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Vehicle manoeuvers as surrogate safety measures: Extracting data from the gps-enabled smartphones of regular drivers

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ABSTRACT

Network screening is a key element in identifying and prioritizing hazardous sites for engineering treatment. Traditional screening methods have used observed crash frequency or severity ranking criteria and statistical modelling approaches, despite the fact that crash-based methods are reactive. Alternatively, surrogate safety measures (SSMs) have become popular, making use of new data sources including video and, more rarely, GPS data. The purpose of this study is to examine vehicle manoeuvres of braking and accelerating extracted from a large quantity of GPS data collected using the smartphones of regular drivers, and to explore their potential as SSMs through correlation with historical collision frequency and severity across different facility types. GPS travel data was collected in Quebec City, Canada in 2014. The sample for this study contained over 4000 drivers and 21,000 trips. Hard braking (HBEs) and accelerating events (HAEs) were extracted and compared to historical crash data using Spearman's correlation coefficient and pairwise Kolmogorov-Smirnov tests. Both manoeuvres were shown to be positively correlated with crash frequency at the link and intersection levels, though correlations were much stronger when considering intersections. Locations with more braking and accelerating also tend to have more collisions. Concerning severity, higher numbers of vehicle manoeuvres were also related to increased collision severity, though this relationship was not always statistically significant. The inclusion of severity testing, which is an independent dimension of safety, represents a substantial contribution to the existing literature. Future work will focus on developing a network screening model that incorporates these SSMs.

1. Introduction

The safety of urban road networks is a serious concern that requires the continuous monitoring of crash risk. Considering that parties involved in improving road safety have finite budgets, the common approach is to identify the most dangerous sites in the network and to prioritize them for remediation in order to maximize the efficiency of countermeasures. In this process, known as network screening, candidate high-risk sites are identified as those locations where design or operation "create an increased risk of unforeseeable accidents" (Agerholm et al., 2012). Traditional screening methods have used observed crash frequency or severity ranking criteria, despite the fact that crash-based methods are reactive (Agerholm et al., 2012), require long collection periods (Lee et al., 2006), are subject to errors in collision databases, and are sensitive to underreporting (Kockelman and Kweon, 2002). A screening method to replace the crash-based approach requires a new data source from which crash risk can be computed. Naturalistic driving data is collected unobtrusively in crashes, near crashes, and normal conditions, provides information difficult to observe by other techniques (Bagdadi, 2013; Wu and Jovanis, 2013), and supports safety assessments based on surrogate safety measures (SSMs) rather than crash data. SSMs are any non-crash measures that are physically and predictably related to crashes (Tarko et al., 2009) and have the potential to reduce dependency on crash data in network screening (Laureshyn et al., 2009).

Naturalistic approaches typically yield large volumes of data from which surrogate indicators must be identified (Bagdadi, 2013). Popular methods for surrogate safety analysis include event-based techniques, behavioural techniques, and techniques based on measures of traffic flow. Event-based techniques consider traffic conflicts, interactions between road users, or vehicle manoeuvres. Traffic conflicts were first studied in the late 1960s based on human observation. Though data

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volumes were limited and analysis potentially subjective (Laureshyn et al., 2009), human observation provided a level-of-detail beyond what was possible through objective (crash-based) techniques (Laureshyn et al., 2009). Video-based sensors and computer vision techniques have improved objectivity and increased the amount of data that can be processed. Though video-based sensors provide high temporal resolution (Agerholm et al., 2012) and rich positional data beyond counts and speed (Bahler et al., 1998), the analysis of video data is potentially resource intensive and has spatial limitations (Laureshyn et al., 2009), leading to a desire to implement event-based techniques using other data sources. Behavioural techniques aim to identify individual driver behaviours not related to conflict or crash avoidance, such as infractions and yielding (Dingus et al., 2006). Traffic flow techniques, which use measures of volume, mean speed, or density to estimate risk (Yan et al., 2008), typically require roadside point sensors such as loops, radar, or other sensors (Oh et al., 2001; Golob et al., 2004; Lee et al., 2002). Though successful on freeways, it is impractical and costly to implement roadside sensors across an entire urban network (Herrera et al., 2010), and traffic flow measures have yet to be proven as reliable SSMs in urban networks with at-grade intersections.

For SSMs to be useful in screening applications, data must be captured continuously as drivers move through the network. Thanks to the advent of instrumented vehicles, extracting SSMs across an urban network is now possible. Instrumented vehicles (or probe vehicles) act "as moving sensors, continuously feeding information about traffic conditions" (El Faouzi et al., 2011). GPS devices are reliable sources of naturalistic driving data (Jun et al., 2007) and may be complemented by additional vehicle kinematics from accelerometers or gyroscopes and environmental factors collected by external sensors such as radars. These sensors provide long periods of continuous data for a relatively small sample of road users (Agerholm et al., 2012). Though limited in terms of the studied population of drivers, the spatial coverage of GPS data makes it ideal for network screening applications. Smartphones are inexpensive, simple, and user-friendly data collection devices that eliminate the need for external sensors (Eren et al., 2012; Johnson and Trivedi, 2011). Despite the advent of smartphone GPS data in the last years, few studies have investigated its use in the network screening process. Accordingly, the purpose of this study is to examine vehicle manoeuvres extracted from probe vehicle data collected by the GPS-enabled smartphones of regular drivers. More specifically, this research contributes to the field by introducing a methodology for collecting, cleaning, and analyzing GPS travel data, extracting vehicle manoeuvres from the GPS data of regular drivers, and investigating the relationship between vehicle manoeuvres and historical collision frequency and severity across different facility types.

2. Literature review

Although probe vehicles have primarily been used in spatio-temporal applications such as traffic monitoring and origin-destination studies (Herrera et al., 2010), they have also been applied less frequently, in studies of road safety. This underutilization can be partially attributed to the difficulties of collecting large volumes of data using dedicated GPS devices that are installed for a specific research purpose. Studies using probe vehicles with dedicated GPS tracking devices must overcome low penetration rates which may be insufficient for providing "an exhaustive coverage of the transportation network" (Herrera et al., 2010). This shortcoming has been apparent in the field of automated incident detection (AID), which involves the identification of "non-recurring events such as accidents" through pattern classification of traffic flow (Dia and Thomas, 2011). In AID studies, dedicated GPS devices have been supplemented by roadside sensors (El Faouzi et al., 2011) or simulation. Sethi et al. (1995) found that probe vehicles were useful in AID, though only when using a proportion of probe vehicles beyond what could be expected in practice (Sethi et al., 1995). Dia and Thomas (2011) found the best results when probe vehicles comprised 20% of the traffic flow.

Despite this, several studies have attempted to extract vehicle manoeuvres from probe vehicles as SSMs. Jun et al. (2007) analyzed spatio-temporal driving activity and crash involvement using dedicated GPS devices and self-reported safety data for 460 light-duty vehicles. The study found that drivers involved in crashes tended to travel longer distances and at higher speeds and "engaged in hard deceleration events" (greater than $2.7\,m/s^2$) more frequently (Jun et al., 2007). Though failing to show a causal link, the authors suggest that decelerations 'may be employed as roadway safety surrogate measures' (Jun et al., 2007). This study highlights an additional shortcoming of dedicated devices; that drivers behave more safely when monitored (Johnson and Trivedi, 2011). In studies using dedicated devices, installations are often biased towards a specific segment of the population (such as light-duty vehicle drivers or taxi drivers). Ellison et al. (2013) studied 106 drivers using dedicated GPS devices along with demographic surveys for each driver. By controlling for temporal and spatial factors including geometry, weather, time of day, trip purpose, and vehicle occupancy, the authors found that the road environment was a significant influencer of driver behaviour (Ellison et al., 2013). Although speed is often regarded as an important surrogate measure, changes in speed (acceleration, the first derivative of velocity, or jerk, the second derivative) may be more important (Laureshyn et al., 2009). Agerholm et al. (2012) collected data from six drivers over a 3-month period using GPS devices and accelerometers. The authors stated that 'braking was the evasive action […] in 88% of the accidents in built-up areas' (Agerholm et al., 2012), making decelerations a logical indicator to extract. Jerk was found to be correlated with accident occurrence (Agerholm et al., 2012). Bagdadi (2013) noted that the most common crashes are rear-end collisions. The study used GPS, accelerometer, and radar data from 109 participants and found that jerk could correctly identify self-reported near misses at an 86% success rate (Bagdadi, 2013).

The use of smartphones as a potentially rich source of safety data became popular in the early 2010s. Johnson and Trivedi (2011) developed a system to distinguish non-aggressive and aggressive driving behaviour. Their system fused accelerometer, gyroscope, magnetometer, GPS, and video data from smartphones to monitor drivers. However, at the time of publication, the system had only been installed in three vehicles. Eren et al. (2012) similarly studied manoeuvering using the smartphone accelerometer and gyroscope data of 15 drivers. Guido et al. (2012) attempted to evaluate time-to-collision (TTC) and deceleration rate as measured from smartphone GPS data as possible SSMs for rear-end collisions on a two-lane rural highway. The study used only three drivers and no attempt was made to correlate the results to actual collision risk. Fazeen et al. (2012) used smartphone accelerometer data to classify 'safe' accelerations and decelerations from 'unsafe' ones (approximately $3\,m/s^2$ or greater), though failed to demonstrate whether 'unsafe' behaviour led to increased collision risk and used only a single smartphone.

Several shortcomings are apparent in the existing literature, which this study attempts to address. First, there has been no attempt to derive SSMs from smartphone-collected GPS data of regular drivers alone. Existing studies have used dedicated probe vehicles (resulting in sample sizes of 100 drivers or less) or dedicated GPS devices with supplemental accelerometer data. Studies using smartphones have used extremely few drivers, despite the potential for application to the population at large. Second, there has been no comprehensive comparison of GPS-based SSMs to large quantities of crash data at the network scale. Instead, studies have compared indicators to sample safety data, which is often self-reported.

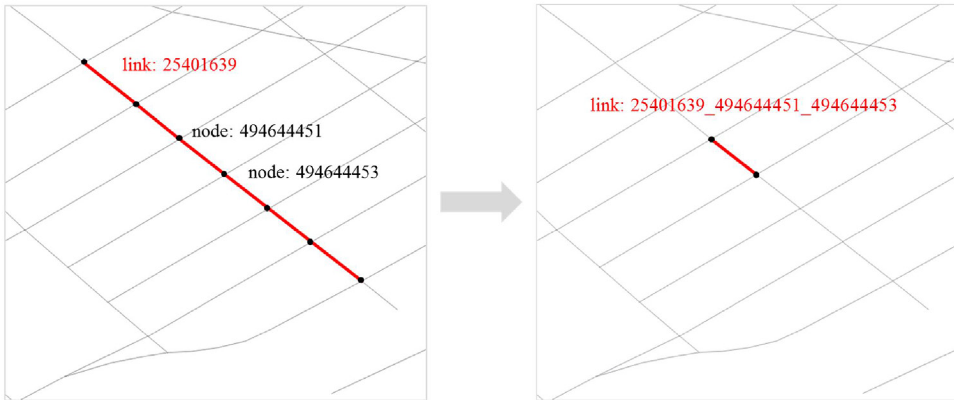

Fig. 1. Redefinition of OSM Links.

3. Methodology

3.1. Data structure

The benefits of collecting GPS data from smartphones include minimal impact to driver behaviour, cost effectiveness, and eliminating the need for external sensors. Drivers voluntarily download a smartphone application and begin logging trips. For each trip, i, logged into the application, GPS travel data is returned as a series of observations, O_{ij}, in the format

$$\text{trip}_i = \begin{Bmatrix} O_{i0} \\ O_{i1} \\ \vdots \\ O_{ij} \\ \vdots \\ O_{in_i} \end{Bmatrix} = \begin{Bmatrix} i, & c_{i0}, & t_{i0}, & x_{i0}, & y_{i0}, & z_{i0}, & v_{i0} \\ i, & c_{i1}, & t_{i1}, & x_{i1}, & y_{i1}, & z_{i1}, & v_{i1} \\ \vdots \\ i, & c_{ij}, & t_{ij}, & x_{ij}, & y_{ij}, & z_{ij}, & v_{ij} \\ \vdots \\ i, & c_{in_i}, & t_{in_i}, & x_{in_i}, & y_{in_i}, & z_{in_i}, & v_{in_i} \end{Bmatrix}$$

where i is a unique trip identifier, O_{ij} is the jth observation in trip i, c_{ij} is a unique coordinate, t_{ij} is the datetime, x_{ij}, y_{ij}, and z_{ij} are the latitude, longitude, and altitude, and v_{ij} is the speed. From each trip, several key pieces of trip information include the origin (x_{i0}, y_{i0}) and destination (x_{in_i}, y_{in_i}) and start (t_{i0}) and end times (t_{in_i}). Total travel time can also be computed ($t_{in_i}-t_{i0}$). The time between consecutive observations is typically between 1 and 2 s. Once a trip is logged, some systems complete an initial pre-processing of the data using methods including Kalman filtering (Bachman, 2011) to smooth the data and reduce its variability, before the trip data is stored in a centralized databased.

3.2. Map matching

Although rich in spatio-temporal information, the GPS traces contain variability in both position and speed, even for systems with integrated pre-processing. Most popular techniques for reducing positional noise provide only a smoothed latitude and longitude and do not explicitly associate trips to the links in the network where they occurred. TrackMatching is a commercially available, cloud-based web map matching software service (Marchal, 2015) that matches GPS trip data to the OpenStreetMap (OSM) road network (OpenStreetMap, 2015). Individual trips are extracted and formatted to include the coordinate ID, timestamp, latitude, and longitude for each observation. The software returns a new latitude and longitude, x'_{ij} and y'_{ij}, which correspond to a specific OSM link ID, l_{ij}, as shown below.

$$\{c_{ij},\ t_{ij},\ x_{ij},\ y_{ij}\} \rightarrow \text{TrackMatching} \rightarrow \{c_{ij},\ t_{ij},\ x'_{ij},\ y'_{ij},\ l_{ij},\ s_{ij},\ d_{ij}\}$$

x'_{ij} and y'_{ij} are chosen based on the Euclidean distance from the unfiltered GPS points to the nearest link and on network topology (Marchal et al., 1935). Track Matching also returns the source, s_{ij}, and destination nodes, d_{ij}. The algorithm generates a set of candidate paths and then assigns the trip to the most probable path from origin to destination. TrackMatching returns a latitude and longitude for every observation that correspond exactly to a location on the road network. As important information including speed and time is lost through the map matching process, the results are merged back with the original data to preserve all the necessary information.

3.3. Network definition

The use of the OSM road network in the TrackMatching algorithm presents a challenge. Ideally, road links would never be divided by an intersection (Sioui and Morency, 2013). In other words, each link should connect nodes located at adjacent intersections. The OSM road network is generated non-systematically by users, and so OSM links do not always meet this definition. It is desired to redefine the network such that each link is properly defined between adjacent intersections. Redefining the network requires the following steps, which can be completed in any GIS software environment. The outcome of this procedure is illustrated in Fig. 1.

1. Identify all nodes that represent an intersection in the road network. In doing so, nodes that only define network topology are ignored.
2. Split the road network at the identified nodes. Any link connecting more than two intersections is broken into several smaller links. Links defined properly are unchanged.
3. Rename each link according to its original ID and the nodes on either end of the link in order to have a unique identifier.
4. Remap the GPS observations to the new network. Travelled links in the GPS trip data are renamed using the same scheme as the mapping data, by concatenating the link ID, source node, and destination node into a unique identifier.

3.4. Speed and acceleration filtering

With the positions filtered using map matching, an additional filter is required to eliminate noise in the GPS speeds. Although several different filters have been proposed and tested, both Zaki et al. (2014) and Bagdadi and Varhelyi (2013) found that the Savitzky-Golay filter was adequate for this application, noting that the filter is suitable for time series with fixed and uniform intervals and with limited discontinuities in the data (Zaki et al., 2014). This digital filter is “a weighted moving average–based filter, with weighting described as a polynomial model of arbitrary degree” (Zaki et al., 2014). In the Savitzky-Golay, both the degree of the fitted polynomial and the window size (the number of points to which the polynomial is fitted) can be varied to adjust the amount of filtering. There is always a compromise between maintaining the signal and eliminating the noise (Bagdadi and Varhelyi, 2013). With too little smoothing, noise in the GPS data may be wrongly interpreted as a vehicle manoeuvre (false alarm or type II error). With too much smoothing, actual vehicle manoeuvres may be eliminated (false negative or type I error). Previous studies have suggested that a polynomial of degree two is adequate, although less guidance exists for selecting the window length. Windows of 3, 5, and 7 points were tested in this study.

An additional benefit of the Savitzky-Golay filter is the ability to filter not only the data, but also its derivatives. Therefore, the acceleration rate can be determined for every observation by estimating the derivative of the filtered data. With map matching and filtering complete, the results are combined with the original data to yield the analysis data set. This contains the refined latitudes, longitudes, speed measurements, v'_{ij}, and acceleration rates, a_{ij}, and also ties each observation to a specific OSM link l_{ij} in the road network as shown below.

$$\text{trip}_i = \begin{Bmatrix} i,\ c_{i0},\ t_{i0},\ x'_{i1},\ y'_{i0},\ z_{i0},\ v'_{i0},\ a_{i0},\ l_{i0},\ s_{i0},\ d_{i0} \\ i,\ c_{i1},\ t_{i1},\ x'_{i1},\ y'_{i1},\ z_{i1},\ v'_{i1},\ a_{i1},\ l_{i1},\ s_{i1},\ d_{i1} \\ \vdots \\ i,\ c_{ij},\ t_{ij},\ x'_{ij},\ y'_{ij},\ z_{ij},\ v'_{ij},\ a_{ij},\ l_{ij},\ s_{ij},\ d_{ij} \\ \vdots \\ i,\ c_{in_i},\ t_{in_i},\ x'_{in_i},\ y'_{in_i},\ z_{in_i},\ v'_{in_i},\ a_{in_i},\ l_{in_i},\ s_{in_i},\ d_{in_i} \end{Bmatrix}$$

The process of collection and cleaning of the GPS data from smartphones is illustrated in Fig. 2.

3.5. Extracting surrogate safety measures

Deceleration is perhaps the most common evasive manoeuvre in urban areas (Agerholm et al., 2012), and selecting hard braking events (HBEs) as a potential SSM is logical. Most studies focused on vehicle manoeuvres have used jerk, observed using accelerometers, as the surrogate indicator (Agerholm et al., 2012; Bagdadi, 2013). Although the resolution of the GPS data is too coarse to calculate jerk, decelerations can also be used to detect unsafe behaviour. For example, Fazeen et al. (2012) suggested using decelerations exceeding $3\,\text{m/s}^2$. Therefore, using a deceleration threshold may be sufficient to define HBEs. Some studies have suggested that hard acceleration events (HAEs) may also be good predictors of safety (Wu and Jovanis, 2013; Agerholm et al., 2012). Accelerations computed using the Savitsky-Golay filter are compared to a braking threshold, a_{min}, and acceleration threshold, a_{max}, to determine which observations correspond to HBEs or HAEs. The status of O_{ij} is determined using the following logic. For each series of consecutive negative (or conversely, positive) accelerations, l_{dec} (l_{acc}), the minimum (maximum) value is obtained. If this value is inferior (superior) to the threshold, $\min(l_{dec}) < a_{min}$ ($\max(l_{acc}) > a_{max}$), then consider that observation an HBE (HAE). This ensures that a single deceleration spanning multiple observations is considered a single HBE, even if several observations exceed the threshold. This algorithm is illustrated in Fig. 3. Although the value of $-3\,\text{m/s}^2$ was chosen for a_{min} as a starting point to develop GPS-based surrogate safety indicators (based on previous studies), thresholds of $-2\,\text{m/s}^2$ and $-4\,\text{m/s}^2$ were also tested. Similarly, values of $2\,\text{m/s}^2$, $3\,\text{m/s}^2$, and $4\,\text{m/s}^2$ were used for a_{max}.

3.6. Data analysis

SSMs must be predictably related to crashes (Tarko et al., 2009), and any proposed measure must demonstrate correlation with actual safety (that is collision occurrence and/or severity). The main objective of the analysis is to quantify the relationship between vehicle manoeuvres (defined as HBEs and HAEs) and collision frequency and severity. To do so, the vehicle manoeuvres must be compared to historical crash data at either the link or the intersection level. Boonsiripant (2009) suggested that separating facilities according to functional classification was necessary if measures were to adequately predict collision occurrence. Therefore, the analysis was completed separately considering five distinct functional classes: freeway, primary, secondary, tertiary, and residential (where primary, secondary, and tertiary are arterials and collectors classified by importance to the road network, with primary being most important). These classes represented nearly all the travelled links in the GPS data.

3.6.1. Collision frequency

Spearman's Rank Correlation Coefficient, or Spearman's rho, indicates how strongly the dependency between two variables is described by a monotonic function and is a popular choice for correlating surrogate safety indicators with crash data. Locations with the most collisions should also have the most vehicle manoeuvres. A rho of 1.0 indicates perfect positive correlation, 0.0 indicates no correlation, and -1.0 indicates perfect negative correlation. Spearman's rho, ρ, is calculated using

$$\rho = 1 - \frac{6\sum (w_L - v_L)^2}{M(M^2 - 1)} \tag{1}$$

For links, w_L is the rank of link L based on collision frequency, v_L is the rank of link L based on the SSMs, and M is the total number of links.

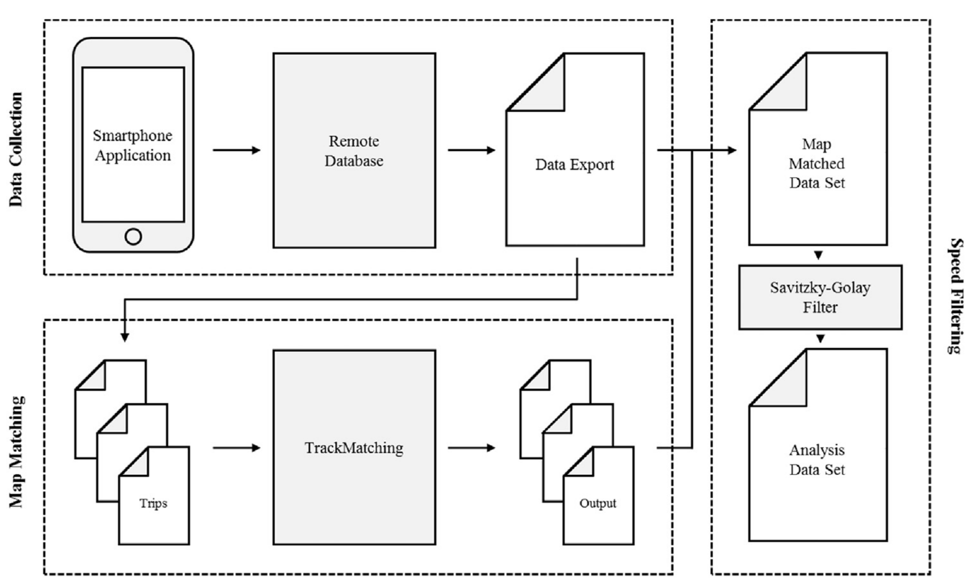

Fig. 2. Collection and filtering of smartphone-collected GPS data.

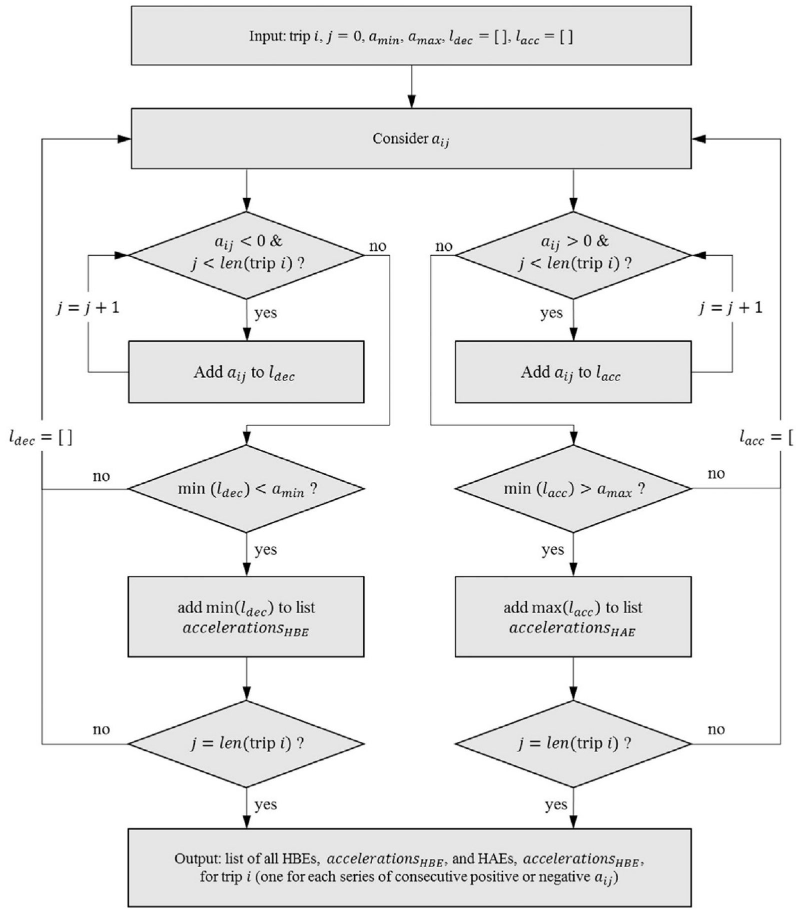

Fig. 3. Algorithm for extracting vehicle manoeuvres from GPS trip data.

Ranks based on the SSMs were easy to determine because the GPS was previously map matched to the road network. To create ranks based on collision data, w_L, the collisions within either a 50 m or 100 m buffer surrounding the link were counted. For intersections, both ranks were determined by counting the number of vehicle manoeuvres and collisions within either a 100 m or 200 m buffer. Different buffer sizes were used to observe the effect of buffer size on the correlation results. This crash assignment method allows a crash to be assigned to multiple links and/or intersections. However, this was found to have little effect on the correlation results.

3.6.2. *Collision severity*

A Kolmogorov-Smirnov test (K–S test) can be used to test equality between two probability distributions. The K-S test is preferred over other statistical techniques because it is nonparametric, requiring no assumption to be made about the probability distributions. The two-sample K–S test is used to compare the empirical cumulative distribution functions, and return the K–S statistic, D, which represents the maximum difference between the two distributions, computed as

$$D = \max_{1 < i < K} |E_1(i) - E_2(i)| \tag{2}$$

where E_1 and E_2 are the empirical cumulative distribution functions of the two samples, and K is the maximum value of observations for which the empirical CDFs are defined. In order to evaluate if the extracted SSMs are statistically linked to collision severity, links and intersections were divided into three groups each; 1) links or intersections with at least one fatal collision; 2) links or intersections with at least one major injury collision, but no fatal collisions, and; 3) links or intersections with only minor injury collisions. A series of pairwise K–S tests were then performed between the distributions of the SSMs for each pair of the above groups by functional classification, to determine if any statistical differences exist at different levels of collision severity, to demonstrate the relationship between SSMs and collision severity.

4. Results

4.1. *Data description*

Several primary data sources were required to complete this study. GPS travel data was collected in Quebec City, Canada using the Mon Trajet application (City of Quebec, 2015) developed by Brisk Synergies (2015). Screenshots from the application are shown in Fig. 4. The application, which was available for Apple and Android devices, was installed voluntarily by drivers and allowed them to anonymously log trips into the application. In total, nearly 5000 driver participants have logged nearly 40,000 trips using the application. The sample for this study contained over 4000 drivers and 21,939 individual trips during the period between April 28 and May 18, 2014. Over the 21 days sampled, 19.7 million individual data points were logged. Crash data for the City of Quebec was obtained from the Ministry of Transportation Quebec for a five-year period from 2006 to 2010. 9248 collisions identified across the 5-year period involved at least one vehicle. Geometric map data was obtained from OpenStreetMaps in order to ensure consistency with the map matching results.

4.2. *Extraction of surrogate indicators*

Table 1 provides the number of vehicle manoeuvres (HBEs and HAEs) identified for each combination of acceleration threshold and filter window size. Both parameters were observed to greatly influence

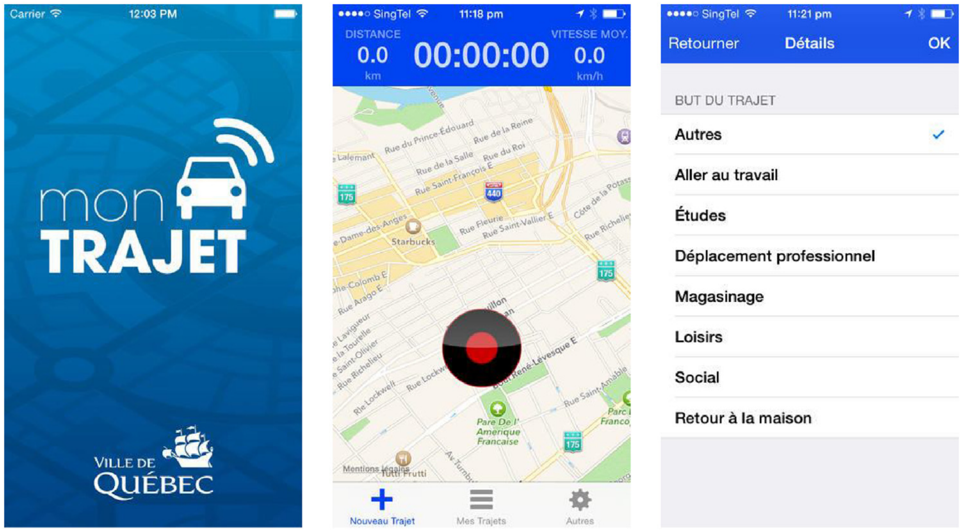

Fig. 4. Smartphone application interfaces.

the number of identified vehicle manoeuvres. In the least restrictive case, accelerations and decelerations make up approximately 1% of the total number of observations. In the most restrictive case, there are fewer than 500 of each vehicle manoeuvre identified (0.025% of the total data set). In general, hard breaking appears to more common than hard accelerating, which supports previous evidence that braking is the most common evasive manoeuvre in built up areas (Agerholm et al., 2012). Table 1 also shows the number of links and intersections with at least one vehicle manoeuvre for each combination of parameters. Obviously the number of events or sites decreases with higher thresholds and larger filter window size, as expected. The results of these tables are further illustrated in Fig. 5. The number of HBEs identified at each intersection is shown in Fig. 5a, while the data for links is provided in Fig. 5b. Although many residential links are missing data (because too few trips were made there, if any), the coverage is sufficient to include most of the main highways, arterials, and collectors, as well as downtown Quebec City.

4.3. Collision frequency

For both HBEs and HAEs, the correlation strength with historical collision frequency was calculated using Spearman's rho, for the five functional classifications, three filter window sizes, three acceleration thresholds, and two buffer sizes at both the link and intersection level. This yielded 360 unique test cases, which are summarized in Table 2 and in Table 3, where the strongest correlation for each functional class is bolded. Considering results at the intersection level, correlations between 0.53 and 0.64 were achieved across all functional classes. The

Table 1
Number of vehicle manoeuvres and number of facilities with vehicle manoeuvres.

Number of HBEs and HAEs

Number of HBEs				Number of HAEs			
	Deceleration Rate (m/s^2)				Acceleration Rate (m/s^2)		
Window	−2.0	−3.0	−4.0	Window	2.0	3.0	4.0
3	206788	66032	16725	3	143632	35077	8014
5	115260	16549	2040	5	74753	7725	1257
7	53567	3748	460	7	31565	2047	432

Number of intersections with at least one vehicle manoeuvre (based on 100m buffer).

	Deceleration Rate (m/s^2)				Acceleration Rate (m/s^2)		
Window	−2.0	−3.0	−4.0	Window	2.0	3.0	4.0
3	9210	7717	5530	3	8733	6555	4030
5	8216	4710	1784	5	7476	3667	1336
7	6323	2227	589	7	5758	1810	567

Number of links with at least one vehicle manoeuvre.

	Deceleration Rate (m/s^2)				Acceleration Rate (m/s^2)		
Window	−2.0	−3.0	−4.0	Window	2.0	3.0	4.0
3	7993	5255	2708	3	7263	4070	1866
5	5868	2192	552	5	5156	1674	465
7	3578	733	151	7	3295	681	187

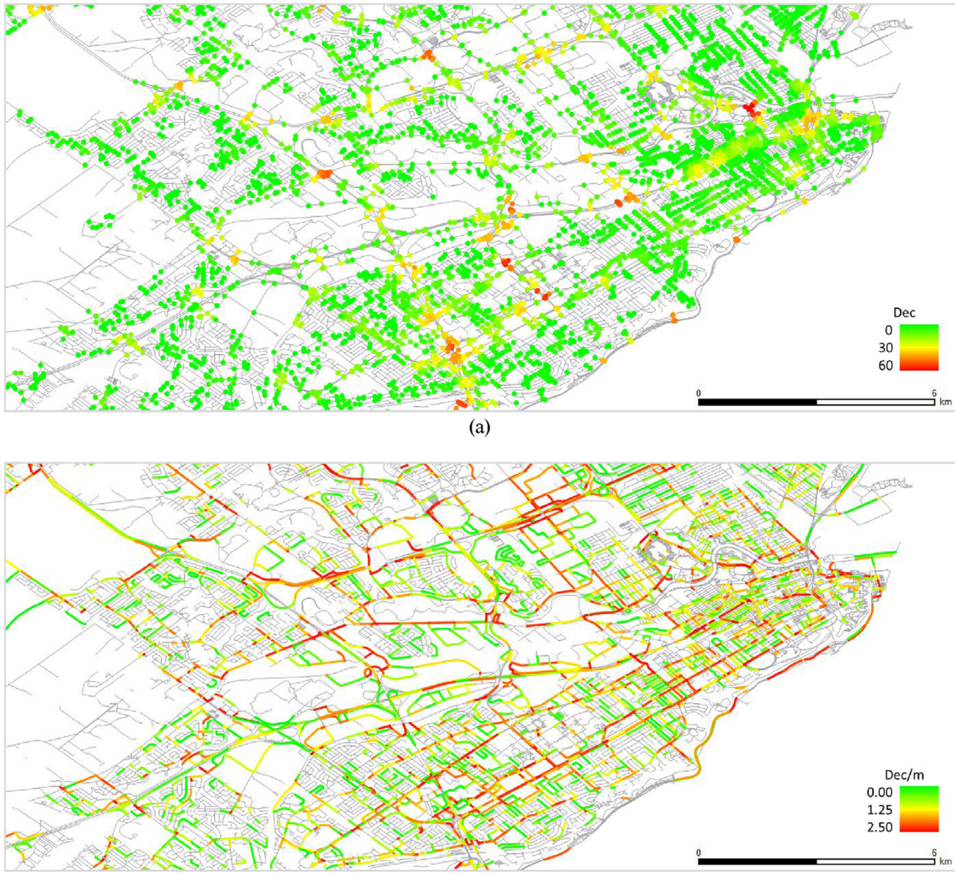

Fig. 5. Maps of the number of HBEs (with the threshold of $-2.0\,m/s^2$, window size of 5 for intersections (a) and HBEs per meter for links (b).

Table 2
Number of Facilities for Determining Spearman's Rho.

Classification	Number of Facilities	
	Links	Intersections
Motorway	1381	827
Primary	664	364
Secondary	1695	1100
Tertiary	1832	1090
Residential	15014	7340

performance was best for motorways and residential streets ($\rho > 0.60$). In all cases, the 200 m buffer provided stronger correlations compared to the 100 m buffer. Setting the acceleration threshold to $\pm\ 2\,m/s^2$ also provided the best results in all but one case (HBEs on motorways). Choosing a window size of 3 for the Savitzky-Golay filter also produced the strongest correlations. Although a window size of 3 results in unsmoothed speeds (a polynomial of degree 2 can be fit exactly to three points, therefore the measured speeds are preserved), the acceleration rate is automatically calculated based on the derivative of the fitted polynomial. This result, that unsmoothed speeds produce the best results, could be due to initial preprocessing of the data. A window size of 5 also produced strong correlations (ρ was reduced by only 0.05 on average) and has the additional benefit of greatly reducing the number of vehicle manoeuvres to analyze (by nearly 50% at $\pm\ 2\,m/s^2$). Although accelerations are less common, the correlation strength is slightly stronger than for decelerations. The overall positive results indicate that intersections that experience a greater number of vehicle manoeuvres also experience a greater number of crashes.

Considering the link-level results, the first observation is the correlation strength is significantly weaker when compared to intersections ($0.12 \le \rho \le 0.33$). Unlike at the intersection level, HBEs and HAEs had the poorest correlation along motorways ($\rho < 0.16$). Again, thresholds of $\pm\ 2\,m/s^2$ and a window size of 3 resulted in the strongest correlations in all but three cases. The 50 m buffer was observed to yield the best results. The overall positive results indicate that links that experience a greater number of vehicle manoeuvres also experience a greater number of crashes, and supports the results found in much of the existing literature (Agerholm et al., 2012; Bagdadi and Varhelyi, 2013; Jun et al., 2007). Also, the relatively high correlation strengths indicate that, if vehicle manoeuvres can be identified, they have the potential to be applied as SSMs. Based on these results, several recommendations are made for the application of this methodology:

1. SSMs based on the considered vehicle manoeuvres (HBEs and HAEs) are best suited for analysis at the intersection level.
2. Facilities should be separated by functional classification prior to analysis.
3. Using the Savitzky-Golay filter, a polynomial of degree 2 and a window length of 3 or 5 is appropriate, depending on the noise in the GPS speeds.
4. Intersection analysis should employ a buffer of 200 m, while links should use a 50 m buffer to assign collisions and/or vehicle manoeuvres to the network
5. An acceleration threshold of $\pm\ 2\,m/s^2$ is most appropriate.

4.4. Collision severity

The results of the collision severity testing are summarized in Fig. 6. The full results of all K–S tests are provided in Table 4. Aggregate plots, which contain data for all intersections regardless of classification, are

Table 3
Spearman's Rho for Vehicle Manoeuvres at the Link and Intersection Levels (by window length, acceleration rate, and buffer size).

Classification	Window	100 m			200 m		
		-2 m/s^2	-3 m/s^2	-4 m/s^2	-2 m/s^2	-3 m/s^2	-4 m/s^2
	3	0.372	0.375	0.355	0.576	**0.603**	0.578
Motorway	5	0.397	0.319	0.171	0.597	0.555	0.385
	7	0.368	0.287	0.094	0.581	0.414	0.125
	3	0.495	0.471	0.450	**0.540**	0.501	0.462
Primary	5	0.441	0.400	0.250	0.462	0.386	0.252
	7	0.357	0.218	0.030	0.334	0.194	-0.093
	3	0.429	0.419	0.389	**0.532**	0.512	0.462
Secondary	5	0.407	0.324	0.196	0.495	0.378	0.189
	7	0.353	0.195	0.067	0.396	0.186	0.040
	3	0.378	0.352	0.311	**0.573**	0.536	0.506
Tertiary	5	0.344	0.283	0.115	0.522	0.410	0.248
	7	0.312	0.133	0.115	0.430	0.253	0.095
	3	0.412	0.394	0.345	**0.615**	0.598	0.553
Residential	5	0.397	0.319	0.171	0.597	0.555	0.385
	7	0.357	0.174	0.105	0.541	0.298	0.132

Classification	Window	100 m			200 m		
		2 m/s^2	3 m/s^2	4 m/s^2	2 m/s^2	3 m/s^2	4 m/s^2
	3	0.387	0.386	0.320	0.618	0.622	0.556
Motorway	5	0.393	0.320	0.170	**0.641**	0.576	0.341
	7	0.382	0.229	0.034	0.617	0.449	0.167
	3	0.501	0.482	0.477	**0.554**	0.536	0.536
Primary	5	0.469	0.430	0.306	0.498	0.487	0.425
	7	0.435	0.362	0.204	0.436	0.397	0.200
	3	0.443	0.409	0.387	**0.536**	0.497	0.445
Secondary	5	0.425	0.383	0.314	0.507	0.403	0.276
	7	0.390	0.298	0.230	0.438	0.309	0.194
	3	0.404	0.377	0.338	**0.584**	0.543	0.513
Tertiary	5	0.381	0.339	0.218	0.548	0.481	0.301
	7	0.351	0.257	0.090	0.483	0.360	0.224
	3	0.475	0.440	0.352	**0.625**	0.594	0.506
Residential	5	0.409	0.306	0.156	0.609	0.487	0.283
	7	0.362	0.170	0.062	0.550	0.306	0.167

Decelerations at the Link Level

Accelerations at the Link Level

Classification	Window	50 m			100 m		
		-2 m/s^2	-3 m/s^2	-4 m/s^2	-2 m/s^2	-3 m/s^2	-4 m/s^2
	3	0.046	0.064	0.067	**0.118**	0.117	0.110
Motorway	5	0.062	0.063	0.047	0.112	0.100	0.076
	7	0.057	0.069	0.019	0.106	0.092	0.058
	3	0.245	0.245	0.227	**0.260**	0.254	0.218
Primary	5	0.249	0.209	0.090	0.256	0.198	0.062
	7	0.219	0.112	-0.076	0.216	0.074	-0.087
	3	**0.261**	0.259	0.231	0.254	0.239	0.201
Secondary	5	0.252	0.216	0.076	0.240	0.186	0.039
	7	0.230	0.114	0.029	0.216	0.075	0.022
	3	**0.213**	0.214	0.196	0.186	0.172	0.150
Tertiary	5	0.200	0.186	0.096	0.164	0.142	0.071
	7	0.192	0.117	0.073	0.149	0.093	0.050
	3	**0.270**	0.235	0.167	0.225	0.185	0.118
Residential	5	0.239	0.144	0.055	0.191	0.100	0.042
	7	0.198	0.065	0.034	0.140	0.046	0.025

Classification	Window	50 m			100 m		
		2 m/s^2	3 m/s^2	4 m/s^2	2 m/s^2	3 m/s^2	4 m/s^2
	3	0.078	0.084	0.081	0.145	0.136	0.133
Motorway	5	0.100	0.067	0.049	**0.155**	0.116	0.087
	7	0.092	0.077	0.004	0.140	0.126	0.064
	3	0.294	0.274	0.236	0.283	0.254	0.199
Primary	5	**0.297**	0.223	0.094	0.272	0.193	0.086
	7	0.267	0.129	-0.016	0.230	0.110	0.002
	3	**0.333**	0.308	0.241	0.297	0.262	0.208
Secondary	5	0.320	0.233	0.148	0.269	0.191	0.123
	7	0.289	0.165	0.069	0.230	0.142	0.053
	3	**0.244**	0.239	0.198	0.193	0.192	0.158
Tertiary	5	0.233	0.182	0.124	0.175	0.149	0.097
	7	0.207	0.140	0.050	0.156	0.110	0.042
	3	**0.256**	0.198	0.145	0.214	0.158	0.112
Residential	5	0.225	0.118	0.052	0.184	0.088	0.039
	7	0.175	0.065	0.037	0.133	0.049	0.022

shown first, followed by an example of a single functional classification. These plots are intended as typical examples of the different classes. As the results for links and intersections are substantially similar, Fig. 6 contains only results for intersections. For decelerations at all intersections (shown in Fig. 6a), it is observed that the distribution of the number of HBEs per site for intersections with minor injury only collisions is shifted to lower values compared to the distribution for intersections with major injury crashes. Furthermore, the distribution of major injury collisions is shifted to lower values compared to intersections with at least one fatal collision. The null hypothesis that the distribution of links with minor and major injuries (and similarly, major injury and fatal crashes) are similar is rejected by K–S test at 90% confidence. The same result is observed when considering only secondary class intersections, as illustrated in Fig. 6b. This pattern, that an increase in the number of HBEs relates to an increase in crash severity, was confirmed to be statistically significant at the 90% confidence level in 3 out of 10 test cases (5 functional classes at both the link and intersection level) and non-significant in an additional 3. In the remaining 4 test cases, the pattern was inconsistent with this result. Similarly, for HAEs, the distribution of the number of HAEs per site for intersections with minor injuries was shifted to lower values than major injuries, which was again shifted to lower values compared to intersections with fatalities. This result was confirmed by K–S test for all intersections (Fig. 6c) and secondary intersections (Fig. 6d). Again, this pattern of increasing severity with increasing number of HAEs was found to be statistically significant at the 90% confidence level in 3 out of 10 test cases, and non-significant in an additional 3 cases. As before, the remaining 4 cases, the pattern was inconsistent.

5. Conclusions

The purpose of this study was to examine vehicle manoeuvres extracted from the GPS-enabled smartphones of regular drivers as potential SSMs at the network scale. Methods for collecting, processing, and extracting the SSMs from the GPS smartphone data of regular drivers are presented. The statistical relationship between HBEs and HAEs (the two considered vehicle manoeuvres) and collision frequency was determined using Spearman's rank correlation coefficient. Relationships with crash severity were analyzed using pairwise K–S tests. In terms of identifying and extracting the SSMs, the window size of the Savitzky-Golay filter (used to smooth speeds and calculate acceleration rates) and the acceleration and braking thresholds were found to greatly affect the number of events. Depending on the exact combination of parameters, vehicle manoeuvres could comprise between 0.025% and 1% of all observations. Selecting these parameters is a crucial step in the presented analysis.

With regards to collision frequency, both HBEs and HAEs were shown to be positively correlated with frequency. Correlations between 0.53 and 0.64 were observed, dependent on functional classification at the intersection level. Observed differences between functional classes support the decision to separate facilities by their type. Results at the link level were worse, with correlations between 0.12 and 0.33 depending on functional classification. These vehicle manoeuvres are more strongly correlated with collision frequency at or around intersections. From a network screening perspective, this makes HBEs and HAEs more capable of identifying dangerous intersections than identifying dangerous links. For the analysis of collision frequency, choices must be made in terms of polynomial degree and window size for the Savitzky-Golay filter, acceleration thresholds, and buffer size for

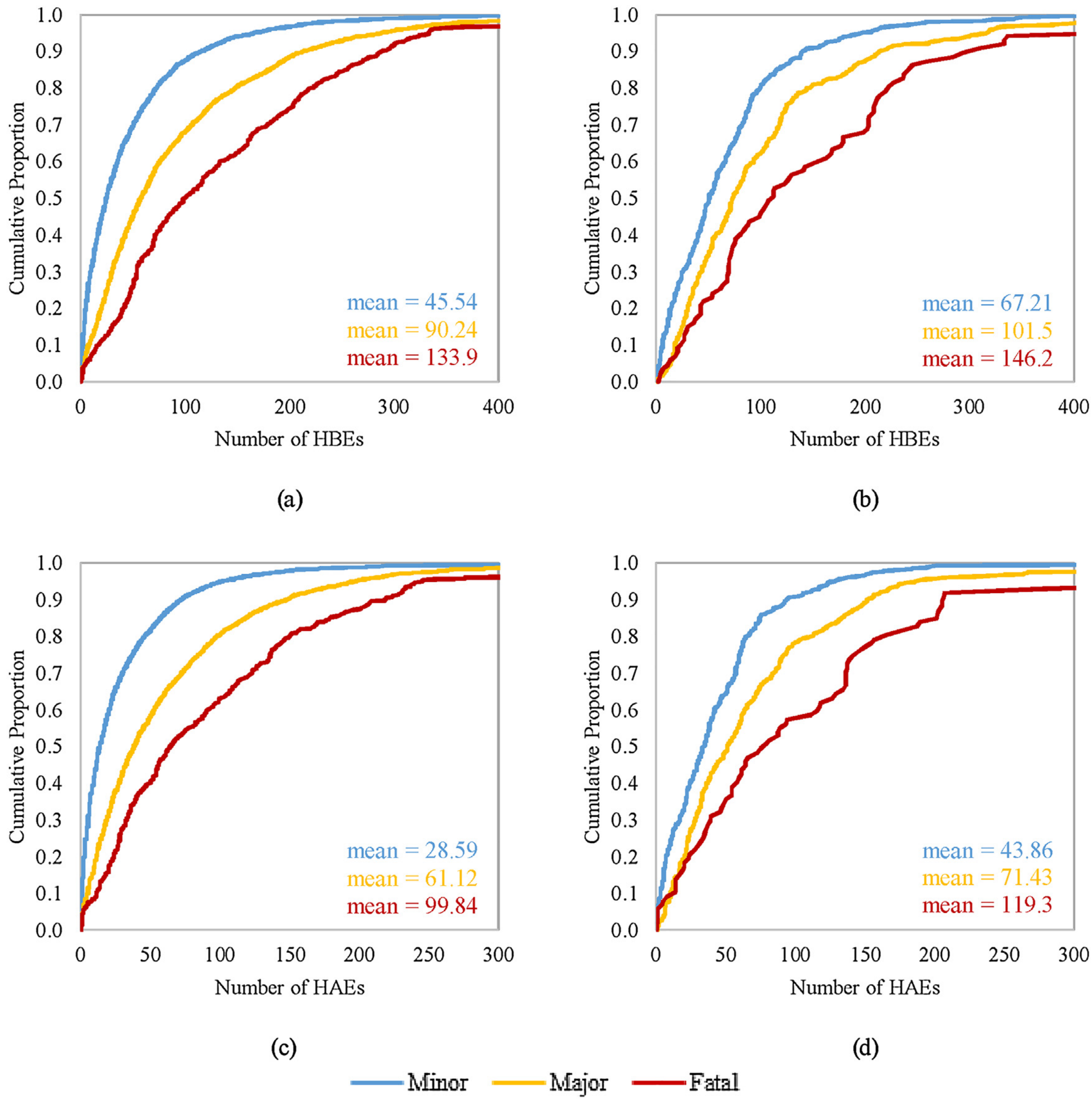

Fig. 6. Cumulative distributions for decelerations, all intersections (a) and secondaries (b), and accelerations, all intersections (c) and secondaries (d) with 200 m buffers.

assigning collisions and vehicle manoeuvres. The results of this study indicate that the following values are appropriate for this type of work, given a time resolution of approximately 1 s; a) polynomial degree of 2 and window length of 3 or 5, b) acceleration threshold of $\pm$ 2 m/s^2, and c) buffers of 200 m for intersections and 50 m for links.

The second stage of analysis was to examine the relationship between HBEs and HAEs and collision severity. An increase in either HBEs or HAEs was shown to be related to an increase in crash severity. In general, the distributions of the number of vehicle manoeuvres at links and intersections that have experienced at least one fatal crash were shown to be shifted to higher values compared to links or intersections with, at worst, major injury collisions, which were in turn shifted higher than facilities with only minor injury collisions (though this relationship was not statistically significant in some cases). This result indicates that sites with many HBEs or HAEs not only tend to have more crashes, but that crashes at those locations may be more severe. Severity, which is an independent dimension of safety, has been much less of a focus in studies based on SSMs. The inclusion of severity analysis represents a substantial contribution to the existing literature, and is the next logical step forward in the development and implementation of SSMs. Although HBEs and HAEs were shown to be significantly correlated with crash frequency, no study to date has shown a relationship with crash severity. As these results indicate, not only are vehicle manoeuvres related to a greater number of crashes, but more braking and accelerating may also be related to increased collision severity (at least for some functional classes).

Safety analysis using SSMs provides opportunities to guide improvements of facilities and reduce safety issues. Crashes themselves are not perfect predictors of safety, and surrogate measures would allow practitioners to identify sites with the potential for collisions to occur, regardless if collisions have occurred there in the past. Future work will focus on developing a network screening model that incorporates these and other potential SSMs. Not only will a network screening model demonstrate the practical application of SSMs derived from smartphone GPS data, but it will also allow for factors ignored in this study (geometry, exposure, etc.). More validation of the data and measures is required. GPS data with higher time frequency or other sensor data could help improve the precision of the measurements.

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Table 4
Results of the Pairwise K–S Tests for Crash Severity.

INTERSECTIONS		All		Motorway		Primary		Secondary		Tertiary		Residential	
		D	P-value	D	P-value	D	P-value	D	P-value	D	P-value	D	P-value
HBEs	Mi/Ma	**0.251**	**0.000**	**0.305**	**0.000**	**0.408**	**0.000**	**0.184**	**0.000**	**0.181**	**0.000**	**0.271**	**0.000**
	Ma/F	**0.195**	**0.000**	-0.157	0.106	-0.146	0.225	**0.222**	**0.001**	**0.189**	**0.025**	**0.234**	**0.000**
	Mi/F	**0.432**	**0.000**	**0.400**	**0.000**	**0.478**	**0.000**	**0.352**	**0.000**	**0.355**	**0.000**	**0.485**	**0.000**
HAEs	Mi/Ma	**0.268**	**0.000**	**0.417**	**0.000**	**0.430**	**0.000**	**0.195**	**0.000**	**0.221**	**0.000**	**0.287**	**0.000**
	Ma/F	**0.184**	**0.000**	-0.234	0.007	-0.123	0.344	**0.221**	**0.001**	**0.216**	**0.008**	**0.227**	**0.000**
	Mi/F	**0.425**	**0.000**	**0.268**	**0.000**	**0.480**	**0.000**	**0.364**	**0.000**	**0.400**	**0.000**	**0.478**	**0.000**
LINKS		**All**		**Motorway**		**Primary**		**Secondary**		**Tertiary**		**Residential**	
		D	P-value	D	P-value	D	P-value	D	P-value	D	P-value	D	P-value
HBEs	Mi/Ma	**0.087**	**0.000**	0.084	0.225	0.066	0.378	**0.069**	**0.051**	0.062	0.137	**0.071**	**0.000**
	Ma/F	0.047	0.204	-0.958	0.462	0.069	0.690	-0.066	0.581	0.107	0.338	0.100	0.133
	Mi/F	**0.121**	**0.000**	0.053	0.735	0.124	0.303	0.089	0.348	0.149	0.100	**0.164**	**0.003**
HAEs	Mi/Ma	**0.117**	**0.000**	0.084	0.225	**0.102**	**0.098**	**0.119**	**0.000**	**0.109**	**0.002**	**0.084**	**0.000**
	Ma/F	**0.059**	**0.077**	-0.096	0.462	-0.117	0.346	0.077	0.473	0.123	0.239	0.083	0.252
	Mi/F	**0.174**	**0.000**	0.053	0.735	0.102	0.449	**0.168**	**0.024**	**0.202**	**0.014**	**0.159**	**0.004**

Notes: Statistically significant values are bolded. Crash severity levels have been abbreviated as Mi (minor), Ma (major), and F (fatal). A positive D statistic means the distribution of the first member of the pair is shifted to lower values, while a negative D statistic means the second of the pair is shifted to lower values.

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