Spatiotemporal Distribution of Traffic Violations in a Medium-Sized City Luzhou

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Abstract. Exploring the spatial and temporal distribution of traffic violations is vital to road safety management. This study investigated the traffic violations of illegal parking and disobeying the guide lane, which are the most observed in a middle-sized city Luzhou. The temporal distributions between the traffic violations are compared in time of day, day of week, and month of year. The underlying spatial dependency and cluster of the violations are investigated by global Moran's *I*, local Moran's *I*, and kernel density. Results show that the frequency of illegal parking is remarkably higher in the period ranging from September to December, weekdays, morning, and afternoon. However, the violations of disobeying the guide lane are more frequently observed in the first-half year and daytime. Both two types of violation are positively correlated in space. Moreover, the density of illegal parking is higher in the upper area of the city where commercial and residential zone are common, while disobeying the guide lane is mostly found in several intersections which are close to the freeway exit. The possible explanations of the spatial and temporal distributions are discussed.

Keywords: Traffic violation · Spatiotemporal distribution · Moran's I test · Kernel density analysis · Illegal parking · Disobeying the guide lane

1 Introduction

Numerous studies have pinpointed that drivers who commit traffic violations frequently were more likely to be involved in crashes [1–3]. Accordingly, traffic violation is viewed as one of the leading causes of road trauma [4, 5]. However, Traffic violations are much more common in developing countries [1, 6]. With these facts in mind, it is worth preventing urban traffic violations with effective approaches.

Generally, the researchers and authorities of road safety tend to focus on several types of urban traffic violations, which are regarded as risky behaviors, such as speeding [7–10], driving under the influence [11–15]. In contrast to those, others including illegal overtaking [16, 17], disobeying the guide lane [18] (driver should use guide lanes to enter intersections to avoid potential conflicts), and illegal parking [19] are less concerned, although they are sometimes more common in the city areas than the "risky violations".

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The guide lane is a turning lane generally set in the entering section of the intersection. Drivers whose turning are inconsistent with the guide lane it is in will get tickets for disobeying the guide lane. Vehicles are not allowed to park in front of the entering of public service buildings, intersections, and narrow roads. Such a violation is called illegal parking. It should be noted that disobeying the guide lane and illegal parking (especially on-road parking) can affect the traffic flow by causing hard-braking and traffic conflict [20–22], which is considered to be a pre-crash improper behavior [23] and significantly associated with pedestrian-related crashes [24]. As such, it is urgent to explore the characteristics of such two types of traffic violations.

The spatial and temporal distribution of traffic violations is commonly investigated. Red-light running was inclined to be detected on alleys, roads with physical dividers, and intersections [25] on weekends, midday, morning peak hours, and evening [26], speeding behaviors are more likely to be found at nighttime [27], and driving without seat belt is more commonly observed on urban roads rather than rural roads [28, 29]. Moreover, traffic violations are found to be associated with both temporal and spatial autocorrelations [30], with certain clustering patterns in space and time are observed. Traffic engineers can have a better understanding of determinants spatiotemporal characteristics and autocorrelation effects in traffic violations. However, the studies have several limitations. In addition to the incomplete researches on some types of violations, the existing study often uses the data of traffic violations collected from the whole country, state, and metropolitan, while the violations from minor sizes (such as medium-sized cities) are ignored.

To fill the knowledge gaps in the literature, this study attempts to explore both the spatial and temporal distribution characteristics of two types of traffic violations, i.e., disobeying the guide lane and illegal parking. Luzhou, a medium-sized city located in Southwestern China, is selected to be analyzed. The temporal and spatial patterns of the traffic violations are investigated on different scales. This effort could provide guidance for road safety management in similar cities.

2 Method

2.1 Data

Data of traffic violations were collected from the Department of Policy in Luzhou City, 2016. Luzhou is a medium-sized city in Sichuan Province, China. The core urban area of this city consists of three districts, namely Jiangyang, Longmatan, and Naxi. Both Jiangyang and Longmatan districts are located in the upper area of the city, while the Naxi district belongs to the lower area of the city. Luzhou is a typical industrial and port city in mainland China, which has considerable needs for cargo shipping and a high ratio of citizens engaged in logistics.

According to data processing, 14 types of traffic violations are identified and ranked in frequency, as shown in Fig. 1. It shows that the violations of illegal parking and disobeying the guide lane make up the majority of total traffic violations in Luzhou (84.6%), while other violations only account for minor parts. Due to the dominance of illegal parking and disobeying the guide lane, the two types of traffic violations are selected to be investigated.

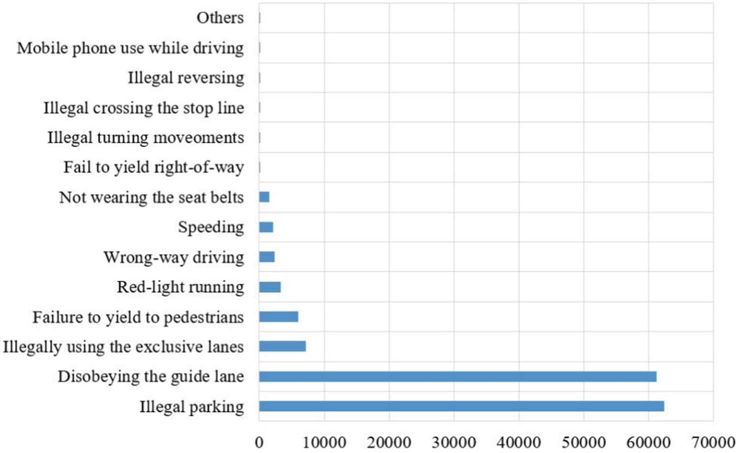


Fig. 1. Frequency of 14 types of traffic violation in 2016

2.2 Analytical Approach

The approaches used to analyze the spatial and temporal distributions of the traffic violations are presented as follows.

1) **Temporal analysis**

Temporal distributions of the traffic violations are measured by descriptive statistics. We explore the distribution of the violation frequency in three-time scales, including time-of-day, day of week, and month of year.

2) **Spatial analysis**

We use global Moran's *I* test, local Moran's *I* test, and kernel density analysis to unveil the spatial pattern of the violations. Global Moran's *I* and local Moran's *I* require spatial units with attributes of interest (e.g., points, lines, grids). Thus, the study area is divided into grids with violation frequency to be analyzed.

(1) Global Moran's *I* test

Global Moran's *I* test is used to examine the underlying spatial autocorrelation of a variable in the entire study area. It can be given by

$$Moran's\,I = \frac{N}{\sum\limits_{ij} w_{ij}} \frac{\sum\limits_{i}\sum\limits_{j} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum\limits_{i}(x_i - \overline{x})^2} \tag{1}$$

where, x_i and x_j are the frequency of a type of traffic violation in the grid i and j, respectively; $\overline{x}$ is the mean value of the traffic violation; N is the total number of the grids; w_{ij} is the spatial weight, specifically, if grid x_i and grid x_j are adjacent, then $w_{ij} = 1$, otherwise, $w_{ij} = 0$.

The interval of global Moran's I statistic is $[-1, 1]$. If the statistic is close to -1, the attributes of interest are more negatively correlated in space. If the statistic is close to 1, the attributes are more positively correlated in space.

(2) Lobal Moran's I test

Moreover, the study uses a local Moran's I test to explore whether a local spatial autocorrelation existing among the adjacent grids [31], it takes the form as

$$I_i = \frac{x_i - \overline{x}}{S^2} \sum_{j}^{n} w_{ij}(x_j - \overline{x}) \tag{2}$$

where S^2 is the variance of x_j.

Local Moran's I test sorts the grids into different patterns of spatial clusters, which are high-high cluster, high-low cluster, low-high cluster, and low-low cluster. High-high clusters and low-low clusters mean that the grids with high violation frequency or low violation frequency are surrounded by similar grids, respectively; while the high-low or low-high clusters mean the target grid which has a high/low value of the violation frequency is surrounded by the dissimilar grids.

(3) Kernel density analysis

In addition to the grid-based approaches, we use kernel density analysis to reflect the continuous spatial distribution of the traffic violations on point elements. Generally, geographic events are more likely to occur in areas with high kernel density and less likely to occur in areas with low kernel density. The equation of kernel density is expressed as

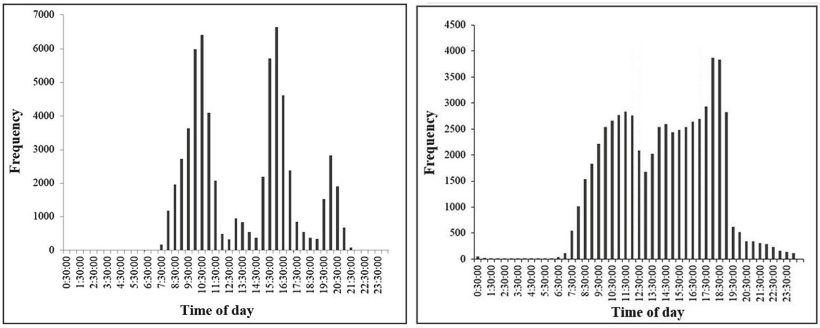
$$f_n(z) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{z - z_i}{h}\right) \tag{3}$$

where, $k(\cdot)$ is the kernel function; h is the bandwidth; z represents the points with attributes; z_i is the adjacent points of z.

3 Results

3.1 Temporal Characteristics

Figure 2 shows the temporal distribution of the traffic violations in time-of-day, which are presented by bar charts. It shows that the violations of illegal parking are mostly found in the morning (9:30–11:30) and afternoon (15:30–16:30) (Fig. 2 (a)). A slight incensement is also found after the evening peak hours (19:30–20:30). For the number of disobeying the guide lane, it is commonly found during the whole daytime (8:30–19:00). We also observe an extreme of such violation in the evening peak hours (see Fig. 2 (b)).

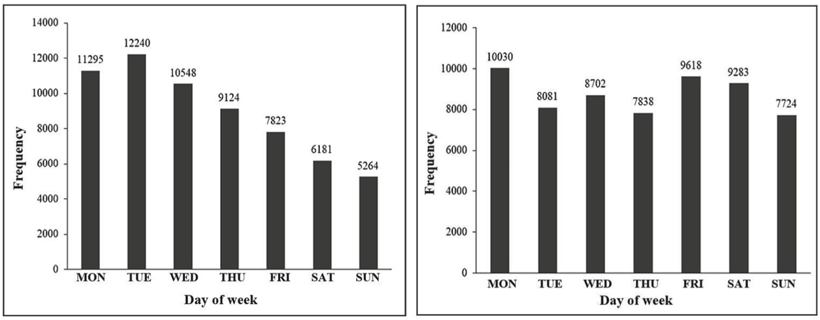


(a) Illegal parking (b) Disobeying the guide lane

Fig. 2. The time-of-day distribution of the two types of traffic violation

Neither the two types of traffic violation are inclined to be found in late night and dawn (21:30–6:30).

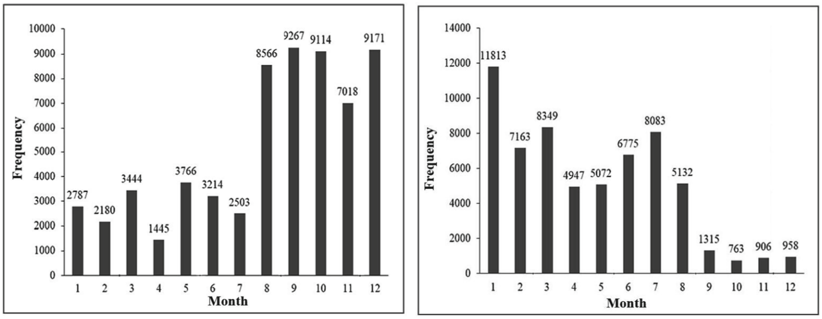
Figure 3 illustrates the distribution on the day of week for the illegal parking and disobeying the guide lane. It can be seen that Monday and Tuesday are the two days with the highest frequencies of illegal parking (12,240 and 11,295 tickets), while Saturday and Sunday have lower frequencies of illegal parking than other days (see Fig. 3 (a)). As to the distribution of disobeying the guide lane, it seems no obvious difference is observed between weekdays and weekends, although the frequency of Monday and Friday (10030 and 9618 tickets) slightly surpasses this of other days.



(a) Illegal parking (b) Disobeying the guide lane

Fig. 3. The day of week distribution of the two types of traffic violation

The monthly distribution of the two types of traffic violations is illustrated in Fig. 4. Results show that illegal parking is more likely to occur in the range from September to December (Fig. 4 (a)), yet the frequency of these violations are much fewer in the first half-year. However, the monthly trend of disobeying the guide lane is quite discrepant in contrast to illegal parking. These violations are commonly observed in the first half-year with the extreme in January, while the frequency at the end of this year is quite low (see Fig. 4 (b)).



(a) Illegal parking (b) Disobeying the guide lane

Fig. 4. The monthly distribution of two types of traffic violations

3.2 Spatial Characteristics

1) Global Moran's *I* Test

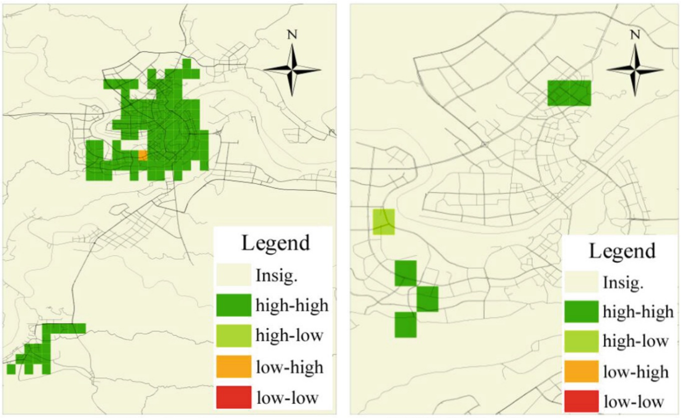
As presented in Table 1, the pseudo *p*-values of the global Moran's *I* statistic show that both the violations of illegal parking and disobeying the guide lane are not randomly distributed in the study area, indicating that there are significant spatial autocorrelations among these violations. Moreover, we found the global Moran's *I* statistic is positive for either the types of violation. This signifies that the violations are spatially clustered rather than dispersed.

Table 1. The results of global Moran's *I* test of two types of traffic violations

Traffic violations	Moran *I*	*Z*-value	*p*-value
Illegal parking	0.2687	311.3763	$p < 0.01$
Disobeying the guide lane	0.0013	2.3451	$p < 0.05$

2) Local Moran's *I* Test

Results of the local Moran's *I* test are shown in Fig. 5. Grids with high-high clusters are mostly found in the center and the southwest corner of the city. This presents that the grids with the high frequency of illegal parking tend to be correlated. Only one grid of low-high outliers is observed in the city center, indicating that the frequency of illegal parking in this grid is relatively less than its neighbors. With respect to the violation of disobeying the guide lane, the grids with high-high clusters are much fewer than those of illegal parking in the upper area of the city. It is also found that a grid with a high-low cluster is located downstream of urban rivers, meaning that the grid with the high frequency of disobeying the guide lane is surrounded by the grids with less violation frequency.

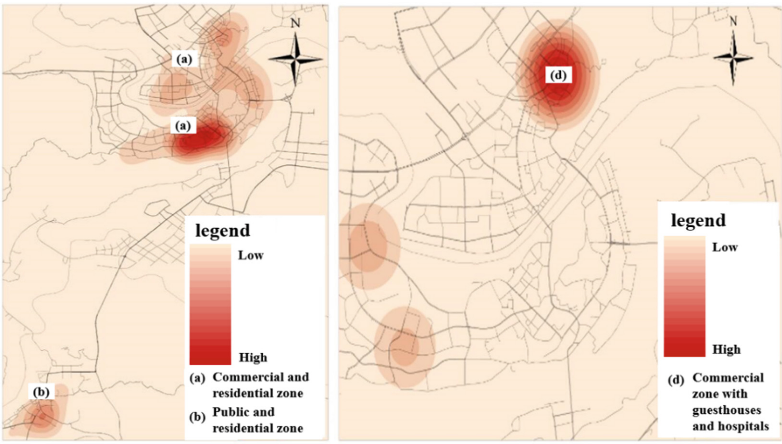


(a) Illegal parking (b) Disobeying the guide lane

Fig. 5. The results of local autocorrelation analysis of the two types of traffic violation

3) **Kernel Density**

The results of kernel density are presented in Fig. 6 (a) and Fig. 6 (b). It is shown that the density of illegal parking in the upper area surpasses that of other areas where land-use is typed as a commercial and residential zone. Moreover, the location with public and residential land-use tends to have a higher density of illegal parking as well. The kernel density analysis for disobeying the guide lane shows that only one location is observed with extremely high density, which is located in the northern part of the city and close to the freeway exit. Some public facilities and commercial buildings are also found in this location, including hospitals, pharmacies, and guesthouse complexes.



(a) Illegal parking (b) Disobeying the guide lane

Fig. 6. The result of kernel density of the two types of traffic violations

4 Discussions and Conclusions

This study explores both temporal and spatial characteristics of illegal parking and disobeying the guide lane in a medium-sized port city. Global Moran's *I*, local Moran's *I,* and kernel density analysis are conducted to uncover the spatial patterns. We also investigate the temporal distribution of the two types of traffic violations on various scales (hourly, day of the week, and monthly). Results show that the frequencies of traffic violations are linked to spatial autocorrelation and spatial-temporal variation.

For the spatial distribution, the illegal parking behaviors are clustered in uncertain areas. The areas serve as the core with a huge amount of traffic activities. The increasing requirements of parking are failed to be met by the parking lots and roadside parking spaces, resulting in considerable illegal parking violations. The violations of disobeying the guide lane are mostly found in the northeastern region of the city. One reason is that the intersections, which are installed with cameras, are located in an arterial close to the freeway exit. Thus, drivers who are unfamiliar with the lane-setting (e.g., cargo shipping drivers and travelers from other cities) may commit the violation easily. Another reason may be attributed to the setting of the camera. Compared to other cameras in other regions, those installed in this region are covert, which could hamper the alert of the surrounding drivers.

For the temporal distribution, the illegal parking violations are mostly detected in the morning, afternoon (before the evening peak hours), and working days. This could be that most vehicles are temporarily parking on the roadside due to business reasons or dining needs. Nevertheless, the frequencies of disobeying the guide lane are uniform during the same range as the traffic volume, and underlying offenders passing the detection point are very large. Interestingly, the two types of traffic violations are remarkably discrepant across the months. It could be that the inner-city traffic activities are less intensive in the first half-year due to the imbalanced activities of such a port city. As a result, it leads to fewer illegal parking violations. Conversely, the city has more cargo-shipping needs from other cities in this period, and there are more vehicles that are detected nearby the freeway exit.

A limitation of our study is the analysis may be affected by the layout of detection devices. New detection approaches such as naturalistic driving data and GPS trajectories are encouraged to figure out more robust conclusions [32–34].

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