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Spatio-Temporal Analysis of Travel Speed for Urban Streets

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Abstract

This research aims to develop a spatiotemporal visualization of travel speed on urban streets to predict traffic conditions. Three segments of major streets and eight minor collector streets within Palestine Street in Baghdad were selected to examine the distribution of average travel speed. This road network comprises three primary links and six minor collector streets: link 1 (Al-Mawal to Al-Nakhala intersection), link 2 (Al-Nakhala intersection to Al-Sakhara intersection), and link 3 (Al-Sakhara intersection to Beirut intersection). The temporary congestion periods are (12 p.m. to 1 p.m.) and (5 p.m. to 7 p.m.) for Link 1, with speeds ranging from 34 to 35 km/hr, whereas Link 3 is more congested, with speeds of about 29 km/hr. Link 2 indicated moderated congestion. Most of the spatial congestion is either on links 1 and 3, which are the major distributors for production and attraction trips on Palestine's urban streets. The visualization method based on field data reflects the actual traffic status of speed values. It reveals the temporal and spatial aggregation characteristics of urban travel speed as an integral part of understanding traffic operation behavior.

Keywords: Spatiotemporal, Travel Speed, Traffic Status, Urban Streets, Visual Analysis.

1. Introduction

The spatiotemporal characteristics of traffic speed predict vehicle movements, which are essential for transportation planning and traffic management. Additionally, it helps traffic engineers accurately predict traffic conditions that are important for various aspects of traffic improvement and the utilization of urban transportation systems. Several studies have explored the use of visual methods for analyzing temporal and spatial field data, accounting for prevailing conditions. Liu et al. [1] developed a visual traffic analysis method based on spatiotemporal graphs using a global positioning system (GPS). Cui et al. [2] developed a vision-based method for congested urban routes using license plate number data. They demonstrated an efficient visual analysis of urban traffic data and presented characteristics of vehicle trajectories. Spatiotemporal urban traffic data are necessary to manage the massive volume of road data and ensure accuracy [2]. Traffic data are generally described by randomness, dynamics, and diversity [3]. Reducing sources of uncertainty and providing accurate, real-time traffic data visualization are essential for testing and processing the collected data in an existing street monitoring system [4]. Chandra and Gangopadhyaya [5] stated that traffic speed may deviate from the standard distribution curve for heterogeneous traffic streams due to considerable diversity in speeds among fast-moving and slow vehicles. These variations led to deviations from normality, resulting in multimodal or bimodal distributions. McFadden et al. [6] used artificial neural networks (ANNs) to develop an operating-speed model for passenger cars on two-lane rural highways. Najjar et al. [7] provided a model of speed based on a neural network to detect the relationship between the geometric design of roadways and the 85th percentile speed on two-lane rural highways. Al-Ghamdi [8] developed a regression model to predict the 85th-percentile speed from spot-speed data on urban roads in Riyadh. The regression model outperforms a model based on the normal approximation. Rao and Rao [9] developed a speed model for the free-flow of urban streets in New Delhi that accounted for side friction, access point density, interchange count, and segment length. They identified several factors influencing the free-flow speed. Free-flow speed is related to posted speed limits on multilane highways and on four-lane urban streets and varies with median width and segment length [10]-[11]. Himes and Donnell [12] explored the effect of roadway characteristics and traffic volume on operating speeds on 4-lane highways. Using the simultaneous-equation framework, a predictive model was developed to assess the relationship between average lane speed and speed deviation. Using big data and applied grids to explore the spatial relationship between street patterns and street vitality, urban street analysis offers greater flexibility in perspective and methodology [13]. To observe the microscopic physical and social spaces, new environmental data were used. The classical urban space is insufficient to account for user behavior [14]. Urban space, as an essential type, will exhibit various characteristics of its time in urban development and technological culture [15]-[18].

The research's main contribution is the development of a spatiotemporal visualization analysis to capture travel speeds on urban streets, which may help traffic managers quickly identify average traffic speeds and areas of congestion. Visual analysis is used to explore the temporal and spatial characteristics of traffic conditions.

2. Methods and Data Collection

Three segments of major streets and eight minor collector streets within Palestine Street in Baghdad were selected to examine the distribution of average travel speed. This road network includes three major links with six minor collector streets, namely, link 1 (Al-Mawal to Al-Nakhala intersection), link 2 (Al-Nakhala intersection to Al-Sakhara intersection), link 3 (Al-Sakhara intersection to Beirut intersection), as presented in Fig. 1. The studied links that belong to major urban streets encompass the corridor that surrounds mixed land use, residential, commercial, and educational. Spatial analysis of speed measures using ArcGIS version. 10.8 is applied to display traffic speed, which includes geo-referencing and digitization of the street map of the case study.

The speed data used in this study comprises location and time information from the global positioning system of the floating car. Different periods are used to identify spatiotemporal traffic patterns in speed during two working days (Monday 14/11/2022, Tuesday 15/11/2022, and Wednesday 19/11/2022), with travel time under good weather (sunny) and visibility conditions, at an appropriate distance. The traffic state was aggregated and averaged over 5-minute intervals across 70 test runs (35 in each direction). Travel speeds are presented for each link, along with statistical measures such as minimum, maximum, standard deviation, range, percentiles, and confidence intervals. See Fig. 2 and Table 1 with different periods: morning periods (8-10 a.m.), (12-1 p.m.), and evening periods (5-7 p.m.).

The traffic performance analysis shows when speed falls significantly below the uncongested speed.

According to the collected field data, travel speed can be used to characterize traffic state in time and space. The statistical normal distribution is produced for the average of selected days and periods. The temporary congestion periods are 12 p.m. to 1 p.m. and 5 p.m. to 7 p.m. for Link 1, with speeds ranging from 34 to 35 km/hr, and are more congested on Link 3, with speeds of about 29 km/hr. Link 2 indicated moderated congestion. Hence, most of the spatial congestion is concentrated on links 1 and 3, the major distributors for production and attraction trips on Palestine's urban streets.

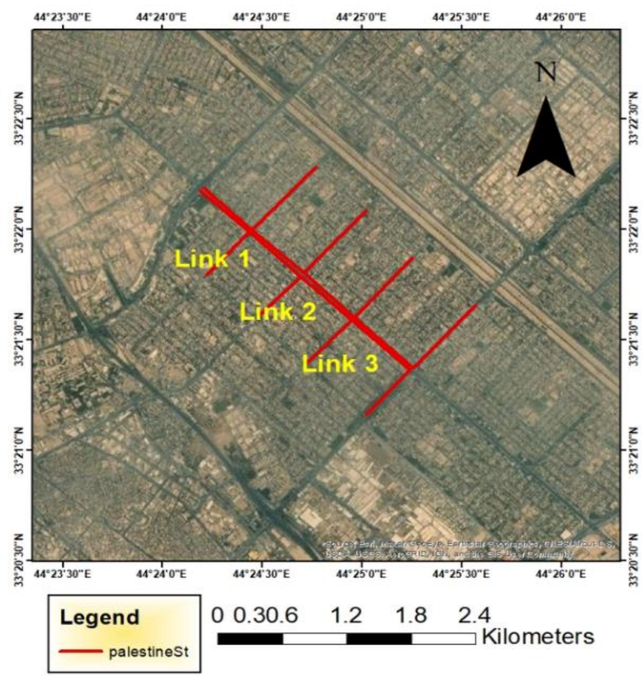
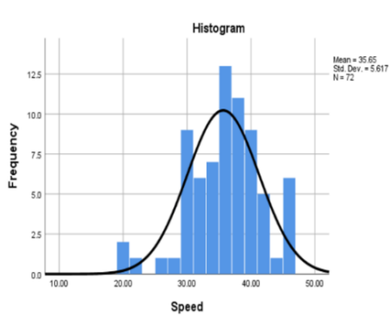
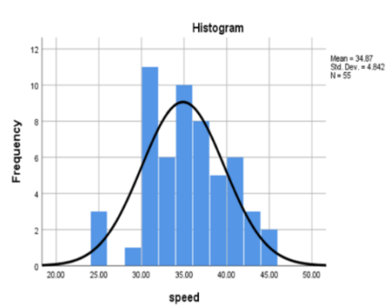


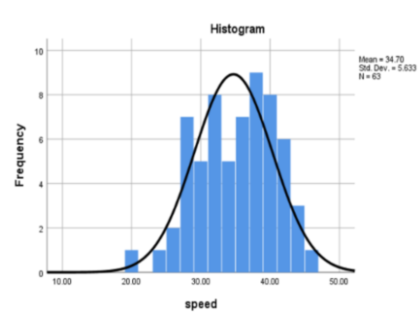
Figure 1. Location of Study Area.



Time 8-10 a.m.

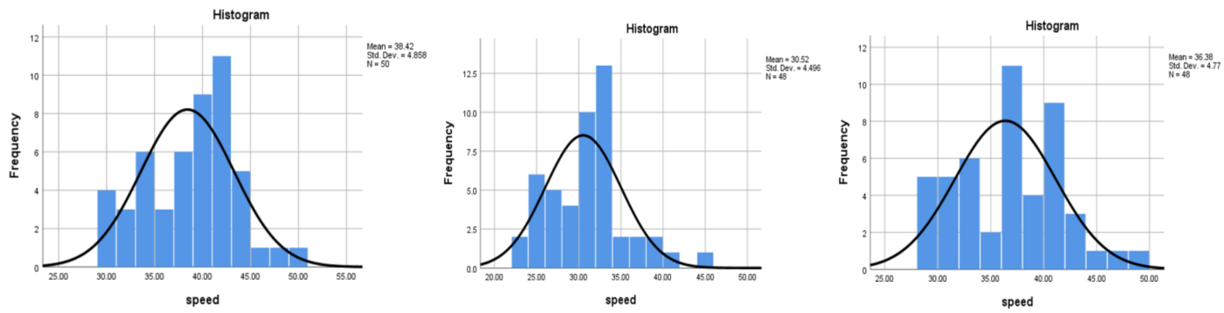


Time 12-1 p.m.



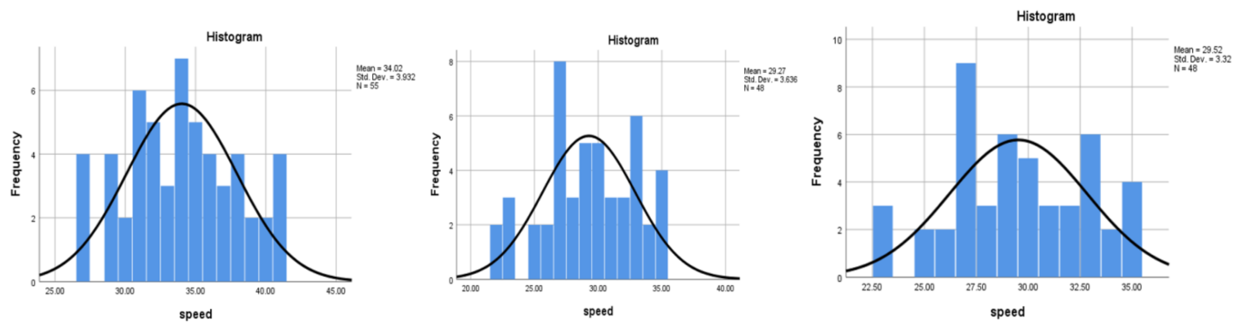
Time 5-7 p.m.

a) Link 1



Time 8-10 a.m. **Time 12-1 p.m.** **Time 5-7 p.m.**

b) Link 2



Time 8-10 a.m. **Time 12-1 p.m.** **Time 5-7 p.m.**

c) Link 3

Figure 2. Average Travel Speed for Links 1, 2, and 3 for Different Morning and Evening Periods.

Table 1. Descriptive Statistics for Travel Speed for Links 1, 2, and 3 with Different Periods.

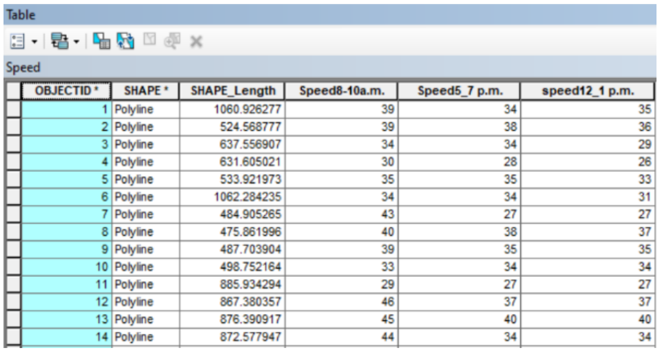
Link 1		
Speed (Time 8-10 a.m)		
N	Valid	72
	Mean	35.6528
	Standard Error of Mean	.66200
	The Median	35.0000
	The Mode	35.00
	Standard Deviation	5.61728
	The Variance	31.554
	Range	25
	Minimum	20
	Maximum	45
Percentiles	15	30
	85	42
Speed (Time 12-1 p.m.)		
N	Valid	55
	Mean	34.8727
	Standard Error of Mean	.65292
	Median	35
	Mode	30
	Standard Deviation	4.84215
	Variance	23.446
	Range	20
	Minimum	25
	Maximum	45
	Sum	1918.00
Percentiles	15	30
	85	40
Speed (Time 5-7 p.m.)		
N	Valid	63
	Mean	34.6984
	Standard Error of Mean	.70969
	Median	35.0000
	Mode	35.00[a]
	Standard Deviation	5.63295
	Variance	31.730
	Range	25
	Minimum	20
	Maximum	45
	Sum	2186
Percentiles	15	28
	85	42

Link 2		
Speed (Time 8-10 a.m)		
N	Valid	50
Mean		38.4200
Std. Error of Mean		.68696
Median		39
Mode		42.00
Std. Deviation		4.85752
Variance		23.596
Range		20
Minimum		30
Maximum		50
Sum		1921
Percentiles	15	32.6
	85	43
Speed (Time 12-1 p.m.)		
N	Valid	48
Mean		30.5208
Standard Error of Mean		.64891
Median		31
Mode		32
Standard Deviation		4.49581
Variance		20.212
Range		21
Minimum		23
Maximum		44
Sum		1465
Percentiles	15	25
	85	34.6
Speed (Time 5-7 p.m.)		
N	Valid	48
	Missing	24
Mean		36.3750
Std. Error of Mean		.68845
Median		37.0000
Mode		40.00
Std. Deviation		4.76970
The Variance		22.750
Range		19.00
Minimum		29.00
Maximum		48.00
Sum		1746.00
Percentiles	15	30.3500
	85	40.6500

Link 3		
Speed (Time 8-10 a.m)		
N	Valid	55
	Missing	17
Mean		34.0182
Std. Error of Mean		.53023
Median		34.0000
Mode		34.00
Std. Deviation		3.93225
Variance		15.463
Range		14.00
Minimum		27.00
Maximum		41.00
Sum		1871.00
Percentiles	15	29.4000
	85	38.6000
Speed (Time 12-1 p.m.)		
N	Valid	48
	Missing	24
Mean		29.2708
Std. Error of Mean		.52486
Median		29.0000
Mode		27.00
Std. Deviation		3.63634
Variance		13.223
Range		13.00
Minimum		22.00
Maximum		35.00
Sum		1405.00
	15	25.3500
	85	33.0000
Speed (Time 5-7 p.m.)		
N	Valid	48
	Missing	24
Mean		29.4167
Standard Error of Mean		.50162
Median		29
Mode		27
Standard Deviation		3.47534
Variance		12.078
Range		13
Minimum		22
Maximum		35
Sum		1412
Percentiles	15	26
	85	33

3. Results and Discussion

The results are presented using a visual analysis system to explore the spatiotemporal distribution of vehicle travel speed on urban roads. The visual analysis system is based on field data depicted at corresponding positions on the OpenStreetMap map, using ArcGIS version 10.8. Fig. 3 presents an image of the attribute table showing the arrangement of average travel speed data for the study area, with selected segments. This paper focuses on travel speed in urban streets, which quantifies the overall operational status of traffic. Traffic speed data enable road staff not only to detect traffic jams but also to capture the spatiotemporal state of congestion in a specific area. The average travel speed map is presented in Fig. 4. The hot links in Palestine's urban streets with low traffic speeds are visualized using a color transition from light to dark blue. Variations in speed by color are observed across various segments of the urban street.



Table

Speed

OBJECTID *	SHAPE *	SHAPE_Length	Speed8-10a.m.	Speed5_7 p.m.	speed12_1 p.m.
1	Polyline	1060.926277	39	34	35
2	Polyline	524.568777	39	38	36
3	Polyline	637.556907	34	34	29
4	Polyline	631.605021	30	28	26
5	Polyline	533.921973	35	35	33
6	Polyline	1062.284235	34	34	31
7	Polyline	484.905265	43	27	27
8	Polyline	475.861996	40	38	37
9	Polyline	487.703904	39	35	35
10	Polyline	498.752164	33	34	34
11	Polyline	885.934294	29	27	27
12	Polyline	867.380357	46	37	37
13	Polyline	876.390917	45	40	40
14	Polyline	872.577947	44	34	34

Figure 3. An image depicting the attribute table of Average Travel Speed Source: researcher.

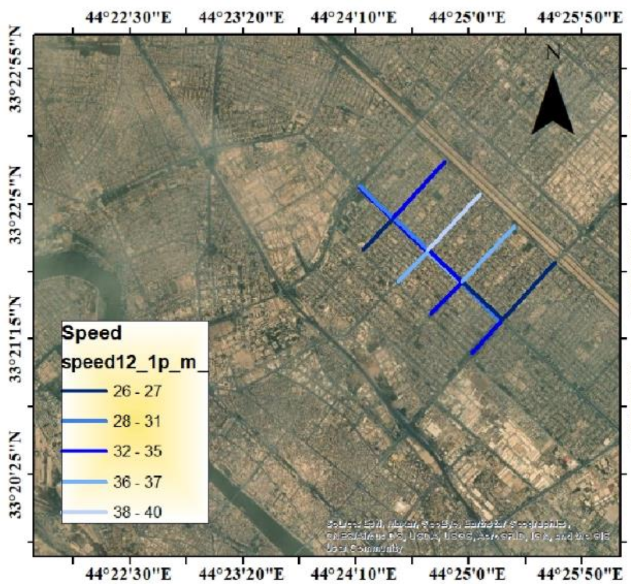


Figure 4. Spatial Distribution Map of average travel speed in the studied network. Source: researcher.

Within the scope of this study, this paper developed a visual analysis of field data to explore traffic speed across different segments of the urban street at varying times of day. Fig. 5 shows a spatiotemporal map of traffic speeds across different periods generated in ArcGIS. The regional traffic speeds are captured for various periods (8-10 a.m.), (12-1 p.m.), and (5-7 p.m.), respectively, indicating that low speed and congestion forming on Link1 and three at 8-10 a.m. and until 5-7 p.m. which is usually the peak periods of the region that support by [19],[20].

The visualization method based on field data reflects the actual traffic status of speed values. It reveals the temporal and spatial aggregation characteristics of urban travel speed as an integral part of understanding traffic operation behavior. The spatiotemporal map of the street network is useful for road managers to quickly identify traffic-congestion segments and characterize the management policies required to alleviate congestion and implement improvements, such as intelligent transportation systems. Also, it can help in trip planning and urban design by understanding and capturing vehicle traffic movements (spatiotemporal variations) and exploring their characteristics.

Figure 5. Spatio-temporal Distribution Map of speed in the studied network. Source: researcher.

4. Conclusions

The temporary congestion periods are 12 p.m. to 1 p.m. and 5 p.m. to 7 p.m. for Link 1, with speeds ranging from 34 to 35 km/hr. Link 3 tends to be more congested, with speeds of approximately 29 km/hr. Link 2 indicated moderated congestion.

Most of the spatial congestion is on links 1 and 3, which are the major distributors of production and attraction trips on Palestine's urban streets.

The regional traffic speeds are captured for different periods (8-10 a.m., 12-1 p.m., and 5-7 p.m.), respectively, indicating that low speed and congestion form on Link1 and three at 8-10 a.m. and until 5-7 p.m., which are usually the peak periods of the region.

The visualization method based on field data reflects the actual traffic status of speed values. It reveals the temporal and spatial aggregation characteristics of urban travel speed, thereby serving as an integral component of understanding traffic operational behavior. Also, it can help in trip planning and urban design by understanding and capturing vehicle traffic movements (spatiotemporal variations) and exploring their characteristics. The spatiotemporal map of the street network can aid road managers in quickly identifying traffic-congestion segments and characterizing the management policies required to alleviate congestion and implement practical improvements, such as intelligent transportation systems.

Acknowledgment

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Contribution of the Authors

Zainab Ahmed Alkaissi developed the research objectives and aims, analyzed and presented the results using statistical and GIS tools, and discussed and drew the main conclusions.

Mohammad Sadar Jasim and Abbas Mohammed collected field data for the traffic work.

Conflict of interest

There is no conflict of interest.

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