge in evaluating network level changes in cycling safety is that cycling collisions are mapped as point locations. Most of the methods designed for analysis of point data are unsuitable for phenomena constrained to network space (Yamada and Thill, 2004). Over the past two decades, spatial scientists have extended many traditional point pattern analysis methods to one dimensional, network space. For example, Okabe and Yamada (2000) developed a network specific K-function. Several others have developed kernel density estimation (KDE) techniques suitable for network based analysis which use network distances instead of Euclidean distances (Borruso, 2005; Okabe

* Corresponding Author.
E-mail addresses: dboss@uvic.ca (D. Boss), trisalyn.nelson@asu.edu (T. Nelson), mwinters@sfu.ca (M. Winters).

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et al., 2009).

Network constrained KDE has been applied in a variety of disciplines including analysis of economic activities (Produit et al., 2010) traffic incidents (Harirforoush and Bellalite, 2016; Xie and Yan, 2008) and cycling infrastructure planning (Lachance-Bernard et al., 2011). Network KDE has also been integrated with local measures of spatial autocorrelation in the analysis of traffic incidents (Xie and Yan, 2013). While standard KDE has been used as a visualization tool for cycling incident density (Delmelle and Thill, 2008), the application of network KDE to studies of cycling incidents is very limited. Network KDE has potential to advance spatially explicit methods of monitoring change in cycling incidents throughout a city, which is beneficial when evaluating the impact of cycling infrastructure. Assessment of infrastructure enhancements is often limited to a small set of road segments where comparisons are made using space for time substitutions. Few spatially explicit approaches exist for evaluating changes in the distribution of cycling incidents across a city following improvements to cycling infrastructure.

Our goal was to develop a method for monitoring statistically significant changes in the spatial and temporal variation of cycling incidents following changes in infrastructure. We analyzed cycling incident data from the city of Vancouver, Canada from January 1, 2009 to December 31, 2013 according to the following objectives. First, we compared the suitability of planar KDE versus network constrained KDE for measuring cycling incident intensity across the study region. Second, official reports of cycling incidents were used to quantify incident intensity annually from 2009 through 2013. Third, the resulting network constrained density maps were compared to identify areas with statistically significant change in the intensity of cycling incidents following the installation of cycle tracks in downtown Vancouver in 2010.

2. Methods

2.1. Study area

The case study area is the city of Vancouver, Canada with a population of 603,000 (Statistics Canada, 2011a) (Fig. 1). Vancouver's mild climate is favorable to cycling commuting year round and 4.4% of workers commute by bicycle (Statistics Canada, 2011b). Monthly average minimum temperatures are greater than 0 °C in the winter and monthly average maximum temperatures below 23 °C in the summer, though the city receives a significant amount of precipitation, averaging nearly 1200 mm per year (Goverment of Canada, 2010).

2.2. Transportation infrastructure

The city has a wide variety of transportation infrastructure including arterial, collector and local streets. Vancouver has been promoting cycling as a safe and convenient mode of transportation since 1988 (Vancouver, 1988). Historically, Vancouver's primary emphasis has been the development of local street bikeways (Vancouver, 1999), but the downtown core, which is our region of focus, has few local streets that are used as bikeways. In 2009, there were mainly painted bike lanes downtown. In 2010 dedicated cycle tracks were installed along two major corridors (Fig. 1). Since the time frame of this case study there has been substantial investment in a cycling network downtown; however, we could not extend our study period since cycling incident data beyond 2013 was not available.

Transportation infrastructure data was obtained from the city of Vancouver's Open Data catalogue (Vancouver, 2017). The portion of the network used in this study consists of 1763 street segments and 1119 nodes. The network data was preprocessed to ensure correct topology and subsequently modeled as an undirected graph. Cycling network data was also obtained from the city's Open Data catalogue (Vancouver, 2017).

2.3. ICBC cycling incident data

The cycling incident data were sourced from the Insurance Corporation of British Columbia (ICBC), the provincial insurance provider supplying mandatory coverage to all motor vehicles in BC. The data contains all reported crashes between bicycles and motor vehicles from 2009 to 2013 (Table 1). The location of incidents are reported as street addresses or intersections which were geocoded to the street network.

2.4. Kernel density estimation

In order to detect change in cycling safety, we first mapped spatial variation in cycling safety along a network in two time periods (t_0 and t_1) and then quantified change between t_0 and t_1.

The standard implementation of KDE is used to produce a smoothed density surface from point events in two-dimensional space. A grid surface is superimposed on a study area. A kernel function is used to calculate the density of point events for the centroid of each cell in the grid. The kernel function weights points within a circle of influence according to the Euclidean distance between a centroid and the points. The general form of a kernel estimator is:

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{r^2} k\left(\frac{d_{is}}{r}\right)$$

where $\lambda(s)$ is the density at the location of measurement s, r is the bandwidth or smoothing parameter, d_{is} is the distance between s and point i, k represents a kernel function that weights the value of i at s and n is the number of events within the bandwidth from location s. A variety of kernel functions are commonly used including Gaussian, Quartic, and Epanichnekov. We used a Gaussian kernel as it was computationally efficient, though the choice of kernel function has less impact on the final density surface than the choice of bandwidth (O'Sullivan and Unwin, 2002; Silverman, 1986).

The challenge with the standard implementation of the KDE for cycling safety is that mapping to planar space tends to be good for identifying hot spots of safety concern at intersections, but linear features along road corridors can be missed due to the circular geometry of bandwidths. Constraining a kernel density estimator by a network uses distances along the network as opposed to Euclidean distance for creating the bandwidth (Fig. 2).

The general form of a network constrained kernel estimator is:

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{r} k\left(\frac{d_{is}}{r}\right)$$

where r and d_{is} are measured over the network. The resulting intensity value is based on linear units instead of areal units. As for standard KDE, the choice of kernel function k for network KDE is less important to the resulting density estimate than the choice of bandwidth r (Xie & Yan, Kernel Density Estimation of traffic accidents in a network space, 2008).

Two primary methods have been developed for network constrained KDE, differing in their choice of the basic spatial unit (BSU) of analysis. One method overlays a grid on the study area and uses a grid cell as the BSU (Borruso, 2008; Produit et al., 2010). The second method attempts to divide the network into segments of equal length and uses these as the BSU (Xie and Yan, 2008). The division of a network into basic spatial units of equal length is non-trivial and results in residual segments which are shorter than the defined lixel size (Xie and Yan, 2008). Furthermore, as the underlying network changes, such as through the construction of new streets or cycling paths, the absolute position of lixels within the network may not be consistent between two time periods. We elected to use the grid cell as our basic spatial unit as it has the advantage of producing a surface where the location of grid cells is invariant with respect to changes in the underlying network over time.