Vehicular Social Networks: Enabling Smart Mobility

Zhaolong Ning[1,2], Feng Xia[1,2,*], Noor Ullah[1], Xiangjie Kong[1,2], and Xiping Hu[3]
[1]School of Software, Dalian University of Technology, China
[2]Key Laboratory for Ubiquitous Network and Service Software of Liaoning Province, China
[3]Bravolol Limited, Hong Kong

***Abstract*—**Vehicular transportation is an essential part of modern cities. However, the ever-increasing numbers of road accidents, traffic congestions, and other such issues become obstacles for the realization of smart cities. As the integration of Internet of vehicles and social networks, Vehicular Social Networks (VSNs) are promising to solve the above-mentioned problems by enabling smart mobility in modern cities, which are likely to pave the way for sustainable development by promoting transportation efficiency. In this article, the definition and brief introduction of VSNs are presented at first. Existing supporting communication technologies are then summarized. Furthermore, we introduce an application scenario on trajectory data analysis-based traffic anomaly detection for VSNs. Finally, several research challenges and open issues are highlighted and discussed.

I. INTRODUCTION

The objective of smart cities is to improve the quality of citizen’s life. In this regard, the transportation sector is of great significance due to the rapidly increasing number of vehicles in big cities, which makes traffic management for smart cities rather challenging. As a vehicular user-centric network, Vehicular Social Network (VSN) deeply integrates social networks and Internet of Vehicles (IoVs). Recently, vehicular communication networks are at the turning point, whose application targets are transforming from road traffic safety and transportation efficiency to VSNs, which can provide comprehensive social services for citizens. Various leading IT companies are entering this area. For instance, Apple launched the vehicle system “Carplay” in March 2014, by which users can participate in social activities easily and safely. Google joined into the development of VSNs by releasing the product of “Andriod Auto” in June 2014.

Vehicular communication technology has evolved explosively in the past two decades. The novel design of technologies and protocols has been the focus of both industry and academia. For instance, a 75MHz spectrum was licensed at 5.9GHz band as Dedicated Short Range Communication (DSRC) by US Federal Communications Commission (FCC) to provide wireless communication among vehicles. IEEE then standardized the whole communication stack as Wireless Access for Vehicular Environment (WAVE) under IEEE 802.11p, which provides support for the interconnection among vehicles, and between vehicles and roadway. For the sake of studying the access to social networks and social information sharing among car users, a joint research plan for the next generation of IoVs has been launched in May 2014 by four top universities in the USA (i.e. Carnegie Mellon University, University of Wisconsin, Duke University and Boston University), which sparked the high attention of VSNs in academia.

Enabling smart mobility and fulfilling high-efficiency content transmission are challenging due to the intrinsic features of VSNs. Although VSN is a brand-new communication paradigm with interests from both academia and industry, the convergence of social networks with IoVs is still in its infancy. With the objective of making VSNs practical and widely utilized, their specific research challenges and feasible solutions deserve to be studied, which motivates our work. The rest of this article is organized as follows. The concept of VSNs is introduced in Section II. Supporting communication technologies in VSNs are summarized in Section III. In Section IV, a case study for VSNs is developed. Section V discusses the challenges and possible solutions in VSNs, and Section VI concludes our work.

II. WHAT ARE VEHICULAR SOCIAL NETWORKS?

The study of IoVs has sprung up, where vehicles perform as sensor hubs to capture information by the in-vehicle or smartphone sensors, then publish them for the consumers. The integration of intelligent sensors and communication technologies opens up an entirely new frontier for IoVs in smart cities since vehicles have changed dramatically.

A. From IoVs to VSNs

For the sake of information dissemination and connectivity improvement, opportunistic routing has been extended into IoVs, whose applications have natural contact with social networks. As human factors are involved, this emerging paradigm is often named socially-aware networking, which makes use of social relationships among device users for the construction of mobile social networks. Since social features and behaviors of individuals are more stable than their mobility patterns, it is promising to combine socially-aware networking with IoVs [1]. *We define VSNs as deep integrations of social networks and IoVs, which not only incorporate the social networks describing relationships among vehicle users, but also embrace the vehicular networks for communications among vehicle users with social relationships.* Specifically, VSNs contain not only conventional Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication frameworks, but also human factors that impact vehicular connectivity.

A social framework for vehicular communication along with an application named Roadspeak has been proposed in [2]. It is called the VSN, and was initially defined as: “A social network of vehicles, enabled by spatial and temporal localities on the road”. This opened up a new paradigm

Corresponding author: Feng Xia; email: f.xia@ieee.org

enabling drivers and passengers to socialize on the roads. VSNs can solve the problems faced by IoVs and Delay Tolerant Networks (DTNs) by integrating their features with social properties of the users and vehicles.

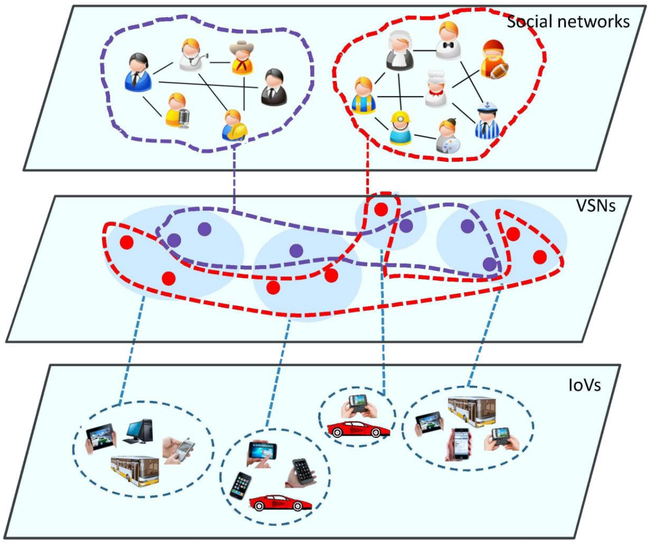


Fig. 1 Schematic diagram of VSNs.

B. *Architecture of VSNs*

The schematic diagram of VSNs is illustrated in Fig. 1. The bottom level embraces the communication networks among vehicles and smart terminals, and can be viewed as a social network including physical communities. The spatiotemporal properties are critical for social relationship construction in VSNs since vehicles connect each other when they encounter each other on the road. Meanwhile, the virtual social networks are constructed by mobile users in the light of their inherent social ties on the upper level. In VSNs, the smart devices can be embedded into on-board units, Road Side Units (RSUs), and pedestrians. Individuals communicate with each other by exploiting social behaviors, which support various wireless communication technologies and enable communication at close proximities. Interactions among these devices/users can be divided into three types: human-to-human, humans-to-machines, and machine-to-machine. The architecture of VSNs is flexible, including: 1) Centralized architecture, where a centralized server manages the system enabling V2I communication; 2) Decentralized architecture, where V2V communication is carried out opportunistically via DSRC or WAVE; and 3) Hybrid architecture, where users can be connected to the Internet via cellular networks like 3G/4G through RSUs.

C. *Characteristics of VSNs*

VSNs could be broadly leveraged in smart cities since they can obtain individuals' social relationship through network analysis, and extend users' social activities in IoVs by providing data services. The main intrinsic features in VSNs can be summarized from the social and mobile aspects.

Compared with Online Social Networks (OSNs), the construction of VSNs is more dynamic. Social relationships in VSNs are weaker than those in OSNs, because VSNs are no longer active when users depart from the network. Besides, social connections among vehicles may be established even if they do not know each other before. Individuals in VSNs are more likely to have common interests, instead of family members or friends.

Several factors influence the mobility of VSNs, including the mobility model, selfishness status, and preferences of human beings. Based on mobility model in the community, some locations would draw high social attractiveness (such as restaurants, malls, and theaters), and become communication hotspots. Furthermore, mobility model in VSNs is time-varying and has some trajectory characteristics. For example, individuals move toward the office in the morning and return home at night.

Other characteristics of VSNs include large scale, high dynamics, limited bandwidth, data heterogeneity, individual sociality, and so on. The main differences between VSNs and OSNs are summarized in Table 1.

TABLE 1 MAIN DIFFERENCES BETWEEN VSNS AND OSNS

	Network access	**Social relationship**	**Life time**
VSNs	Given scenarios (specific position, content and social relationship); Given time (by encounter, on-the-fly, sporadic).	Dynamic and weak, people with common interests instead of family members or friends, even anonymous users.	Limited life time, no longer active when users depart from the network.
OSNs	Anytime and anywhere.	Stable and relatively strong, mostly based on social relationship and friendship.	Unlimited life time, once formulated, "always-on".

D. *Applications of VSNs*

The traditional applications of VSNs mainly focus on safety-related and entertainment-based applications. The former concentrates on enhancing the safety on roads to lower the probability of road accidents according to the information of vehicle's position, speed, direction, and so on. The latter focuses on sharing and downloading of multimedia services based on user's interest.

Recently, the studies of data-driven applications are prevalent in VSNs. The periodic moving patterns offer an insightful and concise illustration, and could help to compress trajectory data and forecast the future movement of vehicles [3]. A trajectory, generated by the traveling vehicles in geographical spaces, can be gained by mobile computing techniques. Our daily life emerges an army of GPS-equipped vehicles, including taxis, buses, and ambulances. These vehicles can report a time-stamped location with a certain frequency interval, by which a great number of spatial trajectories can be generated for vehicle behavior analysis, resource allocation, and transportation efficiency improvement in VSNs. Table 2 demonstrates the taxonomy of VSN applications, which can be further divided into social data-driven vehicular networks, social Vehicular Ad-hoc Networks (VANETs), and data-driven social networks [4].

TABLE 2 TAXONOMY OF VSN APPLICATIONS

Vehicular Social Networks	Social Data-Driven Vehicular Networks	Traffic Information
		E-Advertisements
		News
		Smart Calendar
		Entertainment
	Social VANETs	Cooperative Driving
		Cruise Control
		Navigation
		Location Services
		Platooning
		P2P Networking
		Content Delivery
		Car-Share
		Waze
		Uber
	Data-Driven Social Networks	Theft Control
		Health-Care
		Diagnostic
		Route Planning
		Safety Warnings
		Emergency Alert
		Vehicle Tracking

III. SUPPORTING COMMUNICATION TECHNOLOGIES

Existing communication methods that might possibly be employed in VSNs can be broadly classified into the following four categories.

A. *Context-aware Transmission*

It was reported by Cisco that 300 million passenger vehicles can generate over 400 million gigabytes of data by wireless communications [5]. A large amount of data calls for effective information dissemination mechanisms, because irrelevant information is unwelcomed by drivers. VSNs are promising to filter the information by social relationship recognition, interest comparison and context-aware transmission. Therefore, filtering information on cloud and delivering relevant information by combining the emerging wireless technologies (such as 5G and millimeter waves) will be essential in future vehicular networks.

Generally, the encountering probability of humans with certain social relationships is large. However, the encountering probability and duration time of vehicles may be low even with the same destination, which makes data forwarding and sharing in VSNs challenging. For the sake of fulfilling the requirements of applications and services in smart cities, the concept of social relationships among vehicles could be employed to promote the effectiveness and efficiency of information dissemination in VSNs. Wan *et al.* [6] investigated an architecture supported by mobile cloud for the vehicular cyber-physical system, and designed a context-aware dynamic parking service for smart cities as a case. Our previous work [7] presented an interest-based forwarding scheme for VSNs, which stimulates food foraging behavior of bees to record information passing through different communities.

B. *Reliable Transmission*

The moving speed of vehicles is much larger than human beings, which causes topology changes frequently in VSNs. Data transmission should accommodate the high dynamic topologies. Thus, it is imperative to guarantee the real-time transmission of urgent message, and the correctness of regular information in both dense and sparse environments. For the sake of promoting stability and guaranteeing transmission reliability in VSNs, some mechanisms have been studied for the stimulation of node selfishness, which can be generally divided into the methods based on reputation, tit-for-tat, and virtual currency. A representative game incentive mechanism has been presented in [8], and it can be applied in VSNs by ameliorating the traditional game theory. A distributed incentive model has been designed for VSNs based on the job market signaling model [9], and the selfish nodes are encouraged to perform cooperatively by compensating a certain amount of virtual currency for packet forwarding.

C. *Trustworthy Transmission*

The benefit of sharing common interest among vehicle drivers can be brought into VSNs. However, privacy issues deserve to be considered, which require trustworthy transmission. A trustworthy information sharing scheme for VSNs was presented in [10] by evaluating direct trust from past interacting information and deducing indirect trust from social recommendations among vehicles. As an emerging application in VSNs, a dynamic trustworthy parking scheme has been studied in [11], by which trusted groups of vehicles can be constructed to seek out parking space in the corresponding community area. A framework to construct and maintain VSNs has been constructed in [12], where some trust principles have been proposed to form a social group for admission, and control the interactions among members.

D. *Mobile Crowdsensing*

The objective of mobile crowdsensing is to involve participants from public to contribute sensing data from their mobile terminals in a collaborative method. Crowdsensing has drawn wide attention, due to the ever-increasing use of mobile equipment. Not only an ideal and ubiquitous platform to encourage mobile users for participation by crowdsensing can be supplied in VSNs, but also clients in mobile crowdsensing can be provided by excellent assistance through employing social contexts. The effectiveness of mobile crowdsensing in VSNs has already been demonstrated, which can be leveraged for safety improvement and traffic management [13]. Since traffic prediction and congestion alleviation are important for smart cities, a mobile crowdsensing-based scheme was presented for dynamic route selection [14]. A message delivery scheme for the combination of geographical and topological information has been proposed in [13]. It is adaptive for crowdsensing in vehicular circumstances, and the connection of vehicle-to-infrastructure for cloud services is the main consideration.

Although various kinds of applications can be enabled by crowdsensing, employing it into the real system still has a long way to go in VSNs. Some issues deserve to be investigated further [15], such as: sensing with human participation, data redundancy and inconsistency, and crowdsourced data mining.

IV. A CASE STUDY: TRAJECTORY DATA ANALYSIS-BASED TRAFFIC ANOMALY DETECTION

Some events (such as accidents, celebrations, sports and disasters) would cause traffic anomalies. The objective of traffic anomaly detection is to find the traffic patterns that are not expected, by which traffic problems can be discovered accurately. In this section, we propose a trajectory data analysis-based model to detect traffic anomaly by crowdsensing. *To the best of our knowledge, this is the first work to utilize bus trajectory data to infer urban traffic condition.* Since bus route cannot be changed even if the bus driver encounters traffic conditions on the road, passengers can share the traffic anomaly situations, and provide information for arriving time prediction and other applications for traffic management.

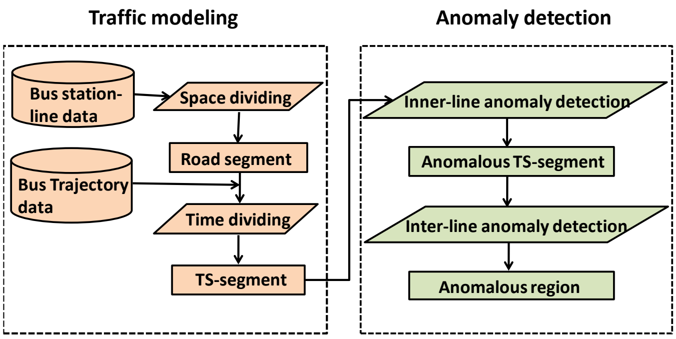


Fig. 2 Framework of the trajectory data analysis-based model.

Due to space limitation, we mainly focus on the utilization of results by crowdsensing. The task allocation is distributed to passengers on the bus, who can report the information of bus trajectory. Task execution can be fulfilled by the GPS and sensors (mobile phones) equipped with bus and passengers respectively.

The framework of our method in Fig. 2 contains two parts: traffic modeling and anomaly detection. We leverage bus station-line data to divide the urban road networks into road segments spatially, and extract Temporal and Spatial (TS)-segments from bus trajectory data according to the divided road segments. Two features are extracted from each TS-segment, i.e. average velocity and average stop time. The former models the real traffic condition on the road, while the latter represents the passenger flow volume of bus. In the anomaly detection part, we use the inner-line anomaly detection method to find the anomalous TS-segments by calculating the Local Outlier Factor (LOF) of TS-segments, and discover anomalous regions with inter-line based method.

A. Traffic Modeling

We first extract the TS-segments from bus trajectory data to describe the traffic conditions around the city. Then, we partition the urban road networks into road segments based on the busline data. After that, we get the TS-segments to describe the real traffic situation around the city. Details are illustrated as follows.

1) *Network partition of the urban road*: Bus station-line data are leveraged to partition the urban road networks into road segments, which contain the information of two adjacent stations. A road segment can be identified uniquely by the bus lineID, line direction, and station number.

2) *TS-segment extraction*: With the results of road network partition, bus trajectory can be divided spatially. First, we search the stopping items, whose location coordinates are in the range of the line's station area. Then, items with adjacent stations in one line can be obtained according to the lineID and station number, which are the results of partition from the spatial aspect.

3) *TS-segment feature*: Each TS-segment has lots of trajectories. The trajectory speed is the ratio between Manhattan distance within the adjacent two stations of a TS-segment and the time bus traveling between stations.

4) *TS-segment matrix construction*: We formulate a matrix for each bus line, and its item presents a TS-segment as a tuple.

B. Traffic Anomaly Detection

We first mine the anomalous TS-segments, which affect bus traveling by calculating the LOF of each TS-segment. Then we partition the city into small regions shown as grids on the map. With the results of inner-line detection, we map the anomalous TS-segments in different lines to the small regions for better understanding traffic condition of the city.

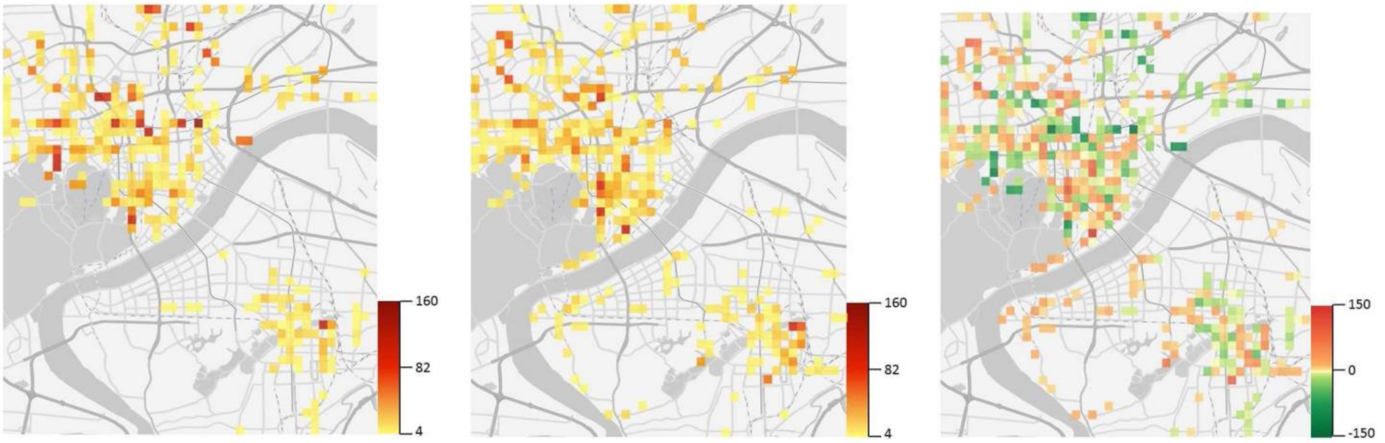
1) *Inner-line anomaly detection*: The average velocity and stop time of a TS-segment are leveraged to find the anomalous one by calculating the LOF in each line. LOF indicates a point's degree of outlier and illustrates the level of a point's anomaly numerically. After calculating the LOF of TS-segment, we can find the collection of anomalous TS-segments, which largely affect the efficiency of bus traveling in one line.

2) *Inter-line anomaly detection*: After the detection of inner-line anomaly, the outlier collection of TS-segments can be obtained. Since hundreds of bus lines with connections coexist in the large city, the TS-segments need to be considered comprehensively. Furthermore, traffic situation tends to be associated with the number of cars apparently.

We use two real datasets in Hangzhou, China: one is the bus station-line dataset, and the other is the bus trajectory dataset. The bus trajectory data were collected in the October of 2014 and the March of 2015, respectively. Figs. 3 and 4 depict the inferred traffic conditions (on average) in these two months, on weekdays and weekends, respectively. The background of the figures is the road network of Hangzhou. The detected anomalous regions are represented by the small grids with colors, which represent the LOFs of the regions.

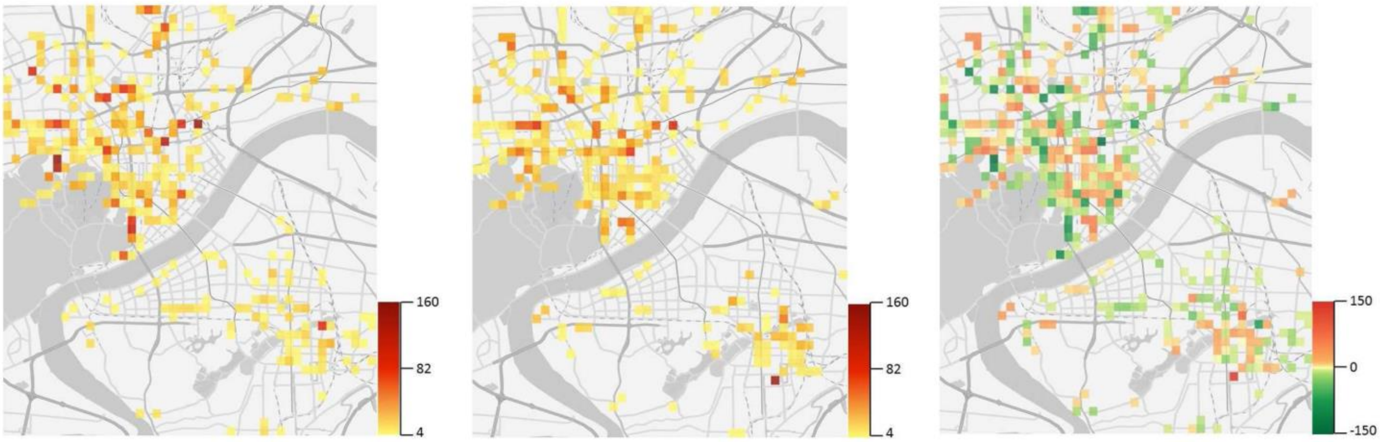
It can be observed from Figs. 3(a), 3(b), 4(a) and 4(b) that two main parts in Hangzhou have serious traffic problems. Deeper colors indicate worse traffic conditions. The first one covers districts like West Lake and Xiacheng, where downtowns, Zhejiang University, the governments of Zhejiang province and Hangzhou city are located. The other one is around the Xiaoshan commercial city, where many office buildings, hotels, and banks are located. Figs. 3(c) and 4(c) show the changes in traffic conditions from the October of 2014 to the March of 2015, on weekdays and weekends, respectively. The green and red colors represent better and worse traffic conditions, respectively. The changes might be caused by some social events or administrative traffic control (e.g. National Day and Spring Festival in China).

Fig. 5 demonstrates the inferred traffic conditions of specific regions on weekdays and weekends in the March of 2015. Figs. 5(a) and 5(b) correspond to an education region near Zhonghe street, where more than ten schools are located. Figs. 5(c) and 5(d) correspond to the scenic area around Xili Lake. These results are quite consistent with the reality, thus demonstrating the effectiveness of our method.



(a) October 2014 (b) March 2015 (c) Changes between the two months

Fig. 3 Inferred traffic conditions on weekdays.



(a) October 2014 (b) March 2015 (c) Changes between the two months

Fig. 4 Inferred traffic conditions on weekends.

(a) An education region on weekdays (b) An education region on weekends (c) A scenic area on weekdays (d) A scenic area on weekends

Fig. 5 Inferred traffic conditions of specific regions in March 2015.

V. Challenges

A lot of challenges still exist for enabling smart mobility with VSNs. We highlight and discuss some of them below.

A. *Message Dissemination*

Delivering relevant messages intelligently to drivers in VSNs is challenging. Since no prior knowledge exists for user interest, the data will be stored on vehicles (or server), or broadcasted to the interested vehicles. How to manage local data to reasonably utilize storage space and effectively disseminate message should be investigated. Generally, a larger number of data copies accompanies with a higher success probability of transmission. A VSN-oriented multi-copy data duplication method deserves to be studied, because overmuch copies increase resource overhead. One promising solution is to integrate vehicular networks with content distribution networks, where the information types of vehicles are identified and classified by information relevance estimation for the decision of whether informing the driver or sharing the information further.

How to address human factors to forward data under limited bandwidth is still an open issue, because user aspiration, node diversity, and selfish variability have not yet been fully studied. Furthermore, nodes in VSNs might exhibit social selfishness, where they only cooperate with whom having social relationships of some sort. This phenomenon causes a lot of problems in reliable data dissemination like increased delay and loss of data packets. One common strategy is to stimulate cooperation among selfish nodes, i.e., to suppress node selfish behaviors. However, node selfishness is an intrinsic feature varying with time. One possible solution is to develop selfishness-tolerant data transmission schemes by viewing individual selfishness as a fundamental social attribute in VSNs (just like mobility).

B. Big Trajectory Data Analysis

The ever-increasing trajectory data require novel technologies to discover data from various sources. Selecting ways to mine big trajectory data and other data sources brings new challenges for researchers. Machine learning and data mining models have been leveraged to handle one single dataset. However, the technology to learn mutually reinforced knowledge from multiple datasets still needs to be studied. Knowledge fusion does not imply merely putting together an array of characteristics extracted from multiple datasets, but calls for deep understanding of each dataset and effective utilization of datasets in different parts of a big data computing framework.

The huge volume of trajectory data makes it possible to analyze the mobility patterns of traveling vehicles and their social relationships in VSNs. However, trajectories of vehicles are not perfectly accurate due to sensor noise and other reasons, for example, the false positioning signals received in some urban areas [4]. Therefore, it is necessary to filter such noise points from traffic trajectories before starting a mining task. After that, map matching is needed to convert an array of raw latitude/longitude coordinates to an array of road segments.

C. Trust, Security, and Privacy

In order to construct VSNs for practical applications, the following four aspects need to be fulfilled: social group formation, trust management and evaluation, decentralized architecture, and data integrity. It is noted that all efforts for network optimization are nothing without trust. For trust transmission in VSNs, two main challenges can be summarized as follows: 1) Constant change of topology caused by the movement of vehicles makes the contact time limited, and a third party is required for trust maintenance. 2) VSNs utilize users' information like location, identity, mobility patterns and social connections to provide services. Potential security threat for the users should also be considered, since their personal information can be exposed to malicious attacks and criminal activities. Similarly, false alarms can be raised in an emergency situation, which may mislead the users or even cause mishaps on the roads.

With the objective of protecting users from privacy information leak owing to disclosing user's trajectories, the trajectory would not be manifested such certain. On one hand, the user's location is encouraged to be obscured; On the other hand, user's satisfaction of service should be guaranteed. Correlational studies mainly focus on two aspects: 1) Location-based services to report the traffic conditions within 1 km around the user, and 2) publication of the historical trajectories. Furthermore, misleading information in utility services may cause wastage of time and energy. So far, few related work has been done to eradicate these issues in VSNs. Therefore, social trust-based strategies can be devised in future for the reliable and secure communications in VSNs.

VI. CONCLUSION

In this article, we have emphasized the importance of high-efficiency and reliable transmissions in VSNs for smart cities. Particularly, we study a case on traffic anomaly detection for VSNs by trajectory data analysis. Although VSNs can be regarded as the integration of social networks and IoVs to improve the quality of life for citizens, the avenues of VSN studies are not flat, and many open issues are still ahead. We believe that VSNs will draw extensive attentions and research efforts in the near future as the integrations of information technology and social network services become more compacted.

ACKNOWLEDGMENT

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Biographies

Zhaolong Ning (M'14) received the M.S. and Ph.D. degrees from Northeastern University, Shenyang, China. He was a Research Fellow with Kyushu University, Fukuoka, Japan. He is an Assistant Professor with the School of Software, Dalian University of Technology, Dalian, China. He has

published over 50 scientific papers in international journals and conferences. His research interests include social computing, network optimization, and big data.

Feng Xia (M'07–SM'12) received the B.Sc. and Ph.D. degrees from Zhejiang University, Hangzhou, China. He is a Full Professor with the School of Software, Dalian University of Technology, Dalian, China. He has published two books and over 200 scientific papers in international journals and conferences. His research interests include computational social science, big data, and mobile social networks. He is the corresponding author.

Noor Ullah received his B.Sc. and M.S. degrees in Electrical Engineering with major in Communication and Electronics from University of Engineering and Technology Peshawar, Pakistan. He is currently a PhD candidate in Software Engineering, with the School of Software, Dalian University of Technology, China. His research interests include vehicular social networks and intelligent transportation system design.

Xiangjie Kong received the Ph.D. degree from Zhejiang University, Hangzhou, China. Currently, he is an Associate Professor in School of software, Dalian University of technology, China. He has published over 30 scientific papers in international journals and conferences. His research interests include big data, social computing, and mobile computing.

Xiping Hu received the Ph.D. degree from University of British Columbia, Vancouver, Canada. He is currently a professor with Shenzhen Institutes of Advanced Technology, Chinese Academic of Science. He was the co-founder and CTO of Bravolol Limited in Hong Kong. His research areas are distributed software systems, mobile social networks, service/cloud computing, and crowdsourcing.

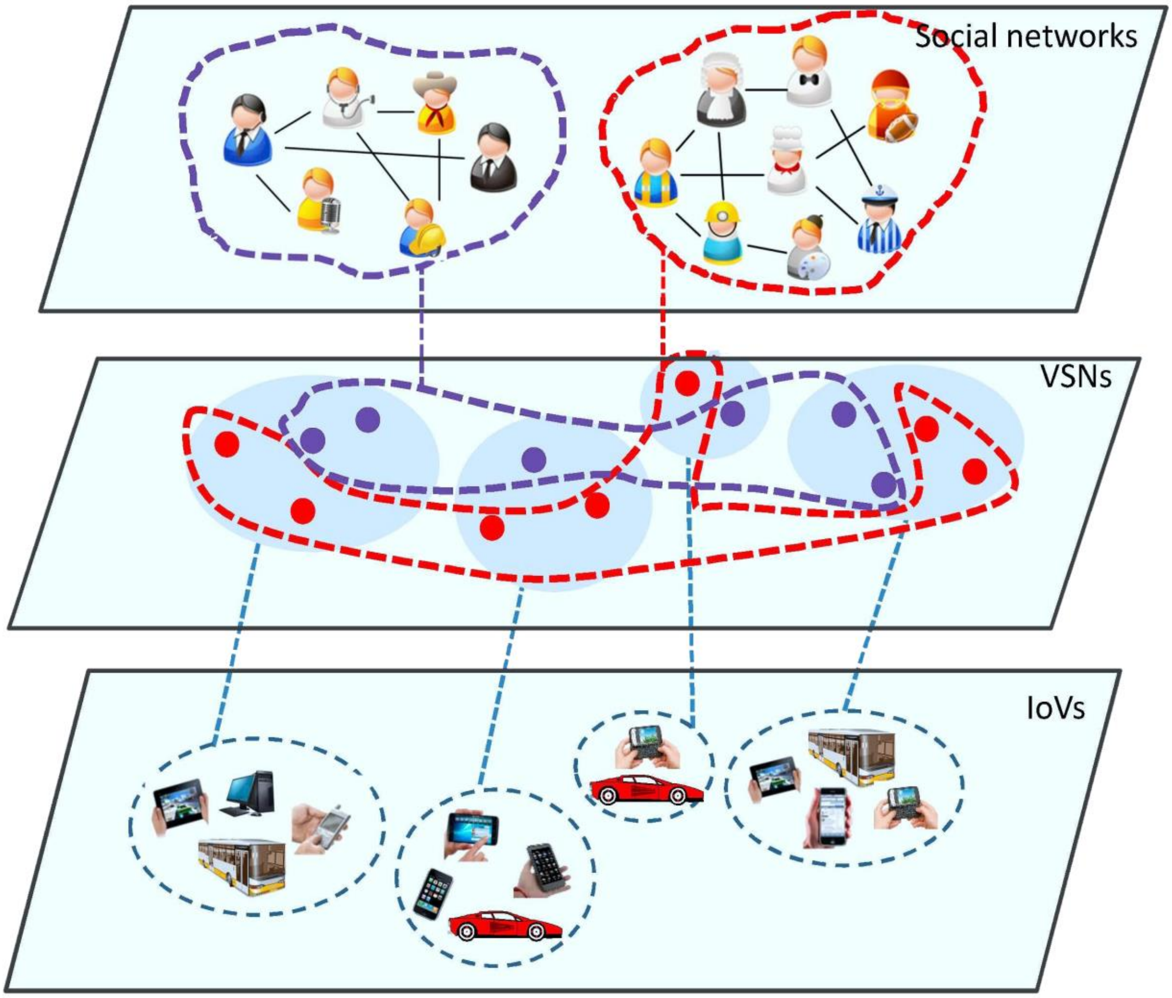


Fig. 1 Schematic diagram of VSNs.

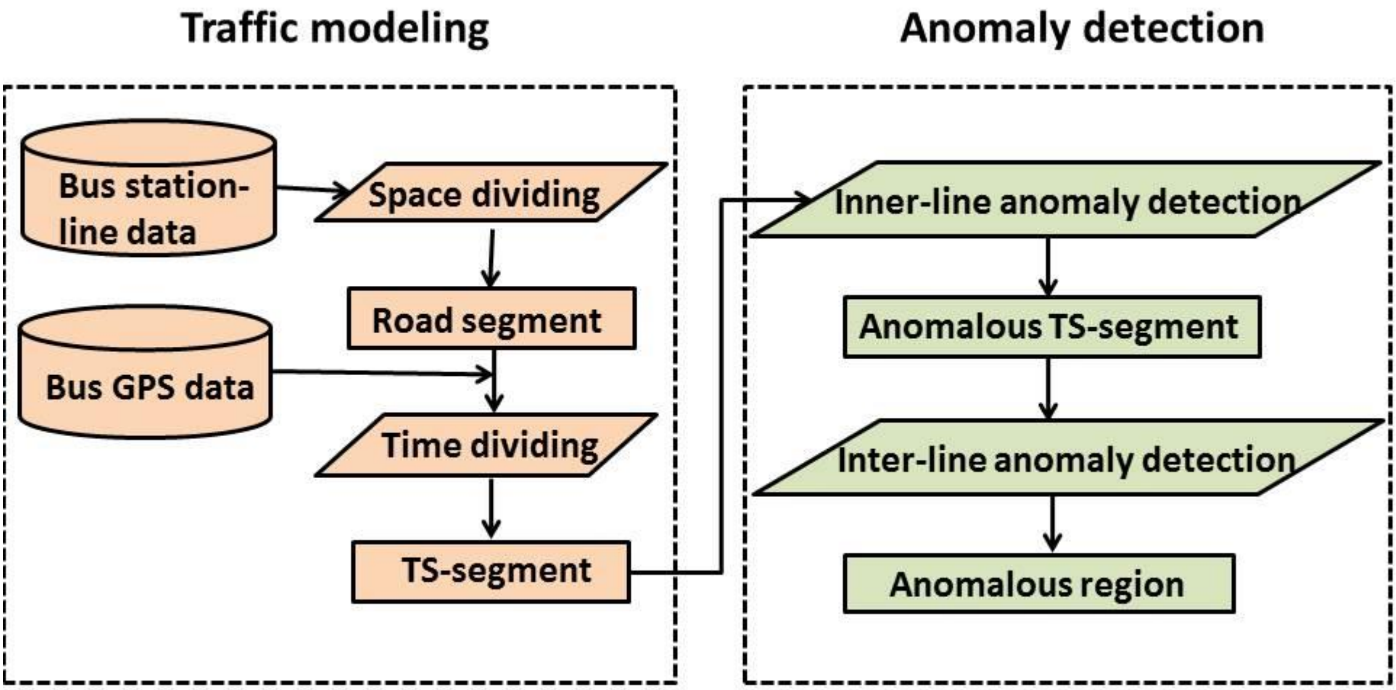
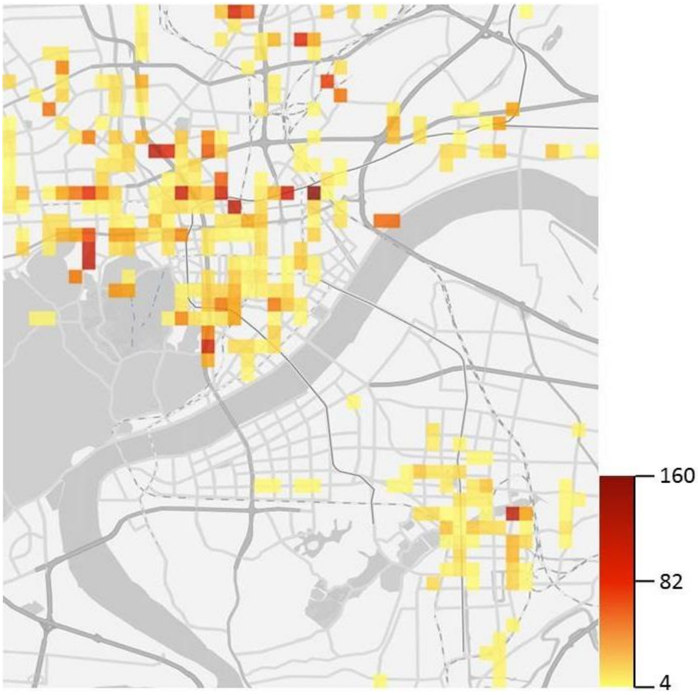


Fig. 2 Framework of the trajectory data analysis-based model.



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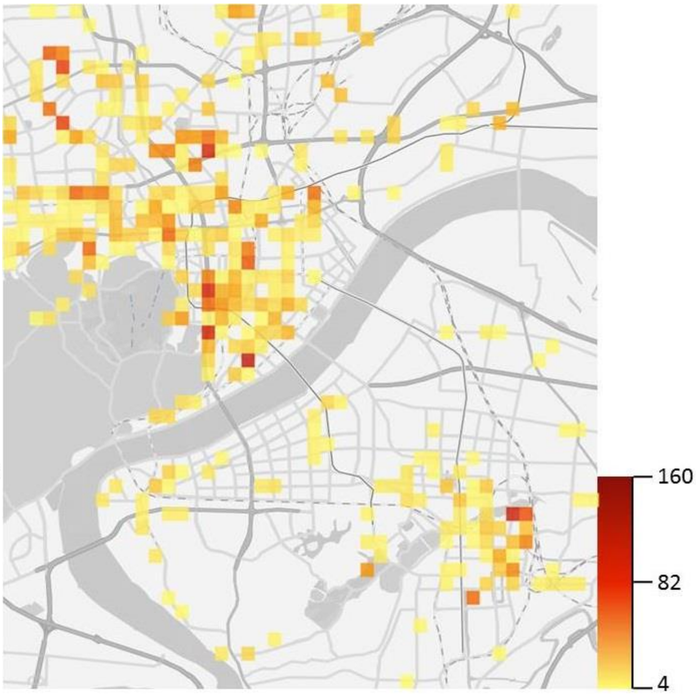

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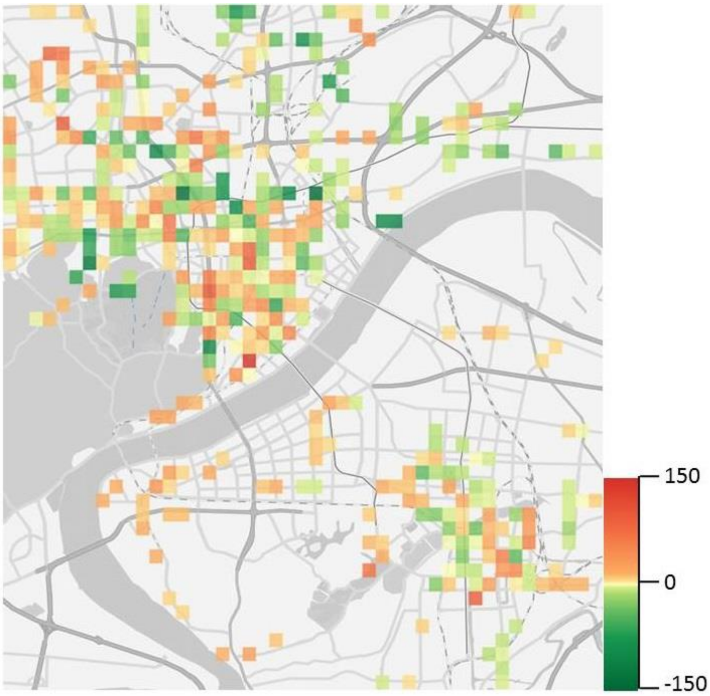
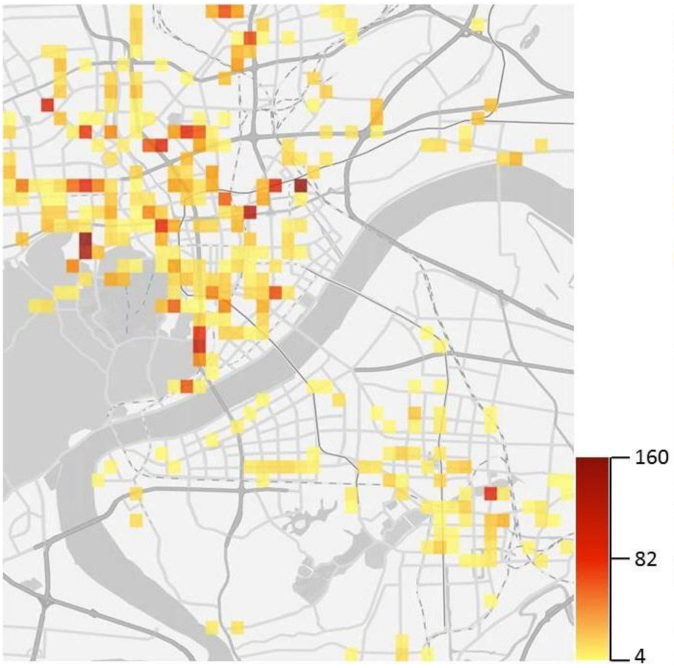
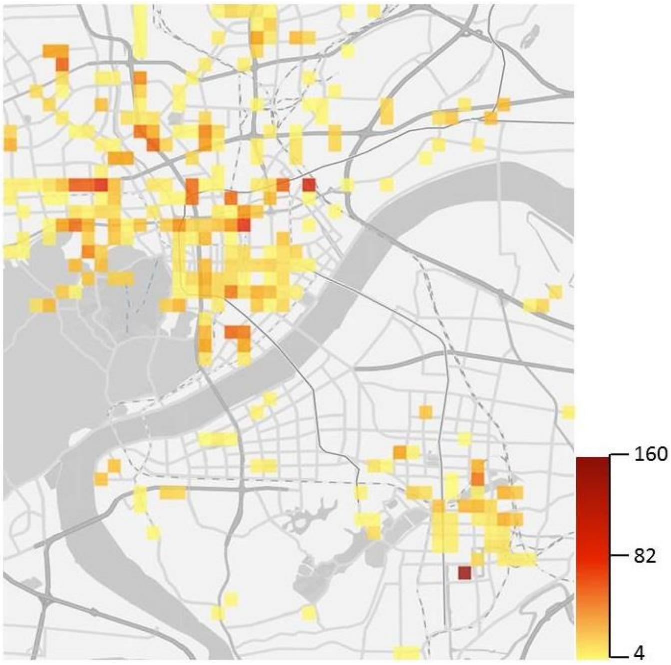


(c) Changes between the two months

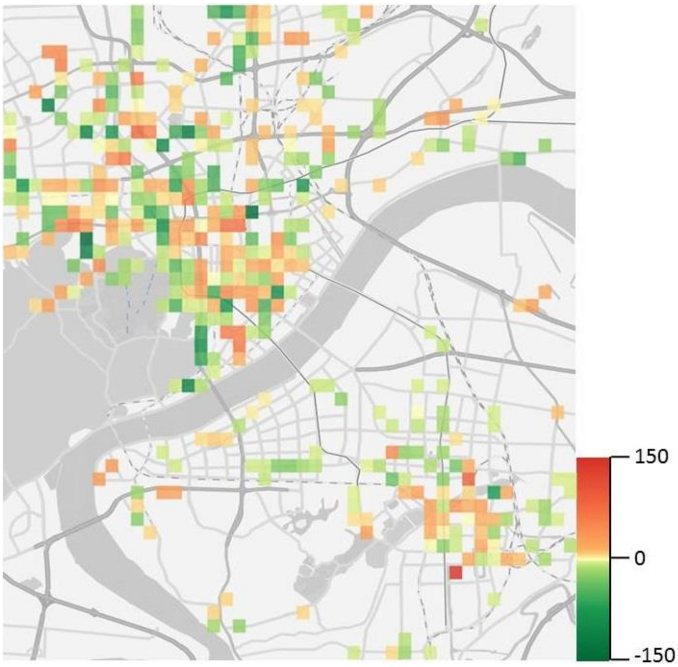
Fig. 3 Inferred traffic conditions on weekdays.



(a) October 2014

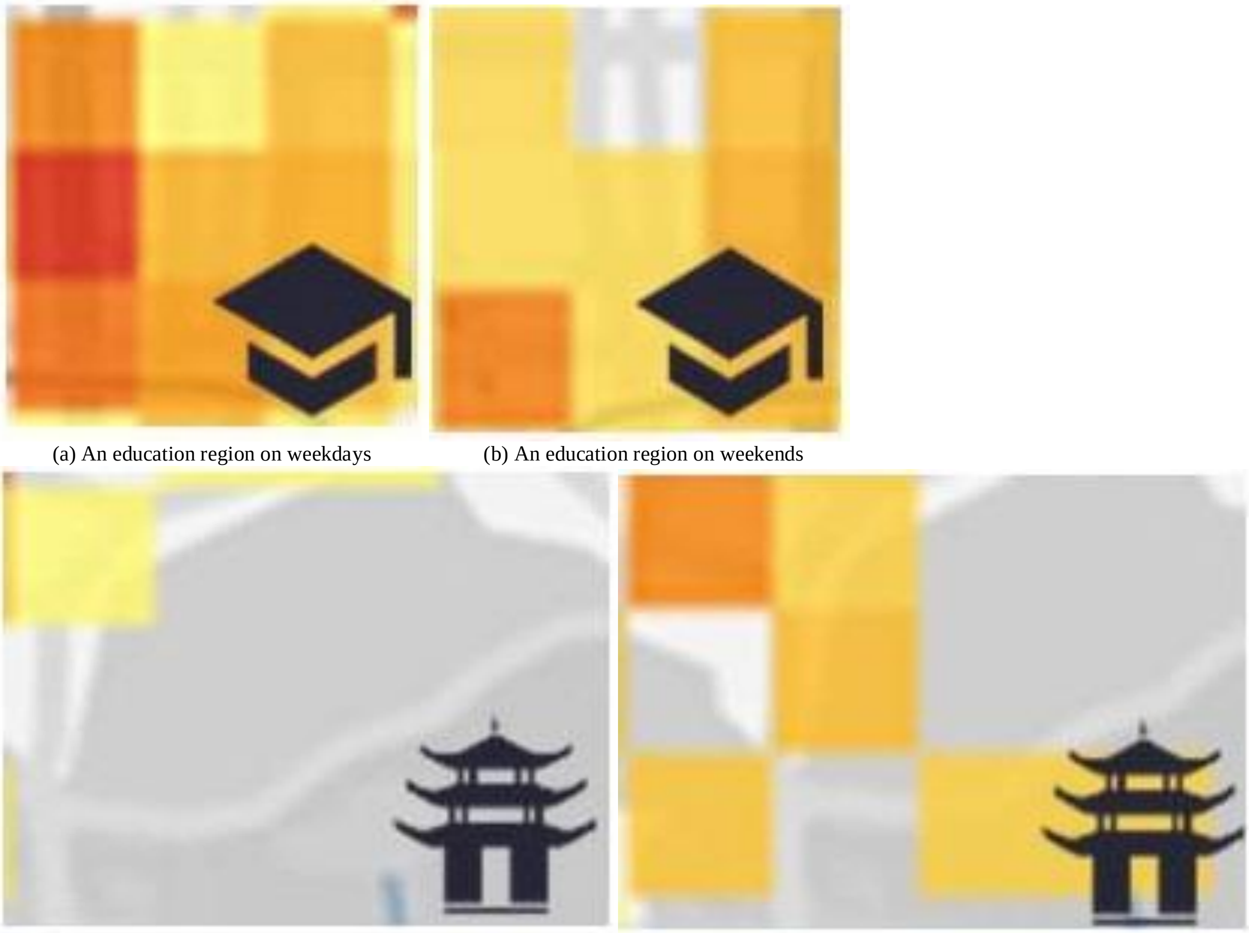


(b) March 2015



(c) Changes between the two months

Fig. 4 Inferred traffic conditions on weekends.



(a) An education region on weekdays (b) An education region on weekends

(c) A scenic area on weekdays (d) A scenic area on weekends

Fig. 5 Inferred traffic conditions of specific regions in March 2015.

TABLE 1 MAIN DIFFERENCES BETWEEN VSNS AND OSNS

	Network access	**Social relationship**	**Life time**
VSNs	Given scenarios (specific position, content and social relationship); Given time (by encounter, on-the-fly, sporadic).	Dynamic and weak, people with common interests instead of family members or friends, even anonymous users.	Limited life time, no longer active when users depart from the network.
OSNs	Anytime and anywhere.	Stable and relatively strong, mostly based on social relationship and friendship.	Unlimited life time, once formulated, “always-on”.

TABLE 2 TAXONOMY OF VSN APPLICATIONS

Vehicular Social Networks	Social Data-Driven Vehicular Networks	Traffic Information
		E-Advertisements
		News
		Smart Calendar
		Entertainment
	Social VANETs	Cooperative Driving
		Cruise Control
		Navigation
		Location Services
		Platooning
		P2P Networking
		Content Delivery
		Car-Share
		Waze
		Uber
	Data-Driven Social Networks	Theft Control
		Health-Care
		Diagnostic
		Route Planning
		Safety Warnings
		Emergency Alert
		Vehicle Tracking