IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 3, 2020, accepted February 25, 2020, date of publication March 2, 2020, date of current version March 12, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2977321

Intersection Congestion Analysis Based on Cellular Activity Data

SHEN LI [1], GUOFA LI [2], YANG CHENG [1], AND BIN RAN [1]
[1]Department of Civil and Environmental Engineering, University of Wisconsin–Madison, Madison, WI 53706, USA
[2]College of Mechatronics and Control Engineering, Institute of Human Factors and Ergonomics, Shenzhen University, Shenzhen 518060, China

Corresponding author: Guofa Li (guofali@szu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 51805332, in part by the Natural Science Foundation of Guangdong Province under Grant 2018A030310532, in part by the Shenzhen Fundamental Research Fund under Grant JCYJ20190808142613246, and in part by the Young Elite Scientists Sponsorship Program through the China Society of Automotive Engineers.

ABSTRACT Intersections are the key joint points on arterials in urban transportation networks. Congestions at intersection areas significantly degrade human travel efficiency. Therefore, analyzing congestion and exploring congestion detection technologies to mitigate intersection congestions is important for intelligent transportation systems. This paper proposed the space mean speed calculation method at intersection related areas and explored the relationship between space mean speed and the number of cellular activities around the examined intersections. The number of vehicles in queue in each traffic signal phase-cycle at signalized intersections in Taicang city of China was counted from videos to verify the effectiveness of our proposed space mean speed calculation method. The results showed that our proposed calculation method of space mean speed at intersection areas were effective in describing traffic status. The investigated relationship between space mean speed and the number of cellular activities indicated that the number of cellular activities near intersections was a promising indicator for congestion detection.

INDEX TERMS Intersection, congestion analysis, cellular activity data.

I. INTRODUCTION

The driving experience on arterial roads in urban environments is heavily affected by traffic congestion. The longer queuing time and increased fuel consumption in congestion significantly increase drivers' negative emotions that lead to more traffic accidents [1]. Therefore, using special sensors to detect traffic congestion effectively is essential to address the existed problems and to improve drivers' driving experience.

Driving speed is the most direct measurement to identify congestion. To comprehensively evaluate the mean vehicular speed on roads instead of analyzing the driving speed of each vehicle individually, two indicators (i.e., time mean speed and space mean speed) were developed. As defined in Highway Capacity Manual (HCM) [2], time mean speed is the average speed of all vehicles passing a fixed location over a certain of the period, and space mean speed is the average speed of all vehicles occupying a given section of a road over a specified time period. Time mean speed needs to be estimated based on laser or radar-based technologies [3], which needs high maintenance, installation and operation costs to limit the practical applications of this method [4]. Therefore, space mean speed is usually adopted to analyze traffic state and status [5].

However, space mean speed cannot be measured directly in the field and it is difficult to be measured based on traffic surveillance systems [4]. Various methods have been proposed to solve this problem [6], [7]. Lee et al. used a convolutional neural network (CNN) to measure space mean speed on straight road sections based on generated images from cameras [4]. Although space mean speed has been extensively analyzed on straight road sections (e.g., highways), how to measure the space mean speed at intersection related areas has not been sufficiently studied. To fill this research gap, this paper aims to propose an innovative method for space mean speed estimation at intersection related areas. Based on the calculated space mean speed, traffic status at intersection related areas could be determined.

As the effectiveness of technologies based on cameras is limited by night vision, bad weather (e.g., heavy rain, snow, and fog), and occlusion, other alternative technologies have been developed for solutions [8]. The vehicle-based

The associate editor coordinating the review of this manuscript and approving it for publication was Eunil Park.

detection system is an alternative approach to collect traffic volume information [9]. The fundamental idea is to consider floating probes in vehicles as mobility sensors of vehicles. The floating probes include beacon-based probe vehicles (e.g., Bluetooth) and cellular probe vehicles (e.g., GPS, cellular activities) [10]–[14]. Although beacon-based probe technology already shows its feasibility in traffic status detection, only a small portion of road vehicles can be used as beacon-based floating probes for data collection. Because of the low penetration rate problem, the effectiveness of beacon-based methods has encountered a bottleneck [15].

Meanwhile, researchers realized that cellular probe is another promising technique to collect real-time data for traffic status detection with a higher penetration rate and less cost of equipment installation and maintenance, especially on arterials in urban areas [16]. Cellular networks provide mobility-related events that can be obtained during conventional operations, such as Location Area (LA) update, Route Area (RA) update, and cell update (handoff) [17]. The results of the CPTIAL-ITS Test and Demonstration Program showed positive potentials for using cellular data to estimate traffic states [16]. After that, many research results reported that cellular probe was a feasible technology to collect traffic data [18]–[21]. The studies in freeway areas demonstrated that cellular probe data had a good performance in daytime [22] and uncongested situations [23]. As for arterial roads, the experiments conducted in the municipality of Lisbon explored the potential of using cellular technologies in an urban area [24]. However, the influence of various disruptions (e.g., non-motorized traffic, signal lights, street parking) significantly increases the difficulties for traffic status detection on arterials [25].

Most of the traffic status detection approaches based on cellular technologies are based on handoff activities [26]. The limitation is that even the same cellphone passes the same link multiple times, the handoff events may occur at different locations. Therefore, it is uncontrollable to estimate speed based on handoff events, which in turn means, detecting congestion is highly unreliable. Besides, due to the fact that handoff events are generated when cellphones have activities (call, text, etc.) passing the handoff area, the sample size is quite small [24]. A handoff only occurs when a cellphone in call, text, or other data exchange activities switches from one cell station to another due to the poor signal strength received from the previous cellular station. However, cellular activities include full records of real-time cellphone communication signals generated by cellular towers while maintaining cellular services both on- and off-call [17], [27]. Such signal data may be related to phone calls, texting, web browsing, video and audio streaming, location-based service and other cellphone activities. Previous studies mainly focus on the capability of handoff information in traffic status detection without comprehensively considering the other available information like location update.

In summary, two research questions are going to be addressed in this study including: (1) how to measure space mean speed at intersection related areas, and (2) what is the relationship between cellular activities and space mean speed. A field experiment was conducted to collect traffic volume data, and cellular activity data were obtained from a Chinese cellular carrier. Space mean speed at signalized intersections was calculated using our developed method. The relationship between cellular activities and space mean speed or the number of vehicles in the queue was analyzed. The main contribution of this study includes: (1) a novel space mean speed measurement method for urban intersection areas was proposed, and (2) the relationship between cellular activities and space mean speed at intersection related areas was investigated.

The rest of this paper is organized as follows. Section II introduces how the used data in this study were collected and pre-processed. Section III proposes the methodology to investigate the connections between cellular activities and traffic status. Section IV presents the results and discussions. Section V concludes this paper.

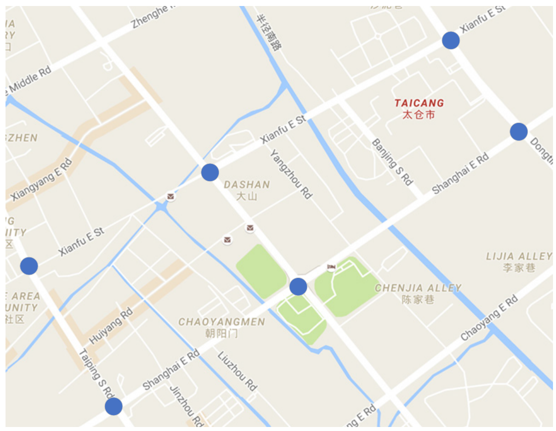


FIGURE 1. Map of the research area in Taicang city.

TABLE 1. Intersections included in this study.

No.	Name
1	XianFu@Dongting
2	Shanghai@Dongting
3	Xianfu@Dongcang
4	Shanghai@Dongcang
5	Xianfu@Taiping
6	Shanghai@Taiping

II. TRAFFIC DATA COLLECTION

A. EXAMINED ARTERIALS AND INTERSECTIONS

The field test data used in this study were collected from Taicang, a county-level city located in the southeast of Jiangsu province, China. This city has 719 thousand registered residents on the total area of 620 km^2. Two arterials (Shanghai Road and Xianfu Road) were selected as the area for data collection. See Figure 1 and Table 1 for the map of the selected research area and the details of the intersections, respectively.

FIGURE 2. Snapshot of Shanghai and Dongting intersection video data.

B. TRAFFIC STATUS INVESTIGATION

Since there were no loop detectors or other fixed-location detecting infrastructures in the research area, other data sources to obtain the traffic status data were needed. In this study, the intersection video recordings were used to extract traffic status information. To obtain the traffic status of the examined intersections, video data collected at the intersections were used. See Figure 2 for a snapshot of the collected videos. The number of vehicles stopped for waiting in each red phase of the signal circles was manually counted. Only the video data during the morning (8:00 am to 9:30 am) and evening (4:30 pm to 6:30 pm) peak hours were provided by the traffic management administration in Taicang. In total, the data in 105 signal circles each day were collected from Monday to Friday. Thus the total number of collected signal circles was 525.

C. SPACE MEAN SPEED

To examine the speed in different traffic situations, we employed the space mean speed for evaluation. As defined in HCM, space mean speed is the average speed of all vehicles occupying a given section of a road over a specified time period. The frequently used accuracy of travel time in traffic status detection is based on space mean speed. To obtain the space mean speed at the examined intersections, we proposed a novel method for calculation which can be divided into two elements. The first element is to calculate the space mean speed in the red time interval. It is assumed that the time for clearing the queue is included in the first element. The calculation is described as follows:

$$SMS1 = \frac{r}{c} \times \left(\frac{3600 \times L}{RT \times L + D} \right) \tag{1}$$

$$D = 0.5 \times r \times Q \tag{2}$$

where $SMS1$ is the first element of space mean speed (km/h), r is the time length of the red phase (s), c is the time length of a complete signal cycle (the time length of each signal phase can be obtained from the collected video data), L is the length of the arterial (km), RT is the traveling time per km (s/km), D is the time of delay (s), Q is the number of vehicles in queue.

The second element describes the free flow speed in the green phase. The corresponding calculation can be expressed as follows:

$$SMS2 = FFS - \frac{r}{c} \times FFS \tag{3}$$

where $SMS2$ is the second element of space mean speed (km/h) and FFS is the free flow speed (km/h). The posted free flow speed was 60 km/h on the examined arterials.

Considering the first and second elements together for space mean speed calculation, it can be described as follows:

$$SMS = \frac{r}{c} \times \left(\frac{3600 \times L}{RT \times L + D} \right) + \left(1 - \frac{r}{c} \right) \times FFS \tag{4}$$

A calculated space-mean speed corresponds to a complete cycle period of a traffic light from the beginning of a red signal phase to the beginning of the next red signal phase.

III. CELLULAR DATA ANALYSIS

A. GEOSPATIAL PROCESSING

It is necessary to get all links that belong to the selected arterials, and the cell stations are located along with links. Usually, the selected roads need to be separated into several small links. Then, we can locate all cell stations into different links based on some mathematic algorithms and can get reliable coverage of each cell station. According to the ArcGIS map of Taicang city, the length of links in the map is short enough to separate all cell stations into reasonable groups so that we can use the links from the ArcGIS map of the city directly. Based on the recorded unique ID for each cellphone and the time that the information exchange occurs between the cell station and the cellphone, we can know where and when information exchange happens between which cellphone and cell tower.

The processing steps are shown as follows: First, we added the global direction for each link manually. In this study, we assumed the eastbound and northbound as the positive direction. Then, all the cell stations were located on the corresponding roads. The assumption was that the distance was the key feature to separate cell stations. The change in the number of vehicles passing a link can be reflected in the cellular activities from the cell stations close to the link. Third, we calculated the distance between the link start points and the projection points of each corresponding cell station. Finally, ArcGIS gave the results including information about the link including global direction, the corresponding cell stations of each link, and the distance between the link start point and the projection points. These information was used in the feature generation as the input parameters.

B. FEATURE GENERATION

It is assumed that one cellphone represents one driver. Therefore, the increase in cellular activities represents the increase of vehicles in the coverage area. When the number of vehicles in the covering area exceeds the available capacity of the road network, congestion happens.

The main goal of this step is to generate features from the full cellular activity data in each cell station to indicate traffic status. Analyzing the sequence of all cell stations that one cellphone is passing in order of time window could easily determine the traveling direction of the probe vehicles. One cell station only has one related link, i.e., the cellular data from one cell station belongs to one link. Hence, summing all activities from cell stations that belong to the same link could get the number of activities on the link level. Therefore, the formula to covert features from the cell station level to the link level is proposed as follows:

$$A\bar{C}T = \frac{\sum ACT}{N} \tag{5}$$

where $A\bar{C}T$ is the average number of activities, ACT is the number of activities from each cell station, N is the total number of cell stations in the link.

C. CLUSTER ANALYSIS

The unsupervised K-means clustering algorithm is a valid and feasible approach to separate data into multiple groups [28]. Therefore, it was adopted to divide the traffic situation into two groups, congestion and free flow. Using a pre-determined number of clusters K, the K-means clustering method can separate the observations into several clusters, where each observation belongs to a cluster whose mean is closest to its value [29]. This method uses the distance as the evaluation index of similarity. It means that a closer distance indicates a greater similarity. Given a set of observations $(x_1, x_2, \ldots, x_n)$, where x_j denotes the number of cellular activities observed at time interval j, the observations are separated into two sets $S = \{S1, S2\}$. In other words, the objective of the cluster analysis is to find the solution of the equation as follows:

$$\text{args} \min_{s} = \sum_{i=1}^{k} \sum_{x_j \in S_i} (x_j - \mu_i)^2 \tag{6}$$

where μ_i is the mean of S_i. The algorithm is composed of three main steps [30].

Initial Step: Select two random observations as the initial clustering centers. Since the purpose of the algorithm is to divide the cellular data into two groups, the values obtaining from the following equation were used as the initial clustering centers.

$$x_1 = \frac{1}{3}(x_{max} - x_{min}) \quad x_2 = \frac{2}{3}(x_{max} - x_{min}) \tag{7}$$

where x_{max} is the maximum number of cellular activities, and x_{min} is the minimum number of cellular activities.

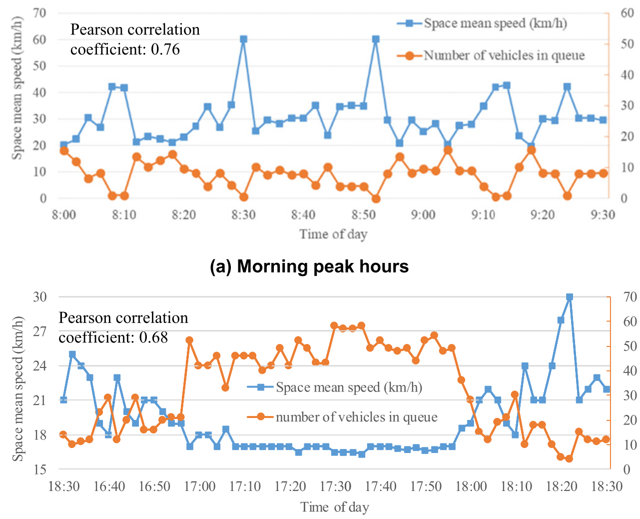
Assign Step: Assign each observation to the cluster with a shorter distance than the other one.

$$S_i^{(t)} = \{x_p : \left(x_p - m_i^{(t)}\right)^2 \leq \left(x_p - m_j^{(t)}\right)^2 \tag{8}$$

where $m_i^{(t)}$ is cluster i, and $m_j^{(t)}$ is cluster j

Update Step: Calculate the means of the new cluster centers after adding each new observation. The new clustering center was updated by:

$$\mu_i^{(t+1)} = \frac{1}{|s_i^t|} \sum_{x_i \in s_i^{(t)}} x_j \tag{9}$$



(a) Morning peak hours

(b) Evening peak hours

FIGURE 3. The relationship between space mean speed and number of vehicles in queue in the morning and evening peak hours.

where $|s_i^t|$ is the total number of cellular activities in cluster i at step t.

Repeat the assign step and the update step until all the observations were clustered into one of the clusters.

IV. RESULTS AND DISCCUSION

To present the effectiveness of the proposed space mean speed calculation method, the relationship between space mean speed and the number of vehicles in a queue in the morning and evening peak hours is illustrated in Figure 3. As presented in Figure 3(a), the number of vehicles in a queue in each red phase is relatively low in the morning peak hours. Most of the red phases had no more than ten vehicles in queue during the morning peak hours, which indicates that not many congestions occurred during the morning peak hours at the examined intersections in Taicang. The relationship between space mean speed and the number of vehicles in queue show a negative correlation between them. The Pearson correlation coefficient between space mean speed and number of vehicles in a queue was 0.76, indicating the effectiveness of our proposed space mean speed calculation method to evaluate traffic status.

Interestingly, the number of vehicles significantly increased around 5 pm, different from the trends during the morning peak hours. See Figure 3(b). A negative correlation between space mean speed and number of vehicles in a queue was also observed. The Pearson correlation coefficient was 0.68. It is obvious that congestions occurred from 5 pm to 6 pm. The space mean speed during this hour was about 17 km/h, the lowest among the examined hours. As can be observed from Figure 3, an observed space mean speed threshold of 17∼20 km/h can be identified as the criteria for congestion detection at intersection related areas in the examined county-level city.

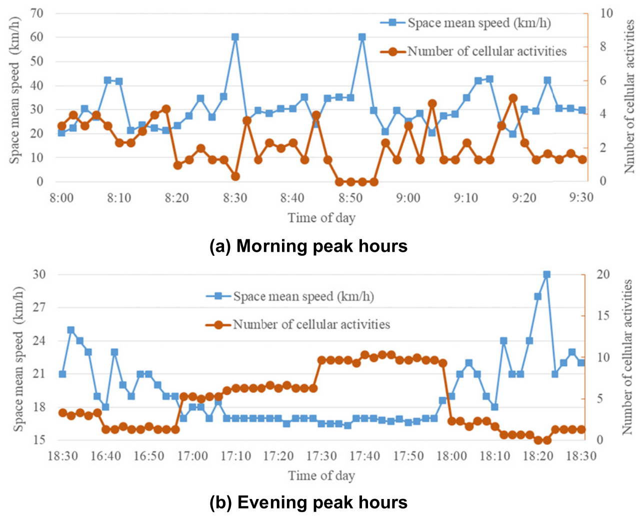


FIGURE 4. The relationship between space mean speed and number of cellular activities in the morning and evening peak hours.

Figure 4 shows the relationship between the number of cellular activities and space mean speed. The illustrated results show that the numbers of cellular activities in the evening peak hours were significantly higher than that in the morning peak hours. It can be observed in Figure 3 that there were exactly no congestions during the morning peak hours, and the numbers of cellular activities were relatively lower. Differently in the evening peak hours, the number of cellular activities significantly increased, and the space mean speed was the lowest indicating traffic congestions. Therefore, it can be concluded that a higher number of cellular activities correspond to a lower space mean speed. This indicates that the change patterns of the number of cellular activities can be used as a potential indicator for traffic congestion detection. Moreover, this idea could be employed in the identification of LOS (level of service) by considering the influence of traffic congestion.

V. CONCLUSION

This paper proposed a new space mean speed calculation method at intersection related areas and investigated the relationship between space mean speed and the number of cellular activities around the examined intersections. Our experiment results showed a negative correlation between space mean speed and the number of vehicles in queue, indicating the effectiveness of our proposed calculation method in describing traffic states at intersection areas. A space mean speed threshold of 17∼20 km/h was identified as the criteria for congestion detection at intersection related areas in the examined county-level city (i.e., Taicang). The change patterns of the number of cellular activities were found to be a promising sensor for traffic congestion detection. Besides the above findings, an interesting conclusion that can be drawn from the observations is that few congestions occurred in the morning peak hours in such a county-level city. The reasons leading to such a difference need to further investigated in future studies.

REFERENCES

[1] S. Shafiei, Z. Gu, and M. Saberi, "Calibration and validation of a simulation-based dynamic traffic assignment model for a large-scale congested network," *Simul. Model. Pract. Theory*, vol. 86, pp. 169–186, Aug. 2018.

[2] R. Dowling, *Traffic Analysis Toolbox Volume VI: Definition, Interpretation, and Calculation of Traffic Analysis Tools Measures of Effectiveness*, document FHWA-HOP-08-054, 2007.

[3] J. A. Khan and S. R. Tarry, "Speed spot study by comparing time mean speed and space mean speed: A case study," *Int. J. Adv. Sci. Res.*, vol. 3, no. 1, pp. 97–102, 2018.

[4] J. Lee, S. Roh, J. Shin, and K. Sohn, "Image-based learning to measure the space mean speed on a stretch of road without the need to tag images with labels," *Sensors*, vol. 19, no. 5, p. 1227, Mar. 2019.

[5] E. Han, A. University, S. B. Kim, J. H. Rho, and I. Yun, "Comparison of the methodologies for calculating expressway space mean speed using vehicular trajectory information from a radar detector," *J. Korea Inst. Intell. Transp. Syst.*, vol. 15, no. 3, pp. 34–44, Jun. 2016.

[6] M. Zedda and F. Pinna, "Prediction models for space mean speed on urban roads," in *Proc. Int. Conf. Comput. Intell. Data Eng.* Singapore: Springer, 2018, pp. 11–28.

[7] S. Mondal, V. K. Arya, and A. Gupta, "Development of speed prediction model for mixed traffic conditions: Case study of urban streets," in *Advances in Transportation Engineering*. Singapore: Springer, 2019, pp. 107–116.

[8] G. Li, Y. Yang, and X. Qu, "Deep learning approaches on pedestrian detection in hazy weather," *IEEE Trans. Ind. Electron.*, to be published, doi: 10.1109/TIE.2019.2945295.

[9] G. Li, S. E. Li, B. Cheng, and P. Green, "Estimation of driving style in naturalistic highway traffic using maneuver transition probabilities," *Transp. Res. C, Emerg. Technol.*, vol. 74, pp. 113–125, Jan. 2017.

[10] Y. B. Y. Yim and R. Cayford, "Investigation of vehicles as probes using global positioning system and cellular phone tracking: Field operational test," in *Proc. California PATH Working Paper*, 2001, pp. 1–61.

[11] R. Long Cheu, C. Xie, and D.-H. Lee, "Probe vehicle population and sample size for arterial speed estimation," *Comput.-Aided Civil Infrastruct. Eng.*, vol. 17, no. 1, pp. 53–60, Jan. 2002.

[12] R. Herring, A. Hofleitner, P. Abbeel, and A. Bayen, "Estimating arterial traffic conditions using sparse probe data," in *Proc. 13th Int. IEEE Conf. IEEE, Intell. Transp. Syst. (ITSC)*, Sep. 2010, pp. 929–936.

[13] F. Zheng and H. Van Zuylen, "Urban link travel time estimation based on sparse probe vehicle data," *Transp. Res. C, Emerg. Technol.*, vol. 31, pp. 145–157, Jun. 2013.

[14] S. E. Li, G. Li, J. Yu, C. Liu, B. Cheng, J. Wang, and K. Li, "Kalman filter-based tracking of moving objects using linear ultrasonic sensor array for road vehicles," *Mech. Syst. Signal Process.*, vol. 98, pp. 173–189, Jan. 2018.

[15] E. Jenelius and H. N. Koutsopoulos, "Travel time estimation for urban road networks using low frequency probe vehicle data," *Transp. Res. B, Methodol.*, vol. 53, pp. 64–81, Jul. 2013.

[16] S. He, Y. Cheng, G. Zhong, and B. Ran, "A data-driven study on the sample size of cellular handoff probe system," *Adv. Mech. Eng.*, vol. 9, no. 4, Apr. 2017, Art. no. 168781401769844.

[17] D. Valerio, A. D'Alconzo, F. Ricciato, and W. Wiedermann, "Exploiting cellular networks for road traffic estimation: A survey and a research roadmap," in *Proc. IEEE 69th Veh. Technol. Conf. (VTC Spring)*, Apr. 2009, pp. 1–5.

[18] *Final Evaluation Report for the CAPITAL-ITS Operational Test and Demonstration Program*, UMD, College Park, MD, USA, 1997.

[19] J.-L. Ygnace, J.-G. Remy, J.-L. Bosseboeuf, and V. D. Fonseca, *Travel Time Estimates on Rhone Corridor Network Using Cellular Phones as Probes. Phase 1: Technology Assessment and Preliminary Results*. INRETS, 2000.

[20] D. J. Lovell, "Accuracy of speed measurements from cellular phone vehicle location systems," *ITS J.-Intell. Transp. Syst. J.*, vol. 6, no. 4, pp. 303–325, Oct. 2001.

[21] R. Cayford and T. Johnson, "Operational parameters affecting the use of anonymous cell phone tracking for generating traffic information," in *Proc. Transp. Res. Board 82nd Annu. Meeting Transp. Res. Board*, no. 1, 2003, pp. 3803–3865.

[22] H. Liu and A. R. R. Danczyk Brewer Starr, ''Evaluation of cellphone traffic data in minnesota,'' *Transp. Res. Rec.*, vol. 2086, no. 1, pp. 1–7, 2008.

[23] B. L. Smith, H. Zhang, M. D. Fontaine, and M. W. Green, ''Wireless location technology-based traffic monitoring: Critical assessment and evaluation of an early-generation system,'' *J. Transp. Eng.*, vol. 130, no. 5, pp. 576–584, Sep. 2004.

[24] M. G. Demissie, G. H. de Almeida Correia, and C. Bento, ''Intelligent road traffic status detection system through cellular networks handover information: An exploratory study,'' *Transp. Res. C, Emerg. Technol.*, vol. 32, pp. 76–88, Jul. 2013.

[25] H. Bar-Gera, ''Evaluation of a cellular phone-based system for measurements of traffic speeds and travel times: A case study from Israel,'' *Transp. Res. C, Emerg. Technol.*, vol. 15, no. 6, pp. 380–391, Dec. 2007.

[26] T. Derrmann, R. Frank, F. Viti, and T. Engel, ''Estimating urban road traffic states using mobile network signaling data,'' in *Proc. IEEE 20th Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2017, pp. 1–7.

[27] Q. Shi and M. Abdel-Aty, ''Big data applications in real-time traffic operation and safety monitoring and improvement on urban expressways,'' *Transp. Res. C, Emerg. Technol.*, vol. 58, pp. 380–394, Sep. 2015.

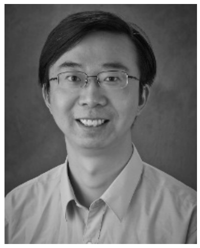
[28] L. Kaufman and P. J. Rousseeuw, *Finding Groups in Data: An Introduction to Cluster Analysis*. Hoboken, NJ, USA: Wiley, 2009.

[29] J. A. Hartigan and M. A. Wong, "Algorithm AS 136: A K-Means clustering algorithm," *Appl. Statist.*, vol. 28, no. 1, p. 100, 1979.

[30] J. Cvid, *Information Theory, Inference and Learning Algorithms*, vol. 50, no. 10, D. J. C. MacKay, Ed. Cambridge, U.K.: Cambridge Univ. Press, Oct. 2003 p. 640.

SHEN LI received the Ph.D. degree from the University of Wisconsin–Madison, in 2018. He is currently a Postdoctoral Researcher with the University of Wisconsin–Madison. His research is about intelligent transportation systems (ITS), architecture design of CAVH systems, cooperative control method of connected vehicles, traffic data mining based on cellular data, and traffic operations and management.

GUOFA LI received the Ph.D. degree in mechanical engineering from Tsinghua University, Beijing, China, in 2016. He is currently an Assistant Professor in mechanical engineering and automation with the College of Mechatronics and Control Engineering, Shenzhen University, Guangdong, China. His research interests include driving safety in autonomous vehicles, driver behavior and decision making, computer vision for environment perception, machine learning, and human factors in automotive and transportation engineering. He was a recipient of the Young Elite Scientists Sponsorship Program by SAE-China, in 2018, the Excellent Young Engineer Innovation Award from SAE-China, in 2017, and the NSK Sino-Japan Outstanding Paper Prize from NSK Ltd., in 2014.



YANG CHENG received the B.S. and M.S. degrees in automation from Tsinghua University, Beijing, China, in 2004 and 2006, respectively, and the Ph.D. degree in civil engineering from the University of Wisconsin–Madison, in 2011. He is currently an Assistant Researcher with the Department of Civil and Environmental Engineering, University of Wisconsin–Madison. His research interests include intelligent transportation systems (ITS), mobile traffic sensor modeling, transportation performance measurement and decision support, transportation big data analytics, and traffic operations and management.

BIN RAN received the B.S. degree in civil engineering from Tsinghua University, Beijing, China, in 1986, the M.S. degree in civil engineering from The University of Tokyo, Tokyo, Japan, in 1989, and the Ph.D. degree in civil engineering from the University of Illinois at Chicago, Chicago, in 1993. He is currently a Professor with the Department of Civil and Environmental Engineering, University of Wisconsin–Madison. He specializes in intelligent transportation systems, the internet of mobility and connected vehicles, the Internet of Things, dynamic transportation network models, traffic simulation and control, and cellphone probe technologies.