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Spatio -Temporal Analysis of Pedestrian Accidents Using Kernel Density Estimation and Radar Graph

Matin Shahri

Ph.D. Candidate of Civil Engineering, School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran.

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*Corresponding Author's Email Address:

*matinshahri@gmail.com

Abstract

Pedestrians are regarded as one of the most vulnerable road users and the source of large number of fatalities or injuries in case of road accidents. Accordingly, in recent years efforts have been carried out to present the methods in order to investigate whether there is and organized pattern among accidents. When dealing with spatio-temporal data such as traffic accidents, the effects of events locating in the neighboring of others cannot be ignored. In this research, pedestrian accidents in Mashhad, Iran over five years of study, 2012-2016 have been considered. By aggregating traffic data over 253 traffic analyses zone (TAZ), spatio-temporal relationships have been conducted using Kernel Density Estimation and radar graphs. In the next step, the meaningful factors affecting the pedestrian accident occurrence have been investigated and inattention and speeding have found to be as the most leading cause of pedestrian occurrence respectively. The results of this paper can provide the traffic engineers with an insight into regions with the clustering of pedestrian accident that need more attention and assigning budget and time from transportation authorities

Introduction

Vulnerable road user is referred to those who are most at risk in traffic and are unprotected by an outside shield. Accordingly, pedestrians are regarded as vulnerable since they benefit from little or no external protective devices that would absorb energy in an accident. It is not surprising since in any contact between vehicles and pedestrian, pedestrian is at a significant disadvantage. On the other hand, the current literatures focus on planning for complete streets which is defined as streets that are multimodal and will lessen the impact of traffic on their communities' streets to promote safer, more livable and sustainable environment for all users (*Roess, Prassas et al. 2010*). Taking large number of injuries and fatalities relating to pedestrians, the safety of such vulnerable users remains a critical issue when improving traffic safety. To date, significant amount of pedestrian safety research has been undertaken and researchers have attempted to analyze the pedestrian-related accidents from different points of view. Pedestrian accident prediction models, severity analysis of pedestrian–vehicle accidents (*Abdul Aziz , Ukkusuri et al. 2013*, *Sheykhfard, Haghighi et al. 2021*, *Alogaili and Mannering 2022*, *Olowosegun, Babajide et al. 2022*), assessing the risk of vehicle–pedestrian road accidents (*Untaroiu, Meissner et al. 2009*, *Waizman, Shoval et al. 2015*, *Sahandifar, Makoundou et al. 2022*) and presenting the methods for visualizing the pedestrian-related accidents (*Rankavat and Tiwari 2013*, *Rabbani, Musarat et al. 2021*) have successfully been conducted by previous researchers.

When dealing with accident data, it is a common practice to conduct the analyses as a long-term years for planning issue (3-5 years) to skip the effects of random effects. However, in order to avoid the information lost in time-varying variables, the analyses are commonly conducted in small time scales as well. Investigating the spatio-temporal patterns of traffic accidents helps the safety specialists to explore the regions having higher number of accidents (*Matkan, Mohaymany et al. 2013*). Such analyses play a crucial role in safety studies because any errors in identifying the high-accident locations or what is known as hot-spots, might lead to identifying the relatively dangerous regions as safe or inversely the truly safe regions as dangerous and consequently insufficient allocation of budgets, time and resources (*Cheng and Washington 2005*).Therefore, an imperative need to understand the location, time and factors affecting the accident occurrence is required to develop strategies to prevent accidents.

In recent years there has been a great interest in developing the measures to take the spatial dependencies of neighboring samples over space and time into account. Such issue can efficiently be addressed through point pattern analysis (*O'Sullivan and Unwin 2010). In point pattern analysis, several methods have* been suggested to model the spatial variations. Some methods describe variations due to changes in the substantive properties of the local environment (Quadrant analysis and kernel density estimation (KDE)) while others describe the interactive effects of events explaining on how the events interact (Reply's K function or Nearest Neighbor) (*Lloyd 2010*, *O'Sullivan and Unwin 2010). KDE has attracted more attention in analyzing the* traffic accident because of its simplicity and easy implementation. It is worth to note that reporting the traffic accidents in most of the developing countries is still based on the traditional pen and paper and no GPS or other innovative GIS-based data collection method is used. In such process errors are inevitable because no exact location is available. Therefore, estimating the density in which a continues surface is extracted, not only captures the spatial effects of accident pattern, but also creates more realistic picture of point pattern. When such regions are detected, they can be investigated in terms of the probable environmental factors which might contribute to accident locations occurring in almost the same locations. A review of the past studies shows that KDE has successfully been employed in several safety studies to detect the accident hot spot regions (*Anderson 2009, Bíl, Andrášik et al. 2013, Xie and Yan 2013, Hashimoto, Yoshiki et al. 2016*).

Different methods have also been suggested to explore the temporal clusters such as single or several time series (Dat's Method, Ederer-Myers- Mantel Method and Grimson's Method) and ordinary graph and tabular format. Due to its simplicity and easy implementation and also its visual power when comes to the matter of comparison the particular interest of this paper is the radar graphs, known spider graphs as well.

Considering the importance of both spatial and temporal effects of traffic accidents, investigating the spatio-temporal relationships have been reviewed by different researchers (*Blazquez and Celis 2013*, *Soltani and Askari 2014*, *Kaygisiz, Düzgün et al. 2015*, *Rahman, Crawford et al. 2018*, *Bíl, Andrášik et al. 2019*). So far, several types of spatial and temporal visualization methods have been employed in accident research including map animation (*Dorling 1992*), isosurface approaches (*Tobler 1970*, *Brunsdon, Corcoran et al. 2007), co-map (Brunsdon, Corcoran et al. 2007, Asgari, Ghaffari et al. 2010*, *Corcoran, Lib et al. 2014*, *Tao, Rohde et al. 2014*), graphical cross-tabulation approach (*Griswold, Fishbain et al. 2011*).

In the present study, Mashhad will be considered as the second most populated city in Iran with the variety of land use which influences the trip generation over regions. Similar to other metropolises, the rapid socio-economic growth during the last two decades in addition to increasing number of vehicles caused the high amount of traffic volume. Furthermore, as a pilgrimage city also, Mashhad attracts the attention of millions of people who pay pilgrimage to this city every year. Temporal analysis using radar graph will be conducted on total number of accidents (TAs) and pedestrian accidents (PA) for different time scales in five successive years from 2012-2016 and the probable reasons of pedestrian-related accidents will be analyzed. KDE is then applied to compare whether there is an organized spatial pattern over the period time of study for the pedestrian accidents resulting from fundamental reasons. Combination of GIS and statistical analyses contributes to characterize the spatial and temporal effects of accidents and provides a quick view of the regions with the clustering of pedestrian accident data that need more attention from transportation authorities.

Data preparation

This research is based on the dataset including the number of traffic accidents available for Mashhad during *5 years from 2012-2016, which has been updated by* Mashhad Transportation and Traffic Organization. The point accident data involved series of locational and attribute information including accident type (injured, fatal, damage), accident day, accident date, accident time, accident type (pedestrian accidents (PA), single vehicle accidents (SVA), multiple vehicle accidents (MVA), fixed object accidents (FOA), motorcycle accident (MA), animal accidents (AA)), accident reason(inattention, speed, incapability…), illumination type and weather type.

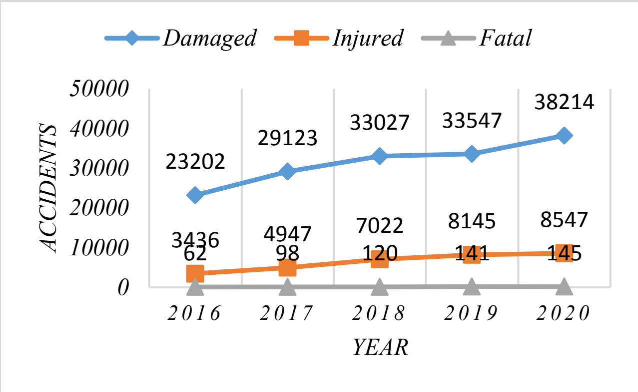


Figure 1 Descriptive description of data

The primary dataset was investigated using several statistical and visualized techniques in terms of the probable outliers and missing data. According to the comprehensive transportation studies, the city has been divided into 253 homogenous TAZs. In the first step, the TAZ borders were investigated for any topological gaps or overlays and the geometrical errors were modified and eliminated. Accident data were then assigned to the TAZs using spatial join analysis and were grouped and allocated to the centroid of the TAZ. Figure 1 illustrates the increasing trend of different types of accidents during the years of study.

Methodology

Spatial Analyses

KDE is known as a nonparametric method (*Silverman 1986, Scott 2008) and has widely been applied to* characterize the pattern of point spatial data. The idea behind density estimation is that the point pattern has a density at any location in the study area not just at the location where the event occurs or is displayed (*O'Sullivan and Unwin 2010*).This is a suitable property which adapts KDE to analyze the discrete data such as traffic accidents, particularly when just their approximate locations are available which leads to create more realistic picture of accident distributions. The procedure for density estimation is followed and so, a density surface is defined for every individual point. The density values then diminish to 0 with distance from any accident location.

The individual density surfaces are integrated in order to generate a continuous density surface over the entire area which are defined as:

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

(1)

where $\lambda_k(y)$denotes the total estimated density calculated for all accidents located at y_i around y, τ is the kernel bandwidth which determines the search radius and is an indicator for the degree of smoothness. As shown in Figure 2, the bandwidth determines the number of observations (accidents) around each data point and controls the distance decay in weighting function. The more the distance between any accident and the location of estimating the density, the less weight is assigned.

KDE calculates density within a circular distance that moves across the study area. Accidents 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 (1). 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 (*O'Sullivan and Unwin 2010*). 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 τ produce to very spiky estimates while larger s values lead to over smoothing.

Spatio-temporal Analysis and Creating Radar Charts

Radar charts, sometimes known as radar, start or web charts, are two-dimensional charts designed to plot one or more series of values over multiple common quantitative variables by providing an axis for each variable and arranged radially as equi-angular spokes around a central point. Radar charts offer a relatively simply understandable means for visualization based on the time of occurrence. Then, every class or category is analyzed by employing one of the spatial identification tools such as Kernel Density Estimation and Grid Thematic Mapping.

In particular, radar charts known allow for the inspection of spatial patterns given the variation of one or two attribute variables for geographical objects and therefore it will produce a sequence of maps or graphs in which the changes over time are detected. The time intervals could vary from hours of the day, days of the week or months of the year (*Brunsdon 2001*). In the present study we employed radar charts to indicate the hourly, daily and monthly variations of pedestrian accidents.

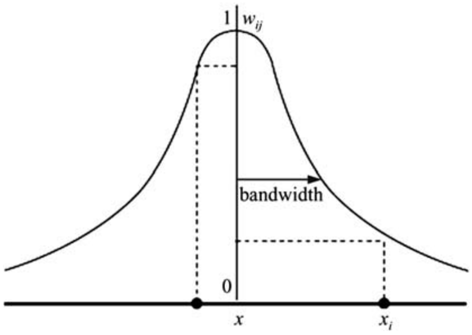
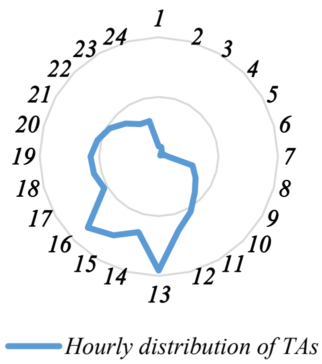


Figure 2 Indication of how Kernel works

Results and Discussion

Temporal analysis

Temporal analysis was performed by generating the radar graph for both total accidents (TA) and pedestrian accidents (PA) to fully compare the hourly, daily and monthly variations between these two types. Then, PAs were compared in terms of the reason contribute to accident occurrence. **Error! Reference source not found.** indicates the hourly distribution of TAs and PAs in Mashhad for years 2012-2016. It would be difficult to show this pattern using quantitative approaches, but is clearly revealed using this visual graphing method. As can be seen, with respect to the time of the day, while TA frequency indicates two distinct peaks of midday about 1:00 PM and 3:00-4:00 PM, the accidents involving pedestrians are more distributed from early afternoon to late evenings. This leads us to conclude that there must be substantial differences affecting the PAs. As the day progresses, PAs climb gradually from 8:00 AM and occur most frequently at 1:00 PM .This coincides the peak hour of traffic when many people are returning home from saying prayer in holy shrine (which constitutes a substantial number of trips at noon in Mashhad) or when children getting back home from morning-shift school (according to **Error! Reference source not found.**, particularly from Sep to May). It is also the lunch-hour for many employees and commuter travels when the higher pedestrian exposure at least on weekdays is expected (the 3D plot in **Error! Reference source not found.** illustrating the number of PAs based on time of the day and day of the week proves the case). Also PAs are more frequent later in the evening through 7:00-10:00 PM, when people are getting from/to home after social activities such as shopping, recreational activities or dining in restaurants. This time period involves the end of the workday when most people return home. This peak hours also coincides with evening peak hours of traffic flow. The concentration of PA distribution to the time after the sunset which is the first hours of darkness also can suggest that the PAs relatively occur higher in partial or full darkness than any other time of the day. It is interesting to examine whether or not there is a significant interaction between the reported factors in accident database (e.g. what relates to driving parameters such as speeding or driver-related parameters such as fatigue or inattention) and a particular time of day or visibility in PAs occurrence.



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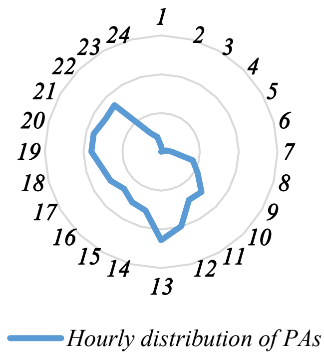

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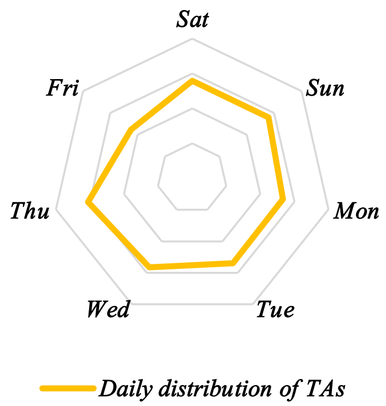
Figure 3 a) Hourly distribution of TAs for years 2012-2016 in Mashhad b) Hourly distribution of PAs for years 2012-2016 in Mashhad

Error! Reference source not found. illustrates the daily distribution of frequency of TAs and PAs. This can provide essential information for the specialists to enhance their safety activities on particular days. Although the pattern indicates low frequency of PAs on Fridays, almost 25% of all pedestrian accidents occur on weekends. Comparing the figures indicates that while PAs and TAs follow almost the same pattern on weekends, the PA frequency on different days of the week indicates substantial differentiations. As can be seen, Saturdays and Mondays experience slightly more PAs. Although it is expected that the number of accidents substantially decline after the weekend which has also been conveyed in the studies of (Mai HOA, DUC et al. 2013), but as can be seen in **Error! Reference source not found.**, both PAs and TAs have increased on Saturdays. The above result could be explained owing to the higher traffic volume on Saturdays, because on the first day of the week, more people are expected to move in-out of the study area.

Examining the PA distribution by time of day and day of week in a 3D plot gives additional insight into the PA patterns (**Error! Reference source not found.**). It is evident that the PA distribution over the time of the day exhibits approximately the same pattern on weekdays. Although PAs frequency are higher on Mondays and Saturdays, the hourly distribution follows almost the same pattern. A substantial different pattern is detected on weekends. On weekdays, accidents seem to be more frequent around noon or in the afternoon (12:00-1:00 PM), with another peak in the evening between 7:00-8:00 PM. On Thursdays, one afternoon peak is detected and another broad range of peak occurs late in the evening (4:00-9:00 PM). Fridays also experience almost the same pattern with less frequency and later starting time. The observed differences between the number of PAs on weekdays and weekends can be associated with the different social behaviors. As an example, one possibility for PAs on weekends could be due to more recreational trips in which more pedestrian walking is expected in evenings.



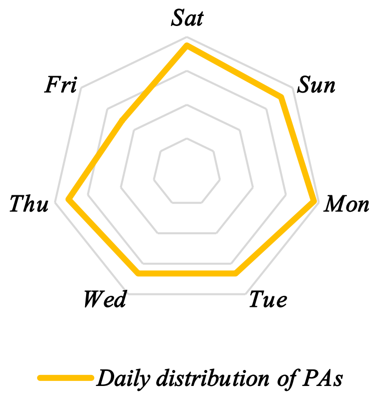
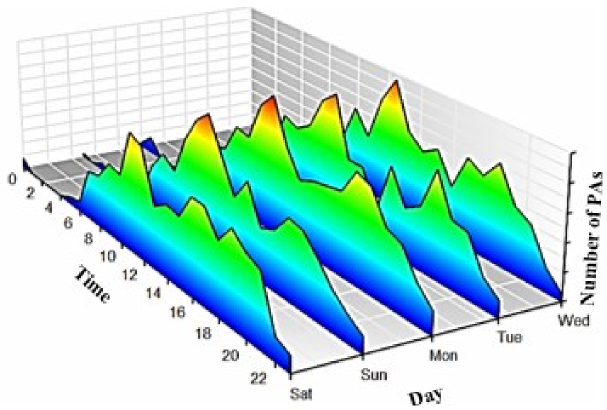


Figure 4 a) Daily distribution of TAs for years 2012-2016 in Mashhad b) Daily distribution of PAs for years 2012-2016 in Mashhad



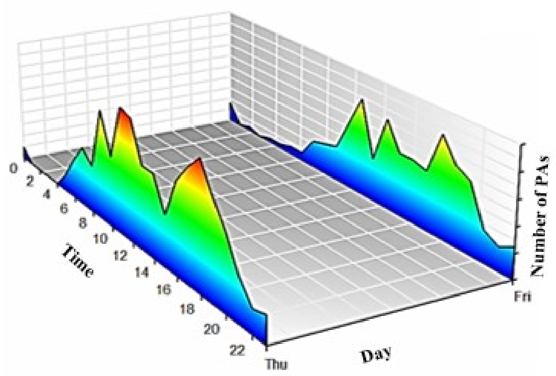
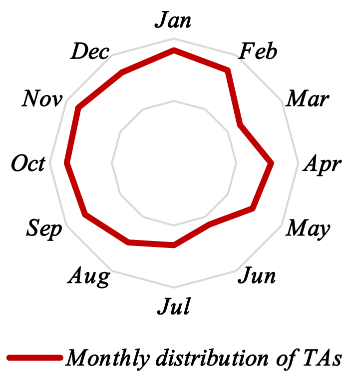


Figure 5 Illustration of distribution of PAs for years 2012-2016 according to the time of day and day of the week in Mashhad



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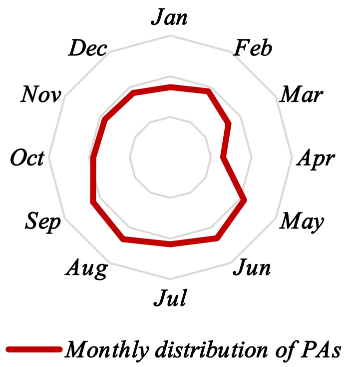

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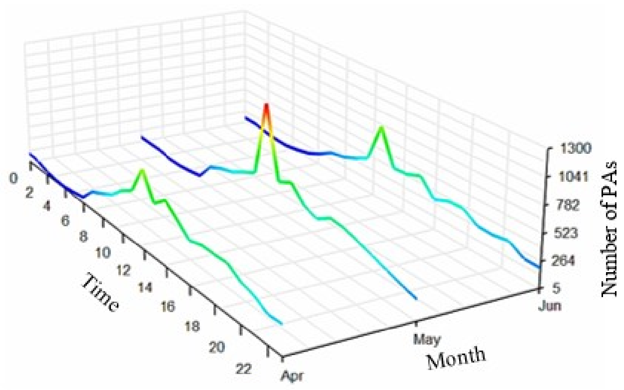
Figure 6 a) Monthly distribution of TAs for years 2012-2016 in Mashhad b) Monthly distribution of PAs for years 2012-2016 in Mashhad

Comparing the monthly variations of PAs and TAs indicates that temporal distributions do not follow the same pattern and pedestrians are not very much involved in cold weather accidents (**Error! Reference source not found.**). The cold seasons of the year (i.e., September through February) indicate the worst for TA, while a lower number of accidents are detected during summer and spring time (i.e., March through August). During the summer-holidays, lower number of educational trips are expected. Another possible reason of less frequency of PAs during winter could be due to the fact that the ability and desire of people to walk are highly influenced under such circumstances and therefore the total kilometers traveling by pedestrians is reduced. On the other hand, driver's awareness of climate change and low skid resistance under rainy and snowy conditions could be regarded as an essential factor to drive more cautiously. According to the distribution of PAs based on the time of the day, it can be inferred that PAs indicate the high peak around 10:00 AM to 2:00 PM during the cold months of the year except for March. It can also be indicated that the months of January and August had the greatest and April had the lowest number of accidents.



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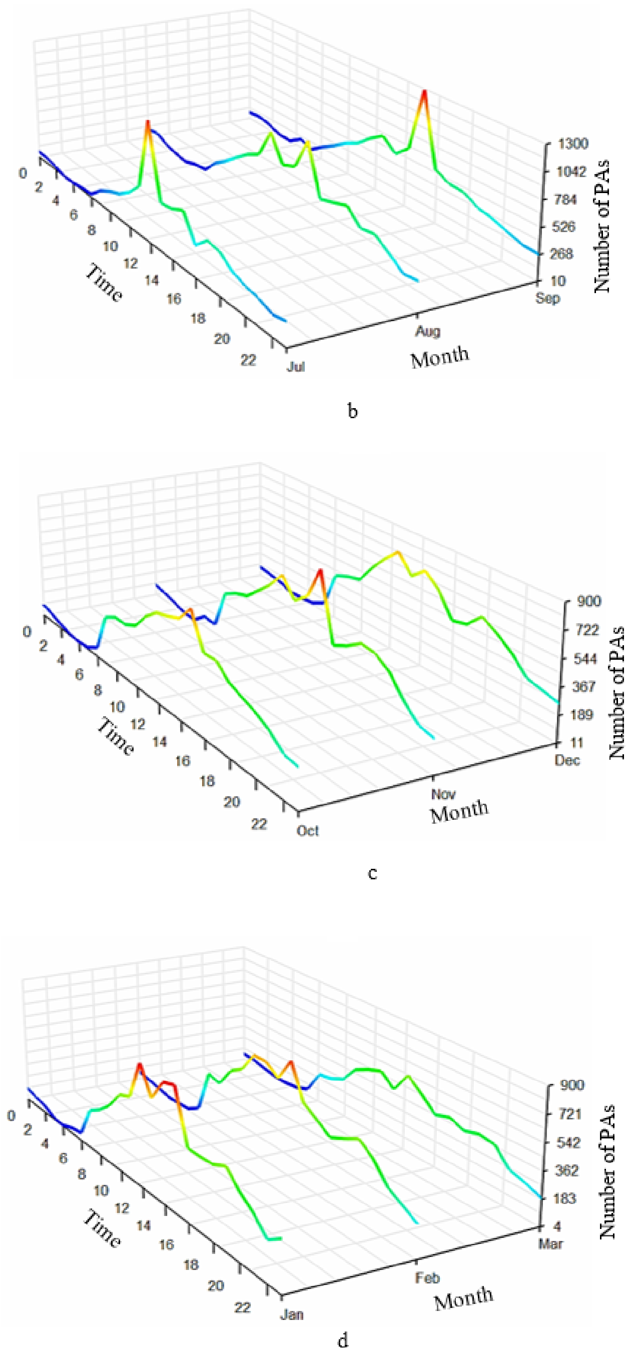


Figure 7 Seasonal distribution of PA for years 2012-2016 in Mashhad a) spring b) summer c) autumn and d) winter

The hourly distribution of PAs based on the month of the year also indicates that in cold months of the year (October to February), the PAs are highly concentrated in a broad range around noon rather than evening (Figure 7). During the warm months of the year, the same pattern can be detected except that a narrower peak is detectable. This leads us to conclude that illumination and weather darkness cannot be considered as the essential cause of PAs during summer and spring. Although in the study conducted by (Griswold, Fischbein et al. 2011) a slight morning peak in accidents in the cold months are shown, which coincides with the early morning pedestrian activity.

Results of kernel Density Estimation

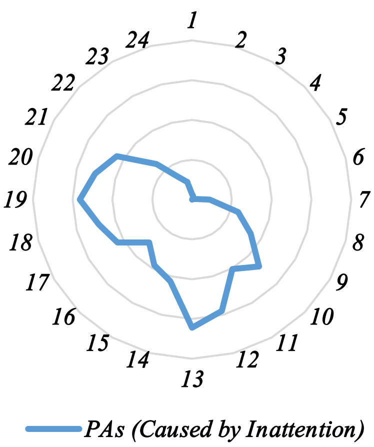
The analysis of temporal distribution of inattention-related accidents and speeding-related accidents indicates some similarities in two important peaks; 1:00 PM and 7:00 PM and relatively few accidents between 1 and 9 AM, although some variations are also detectable (Figure 9-a and Figure 9-b) .

In order to visualize the density maps, the resulting density estimations using kernel density estimation (KDE) method have been shown in Figure 9. The maps extracted by this method clearly describe high-density locations; although the density has been estimated by number of total accidents per kilometer square of areal unit. The estimated densities have been categorized, such that the locations with higher accidents can be seen darker. The advantage of detecting such high-density locations is highlighting the areas which need more safety attention and, request allocating the resources such as budget and time, once they are included in detailed engineering study sites.

The KDE map of PAs caused from inattention has been illustrated in Figure 9-b and Figure 9-c. As can be seen, accidents tend to happen in two distinct areas. Most PAs occurred at 1:00 PM due to inattention are concentered along freeways particularly in northeast of the study area which is the transition areas between Mashhad and its suburbs. Another pattern is detectable in the city center where the CBD with shopping centers and social activities is located. Such organized spatial pattern, leads us to infer that perhaps some environmental factors which leads to driver's distraction could be the contributing factors of occurring the pedestrian accidents. On the other hand, the pedestrian accidents in evening peak (7:00 PM) are evidently clustered in the northern part of the study area.

Based on Figure 9-e and Figure 9-f, the speed-related accidents of pedestrians are more frequent at 1:00 PM and during night (from 7:00 to 10: PM). The results of KDE for PAs caused by speeding at 1:00 PM indicates that PAs have been concentrated along the urban freeways located in north and southeast of the study area. The spatial distribution of PAs in daytime is another evidence for the fact that the pedestrian safety along the urban freeways in which higher speeds are expected, is the issue of concern. The speed-related accidents of pedestrians at night are clustered in the south and southwest of study area.

It is evident that while drivers are not likely to speed up at night, the pedestrian accidents due to exceeding the limited speed is more frequent at nights and therefore the pedestrian behavior during darkness and their awareness of how difficult it is for drivers to see pedestrian, needs to be improved. On the other hand, using the visibility equipment or enhancing the lighting conditions in such area can have a significant positive impact on pedestrian-related safety. This is in line with the findings of (Kim, GF et al. 2008, F. Ulfarsson, Kimb et al. 2010, Hanson, Noland et al. 2013)



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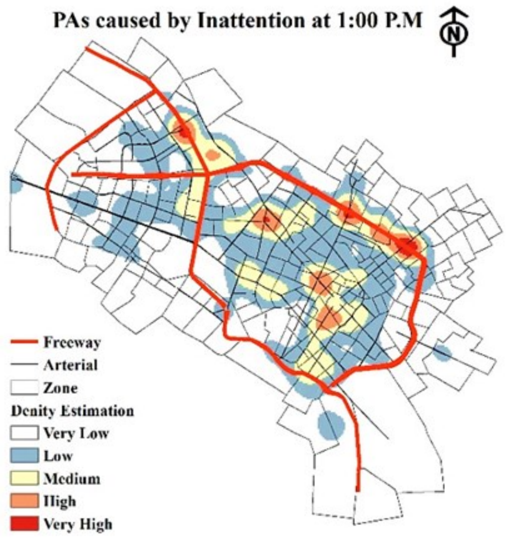

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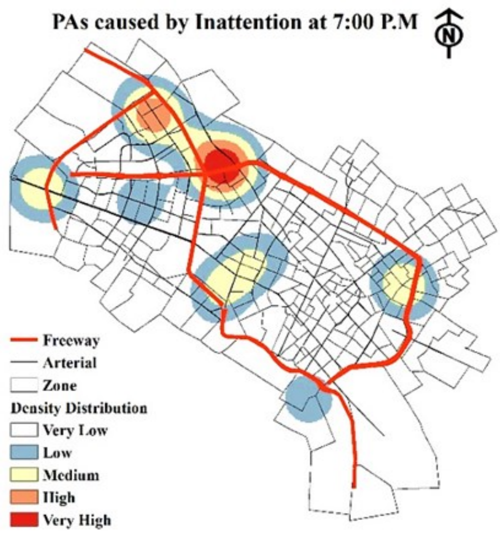

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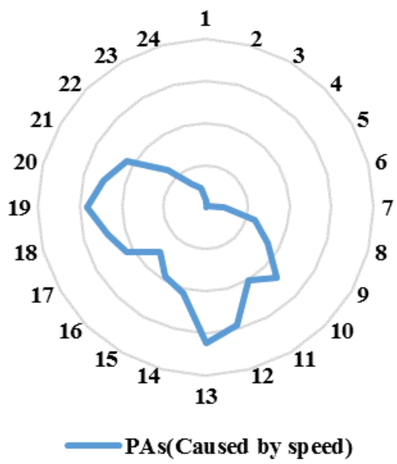

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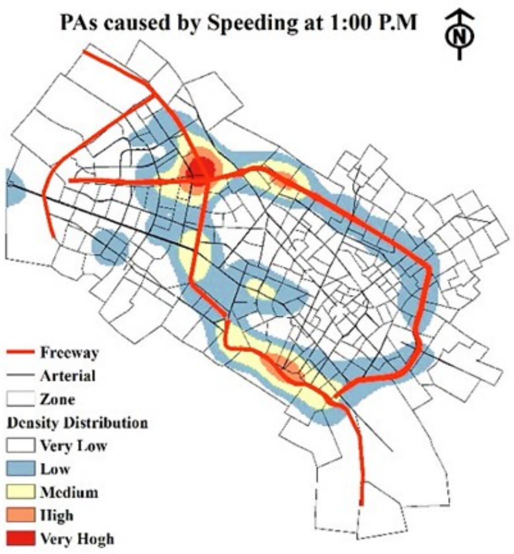

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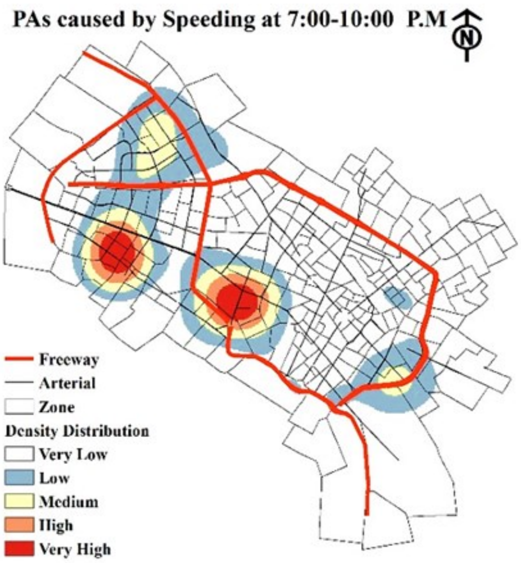

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Figure 9 Temporal distribution of PAs according to inattention and speeding

The maps resulting from KDE on PA have been produced for two important factors of speeding and inattention. In terms of speeding, there is a clear spatial pattern of pedestrian accidents reflected by the fact that the distribution of such type of accidents follow an organized pattern.

Conclusion

In this research, spatio temporal patterns of pedestrian accidents have been analyses using Mashhad accident dataset for successive five years 2012-2016 by employing KDE and radar graphs. For policy makers and transportation planners, these initial findings are useful in several ways. First, the consistent hourly pattern within a day and the consistency of day type

(weekday/Saturday versus holiday/Sunday) suggests that correction factors and forecasting methods are feasible. The daily pattern is likely to vary significantly from place to place and an effort to define a number of pedestrian location types might assist with factor development.

Second, the results indicate that reasons such as driver's inattentions and speed are the main causes of pedestrian accidents. Traffic calming improvements, such as raised crosswalks at street intersections, as well as appropriate warning traffic signs can be regarded as appropriate strategies to slow down vehicles and help improving the safety of pedestrians. The results of this research can be an initial findings for exploring accident hotspots which demand assigning more budget and safety attentions

References

Abdul Aziz , H. M., S. V. Ukkusuri and S. Hasan (2013). "Exploring the determinants of pedestrian–vehicle crash severity in New York City." Accident Analysis and Prevention 50: 1298-1309.

Alogaili, A. and F. Mannering (2022). "Differences between day and night pedestrian-injury severities: Accounting for temporal and unobserved effects in prediction." Analytic Methods in Accident Research 33: *100201.*

Anderson, T. K. (2009). "Kernel Density Estimation and K-Means Clustering to Profile Road Accident Hotspots." Accident Analysis & Prevention 41(3): 359-364.

Asgari, A., A. Ghaffari and J. Levy (2010). "Spatial and temporal analyses of structural fire incidents and their causes: a case of Toronto, Canada." Fire Safety Journal *45(1): 44-57.*

Bíl, M., R. Andrášik and Z. Janoška (2013). "Identification of hazardous road locations of traffic accidents by means of kernel density estimation and cluster significance evaluation." Accident Analysis & Prevention 55: 265-273.

Bíl, M., R. Andrášik and J. Sedoník (2019). "A detailed spatiotemporal analysis of traffic crash hotspots." Applied geography 107: 82-90.

Blazquez, C. A. and M. S. Celis (2013). "A spatial and temporal analysis of child pedestrian crashes in Santiago, Chile." Accident Analysis & Prevention 50: 304-311.

Brunsdon, C. (2001). "The comap: exploring spatial pattern via conditional distributions." Computers, Environment and Urban Syatems 25: 53-68.

Brunsdon, C., J. Corcoran and G. Higgs (2007). "Visualising space and time in crime patterns: a comparison of methods." Computers, Environment and Urban Systems 31(1): 52-75.

Brunsdon, C., J. Corcoran and G. Higgs (2007). "Visualising space and time in crime patterns: A comparison of methods." Computers, Environment and Urban Syatems 31(1): 52-75.

Cheng, W. and S. P. Washington (2005). "Experimental evaluation of hotspot identification methods." Accident Analysis & Prevention 37(5): 870-881.

Corcoran, J., T. Lib, D. Rohdea, E. Charles-Edwardsa and D. Mateo-Babianoa (2014). "Spatio-temporal patterns of a Public Bicycle Sharing Program: the effect of weather and calendar events." Transport Geography 41: 292-305.

Dorling, D. (1992). "Stretching space and splicing time: from cartographic animation to interactive visualization." Cartography and Geographic Information Science 19(4): 215-227.

F. Ulfarsson, G., S. Kimb and K. M. Booth (2010). "Analyzing fault in pedestrian–motor vehicle crashes in North Carolina." Accident Analysis and Prevention 42: 1805-1813.

Griswold, J., B. Fishbain, S. Washington and D. R. Ragland (2011). "Visual assessment of pedestrian crashes." Accident Analysis and Prevention 43(1): 301-306.

Hanson, C. S., R. B. Noland and C. Brown (2013). "The severity of pedestrian crashes: an analysis using Google Street View imagery." Journal of Transport Geography 33: 42-53.

Hashimoto, S., S. Yoshiki, R. Saeki, Y. Mimura, R. Ando and S. Nanba (2016). "Development and application of traffic accident density estimation models using kernel density estimation." Journal of Traffic and Transportation Engineering (English Edition) 3(3): 262-270.

Kaygisiz, Ö., Ş. Düzgün, A. Yildiz and M. Senbil (2015). "Spatio-temporal accident analysis for accident prevention in relation to behavioral factors in driving: The case of South Anatolian Motorway." Transportation research Part F: traffic psychology and behaviour 3

Kim, J., U. GF, S. VN and K. S (2008). "Age and pedestrian injury severity in motor–vehicle crashes: a heteroskedastic logit analysis." Accident Analysis and Prevention 40(5): 1695-1702.

Lloyd, C. D. (2010). Local Models for Spatial Analysis, CRC Press, Taylor & Francis Group.

Mai HOA, D. T., N. H. DUC, N. T. HUONG and N. N. BAO (2013). "On Time-Distributions of Traffic Accident and of Its Related Factors: Pilot Study with Data Analysis for an Urban District with Complex Traffic Situation." Proceedings of the Eastern Asia Society for Transportation Studies 19.

Matkan, A. A., A. S. Mohaymany, M. Shahri and B. Mirbagheri (2013). "Detecting the spatial–temporal autocorrelation among crash frequencies in urban areas." Canadian Journal of Civil Engineering 40(3): 195-203.

O'Sullivan, D. and D. Unwin (2010). Geographic Information Analysis, 2nd Edition, John Wiley & Sons.

Olowosegun, A., N. Babajide, A. Akintola, G. Fountas and A. Fonzone (2022). "Analysis of pedestrian accident injury-severities at road junctions and crossings using an advanced random parameter modelling framework: The case of Scotland." Accident Analysis & Prevention 169: 106610.

Rabbani, M., M. A. Musarat, W. Alaloul, A. Maqsoom, H. Bukhari and W. Rafiq (2021). "Road Traffic Accident Data Analysis and Its Visualization." Civil Engineering and Architecture 9: 1603-1614.

Rahman, M. K., T. Crawford and T. W. Schmidlin (2018). "Spatio-temporal analysis of road traffic accident fatality in Bangladesh integrating newspaper accounts and gridded population data." GeoJournal 83(4): 645-661.

Rankavat, S. and G. Tiwari (2013). "Pedestrian Accident Analysis in Delhi using GIS." Journal of the Eastern Asia Society for Transportation Studies 10: 1446-1457.

Roess, R. P., E. S. Prassas and W. R. McShane (2010). Traffic Engineering, Prentice Hall.