GIS-based method for detecting high-crash-risk road segments using network kernel density estimation

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Identifying high-crash-risk road segments provides safety specialists with an insight to better understanding of crash patterns and enhancing road safety management. The common hotspot identification methods are not robust enough to visualize the underlying shape of crash patterns since they neglect the spatial properties of crash data. Spatial traffic accidents have the tendency to be dependent, a phenomenon known as spatial autocorrelation. Values over distance are more or less similar than expected for randomly associated observations. Modeling the spatial variations can properly be explained in terms of first- and second-order properties. The first-order properties describe the way of varying the expected value of point pattern in space which can be due to changes in the substantial properties of the local environment, while second-order effects describe the interactive effects of events explaining how the events are interacted. Considering the discrete nature of crash data and the limited access to exact locations where crashes occur, it is likely that a continuous surface drawn from discrete points will better reflect crash density, present a more realistic picture of crash distribution. Network kernel density estimation (NKDE) is a nonparametric approach for events distributed over one-dimensional space which facilitates estimating the density at any location in the study region not just at the location where the event occurs. NKDE for road safety applications enables the extraction and visualization of crash density along roadways. The application of suggested method was illustrated for Arak-Khomein rural road in Markazi province, Iran and the stability of hazardous segments by examining the resulted network estimated density during the three years of study (2006–2008) was investigated. The result of this paper helps the traffic engineers and safety specialists to determine the segments which demand more safety attentions from both transportation authorities and drivers and request assigning the resources such as budget and time.

Keywords: crash density; NKDE; Spatial–temporal analysis

1. Introduction

Road crashes linked to the increase in vehicles using roadways have changed into a concern of traffic engineers. The accuracy and precision of safety analysis depends directly on long-term and adequate data collection. Understanding spatial and temporal crash patterns helps the safety specialists to detect the sections having a higher number of crashes as compared to other similar locations are defined as hazardous segments (1). Exploring such risky locations plays a key role in road safety management since any errors in detecting risky locations might lead to identifying the truly hazardous locations as safe or, inversely, the truly safe locations as hazardous and, consequently, will result in insufficient allocation of budget and resources (2, 3).

Dealing with geographic data, such as traffic crashes, requires special attention since they display different properties than aspatial data (4). The most important issue is the presence of spatial effects among neighboring samples over space and time – an issue that can adequately be addressed using point pattern analysis (5). The results of such analyses enable researchers to investigate the autocorrelation structure and if crashes are concentrated or clustered in space, modeling the spatial variations can properly be explained in terms of first- and second-order properties. First-order properties describe variations in the expected point pattern due to changes in the substantive properties of the local environment. In a study of traffic safety, if point objects represent locations of crash occurrences, these will tend to cluster crashes in specific areas given the existence of particular environmental features e.g. bridges, tunnels, and vertical and horizontal curves. Quadrant analysis and kernel density estimation (KDE) are known as the most frequently used methods to analyze such effects. Second-order effects describe the interactive effects of events explaining on how the events interact and are indicated using Reply’s $K$ function or Nearest Neighbor Distance (6, 7). In the case of traffic crashes; the occurrence of one crash at a particular location increases the probability of others nearby. There are many studies that explore the spatial effects of crash data (8, 9).
Among the methods to study the first-order effects, conventional KDE has attracted more attention in crash analysis owing to its simplicity and easy implementation \(^{(10)}\). It is worth noting that crash reporting in most of the developing countries is still based on the traditional pen and paper methods. Errors are inevitable when recording such discrete data with no exact locational information. It is likely that density estimation by extracting a continuous surface not only captures the spatial effects of crash pattern, but also creates more realistic picture of hazardous regions. Such locations can then be investigated in terms of the probable environmental factors which might contribute to crash locations occurring in approximately the same locations. A review on the past studies shows that conventional KDE has been employed in several safety studies to detect the crash hazard regions \(^{(11–13)}\). Although this method has shown acceptable properties when employed in estimating the density, its homogeneous two-dimensional assumption for the events distributed in one-dimensional space, such as crashes, seems to be irrelevant.

In the early 1990s, the statistical analysts set up investigating around the spatial methods to optimize the properties of two-dimensional analysis for one-dimensional space \(^{(14–16)}\). The application of such methods has mainly been undertaken in the areas of ecology \(^{(17, 18)}\) and very few models \(^{(9, 19, 20)}\) were developed in safety studies. Flauhaut et al. in 2003 developed a method for estimating the density along road segments although the technique was only developed for using along single line segments and not for networks as a whole \(^{(9)}\). Yan and Xie in 2008 proposed a network-based method to estimate the density of traffic crashes. Comparing the results with the conventional kernel density indicated that latter one overestimated the density values; but they did not argue on the results \(^{(20)}\).

There are the literatures extended in safety research investigating the temporal aspects of crash analysis. Wang and Abdel-Aty in 2006 investigated the temporal and spatial correlation for longitudinal data and intersection clusters along corridors for the rear-end crashes at 476 signalized intersections in Florida Counties. The temporal analysis indicated the correlation equal to 0.445 for crash occurrence for each successive two years and 0.1984 for years 2000 and 2002 \(^{(21)}\). Li et al. in 2007 presented a Geographic Information Systems (GIS)-based Bayesian approach to investigate the spatial and temporal patterns of rural motor vehicle crashes. The spatial analysis by day of the week (Sunday, Weekdays, Friday, and Saturday) and different years \(1996–2000\) suggested the stability state in high-risk segments \(^{(22)}\). Erdogan et al. in 2008 employed GIS-methods to explore the crash hotspots in city of Afyonkarahisar in Turkey to examine the hotspot conditions. The temporal analysis also showed the seasonal correlation among crashes in the summer and winter time, particularly in crossroad of the villages and small cities and slippery areas. Also, the higher number of crashes was detected in August and December. The daily analysis also highlighted the correlation of crashes concentrating in weekends \(^{(23)}\).

This study aims exploring the spatial variations of crashes and representing the crash hazardous segments using network kernel density estimation (NKDE). Primarily Moran’s I index will be employed on crash raw data to examine whether the raw crash occurrences show any clustering. Since crashes are distributed over a network, Moran’s I indicator will be adapted for one-dimensional space when creating a network spatial weighting matrix. Then, NKDE which mainly applied in ecology will be used to detect high-density crash segments over the 60-km Arak-Khomein rural road in Markazi Province, Iran during the successive three years, 2006–2008. A temporal analysis employed on raw crash data in previous studies will be conducted on estimated network density to check if the location of hotspots remains stable from one year to other. A combination of GIS and statistical analyses contributes to a characterization of the spatial effects in crash data and, therefore, providing a quick view of the relatively risky segments.

2. Methodology

2.1. Data collection/process

This study is based on crash database available for 60-km Arak-Khomein rural road in 2006, 2007, and 2008, being updated by Iran Road Maintenance & Transportation Organization. Since no Global Positioning System was used to report the crashes, the exact geographical locations (longitude and latitude) were not available. The crash data which were referenced to the number of kilometers, were assigned to the related segments under the procedure of geocoding using Linear Referencing tool in ArcGIS9.3. As a result, the crash locations are presented by only a point symbol along the digitized map and in cases where more than one crash occurred in the same segment, it seems as if only one crash occurred at every specific location. In fact, the symbols coincide and the concentration of crashes which have occurred more than once cannot be conveyed precisely.

2.2. Spatial and temporal analysis

Various methods have been suggested to analyze the spatial aspects of geographic data such as spatial autocorrelation and spatial heterogeneity. The methods for assessing the spatial autocorrelation have been mainly stemmed from the work of Moran and Anselin \(^{(24–26)}\) and their application to analyze road crashes has been explained in recent studies \(^{(27, 28)}\). The spatial independency of crashes is an arrangement of crashes such that there are no spatial relationships between them. The basic concept is that the location of one crash does not depend on others or there is no interaction among them. When the crashes are dependent, the positive spatial autocorrelation is said to exist. Among the several methods suggested for testing the spatial autocorrelation
(Moran’s I, Geary C and Getis-Ord), Moran’s I is more prevalent technique defined as below and ranging from 

\[ I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij})(\sum_{i=1}^{n} (y_i - \bar{y})^2)} \]  

(1)

where \( n \) denotes the number of samples (crashes), \( \bar{y} \) is the global mean value for number of crashes, calculated as a simple average value based on all data, \( y_i \) and \( y_j \) are the number of crashes at \( i \)th and \( j \)th locations, \( w_{ij} \) is a spatial weight matrix defined to determine the degree of local effects of crashes and considering the distribution of crash over network, it has been defined based on network distances. The larger the absolute value of Moran’s I, the more significant the spatial autocorrelation and a value of zero means perfect spatial randomness (26). The mathematical formulae of \( z \) score methods testing the significance of the results is obtained by:

\[ z = \frac{I_0 - I_E}{SD_{IE}} \]  

(2)

where \( I_0 \) and \( I_E \) represent the observed and expected number of crashes and \( SD_{IE} \) is the standard deviation for crash frequencies. \( z \) scores are a common scale on which different distributions, with different means and standard deviations, can be compared where the \( z \) score of the mean value is zero and the standard deviation is one. In a normal distribution, 68% of the values have a \( z \) score of plus or minus 1, meaning they lie within one standard deviation of the mean. Ninety-five percent of the values have a \( z \) score of plus or minus 1.96, meaning they lie within two standard deviations of the mean; 99% of the values have a \( z \) score of plus or minus 2.58. In the present study, Moran’s I indicator has been employed to examine the probable spatial autocorrelation to test whether the raw number of crashes are clustered or not.

2.3. KDE over planer and network space

KDE as a nonparametric approach (29, 30) has widely been applied to characterize the pattern in terms of the first-order properties of spatial data. The idea behind density estimation is that the point pattern has a density at any location in the study region not just at the location where the event occurs or is displayed (6, 7). This is a suitable property which adapts KDE to analyze the discrete data, such as crashes, particularly when just their approximate locations are available, creating more realistic picture of crash distributions. The procedure for density estimation is followed and so, defining the density surface for every individual point. The density values then diminish to 0 with distance from any crash location. The individual density surfaces are integrated in order to generate a continuous density surface over the entire area and are defined as (2, 7, 30, 31):

\[ \lambda_k(y) = \sum_{i=1}^{n} \frac{1}{\tau^2} K\left(\frac{y_i - y}{\tau}\right) \]  

(3)

where \( \lambda_k(y) \) denotes the total estimated density calculated for all crashes located at \( y_i \) around \( y, \tau \) is the kernel bandwidth which determines the search radius and is an indicator for the degree of smoothness. As indicated in Figure 1, the bandwidth determines the number of observations (crashes) around each point and controls the distance decay in weighting function. The more the distance between any crash and the location of estimating the density, the less weight is assigned (7).

KDE calculates density within a circular distance that moves across the study area. Crashes within the kernels are weighted based on their Euclidean distance from the kernel center, and the resulting density value is assigned to that center. The distance is weighted according to a kernel function which was displayed by \( K() \) in Equation (3). Any continuous, nonnegative, radically symmetrical kernel that integrates to one can be used to obtain the density estimates such as Gaussian, Quartic, Conic, Negative Exponential, and Epanichnikov (6, 7). The quality of a kernel estimate depends less on the shape of the \( K() \) than on the value of its bandwidth. It is essential to choose the most appropriate bandwidth as a value that is too small or too large is not useful: small values of \( \tau \) produce to very spiky estimates while larger \( \tau \) values lead to over smoothing. Regarding the important issue of selecting bandwidth, previous studies suggested 100–300 meter bandwidth in urban areas based on the average scale of a block or street (16, 32). In the present study, with the purpose of road safety, the bandwidth of 1 km considers regular crash location intervals. The greater the bandwidth, therefore, the more local variation is missed and, hence, risky locations are gradually mixed with the neighboring areas.

Okabe and his colleagues argued that given the linear essence of a network, when a set of points is generated by a network-related process, the application of conventional kernel to estimate the density produces biased estimates. Such misleading results arise from the fact that when the data are distributed uniformly along network,
the resulting density surface is not uniformly distributed anymore. They proposed a NKDE that constraints the kernel on a network. Based on the defined NKDE, points within the kernels are weighted based on their network distance from the kernel center following segments using an unbiased kernel function \((16)\).

Figure 2 illustrates how the conventional and network kernel function work. The fundamental idea of NKDE is that instead of a planar area of influence, each point’s influence extends a chosen distance along the network. For example a 1 km bandwidth on a network means 1 km from a point in shortest path distance. Thus, unlike the conventional KDE in which each point had a circle (or curve depending on the type of kernel function) with radius (or bandwidth) 1 km of influence, the network bandwidth defines shortest path distance. It has been proved that employing conventional KDE creates a pattern of events that often appears more clustered than it actually is \((16)\). Following the density estimation, it is interpreted that the value of the resulted surface is maximum at the location of every point location and decreases as the distance from the location increases. Regarding the crash occurrences over one-dimensional network space, such method is deemed more appropriate; therefore, in the present study, NKDE has been adapted to explore crash hazard road segments.

3. Results

3.1. Results of testing the spatial autocorrelation of crash frequencies

In order to investigate the spatial dependency among crash frequencies, Moran’s I indicator was employed for crashes within three successive years 2006–2008. The common Moran’s I weighs the point events by conceptualizing a kernel weight function which determines the degree of locality based on an Euclidian function. Since the crashes were distributed over one-dimensional space, a network spatial weight matrix was defined to achieve much more accurate results. As can be seen in Table 1, the results illustrate that no significant spatial autocorrelations were found for number of crashes within successive three years as characterized by Moran’s I, the corresponding z-score and with a \(p\)-value > 0.01. Based on the results, the absence of crash interactions can be inferred and, therefore, the occurrence of one crash cannot be affected by the others; in other words, the crash occurrences are statistically independent.

3.2. Exploring hazardous segments using NKDE

The density maps were created using NKDE implemented in SANET Ver. 4.0 \((33)\) coupled with ArcGIS 9.3, to identify the high-density segments and to test the clustering of the crashes. The bandwidth was set to 1 km to create a raster surface. In the present study, equal-split continuous kernel function was employed. The advantage of equal-split continuous kernel function as explained by Okabe is shortening the computation time particularly when applied on a complex network \((16)\). The same justification is stated by Xie in 2008 \((20)\). For more detailed discussion on NKDE, we refer to \((16)\).

The density maps extracted by NKDE for years 2006, 2007, and 2008 have been depicted in Figures 3, 4 and 5, respectively. Although the results are much more sensitive to the bandwidth rather than the type of kernel function, the sensitivity of estimated results could be either analyzed by taking equal-split discontinuous function kernel functions; although the runtime will largely increase. Three-dimensional GIS tools provide the decision-makers with interactive visualization tools.
To adequately visualize the density, the resulting density estimations were shown with 5-km interval labels. The maps extracted by this method clearly delineate high-density segments; although the density has been estimated by number of total crashes per kilometer of road segment and linear unit in NKDE. By categorizing the estimated densities into categories, the hazardous segments can be seen darker. The advantage of detecting such high-density segments is highlighting the areas demanding more safety attention and, consequently, request assigning the resources such as budget and time, once they are included in detailed engineering study sites. The results obtained from estimating density, can be analyzed temporally to explore whether the high-density location of crash occurrences remain the same or not.

3.3. Results of spatial–temporal analysis

Spatial–temporal correlation is an assessment of correlation of a variable over space and time. Studying the distribution of crashes using GIS shows that the clustering of crash points can also be evaluated in particular time (temporal) in addition to location (spatial). It contributes to assess whether the crashes are inclined to cluster in the same locations within particular time intervals or not. The visual comparison of maps reflects the dependency of high-density locations, but our temporal analysis based on Pearson correlation for the estimated densities

Figure 3. Result of NKDE with bandwidth 1 km in 2006.

Figure 4. Result of NKDE with bandwidth 1 km in 2007.

Figure 5. Result of NKDE with bandwidth 1 km in 2008.
between every two years of study confirms the stability of hazardous locations and explicitness of high-risk segments. As indicated earlier, according to our data, the number of individual crashes did not display any significant spatial autocorrelation which echoed the absence of interaction among crash points. The temporal analysis focuses on the change of relative risky segments resulted from NKDE. The estimated values which resulted from NKDE are almost continuous along whole 60-km network; thus, to increase the reliability and precession, the estimated densities within three years were compared for equally corresponded values. Table 2 shows the results for temporal Pearson correlation of estimated network densities for the same segments. The temporal analysis focuses on the change of relative risky segments resulted from NKDE. The estimated values which resulted from NKDE are almost continuous along whole network; thus, to increase the reliability and precession, the estimated densities within three years were compared for equally corresponded values.

Temporal relationships between many of the high-density road segments, indicated by high correlation, reveal that the positions of crash occurrences which have been conveyed more appropriately by estimating the density, remain the same during three years. Such results lead us to infer that the crash occurrences might be affected by the same environmental factors arising from first-order properties of crash data. Such findings provides the road safety specialists to assign the resources, such as budgets and time, by including the high-risk segments in detailed engineering study sites for the road safety improvement projects. For temporal patterns of crashes, reported studies focused mostly on fluctuation of the quantity and rate of crashes, injuries, and fatalities according to different time scales (21–23). In most of the studies, the raw rate of crashes were analyzed which deems to be irrelevant, particularly in case the crash exact locations are not available. Comparing the estimated densities might produce a more realistic picture of high-density locations. The result of spatial–temporal autocorrelation which is the indication of first-order effects of crash data lead us to infer that the crash occurrences might be affected by the same environmental factors. Such locations can then be examined in terms of spatial or aspatial factors along road segments.

4. Conclusion

The spatial essence of geographic data reveals the importance of taking the spatial properties of crashes into account. Examining the crash interactions by deploying Moran’s I was the primary objective of this research to test whether the crashes are clustered or not. Such indicator was developed by adapting the spatial weight matrix based on network distances which deems more appropriate when dealing with data distributed over one-dimensional space. For investigating the impact of the same environmental factors, KDE enables displaying the discrete events (e.g. crashes) by extracting a continuous surface and preparing more acceptable view of high-risk segments. Employing the adapted form of KDE, named NKDE, for the events distributed over one-dimensional space which had mainly been applied in the field of ecology in previous studies was another objective of present study. The application of suggested method was illustrated for Arak-Khomein rural road in Markazi province, Iran and the stability of hazardous segments by examining the resulted network estimated density during the three years of study was investigated. High spatial correlation for the resulted network density increases the probability of occurring crashes in the same location. It also supports the effect of the same environmental factors on crash occurrences. Therefore, the safety researchers can probe for the factors leading to crashes occurred approximately in the same locations which demand more funding and research.

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