Data-Driven Intelligent Transportation Systems: A Survey

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***Abstract*—For the last two decades, intelligent transportation systems (ITS) have emerged as an efficient way of improving the performance of transportation systems, enhancing travel security, and providing more choices to travelers. A significant change in ITS in recent years is that much more data are collected from a variety of sources and can be processed into various forms for different stakeholders. The availability of a large amount of data can potentially lead to a revolution in ITS development, changing an ITS from a conventional technology-driven system into a more powerful multifunctional data-driven intelligent transportation system (D^2ITS): a system that is vision, multisource, and learning algorithm driven to optimize its performance. Furthermore, D^2ITS is trending to become a privacy-aware people-centric more intelligent system. In this paper, we provide a survey on the development of D^2ITS, discussing the functionality of its key components and some deployment issues associated with D^2ITS. Future research directions for the development of D^2ITS is also presented.**

***Index Terms*—Data mining, data-driven intelligent transportation systems (D^2ITS), machine learning, microblog, mobility, visual analytics, visualization.**

I. Introduction

CURRENTLY, transportation systems are an indispensable part of human activities. It was estimated that an average of 40% of the population spends at least 1 h on the road each day. As people have become much more dependent on transportation systems in recent years, transportation systems themselves face not only several opportunities but several challenges as well. First, congestion has become an increasingly important issue worldwide as the number of vehicles on the road increases. For example, Beijing, China, had a total of 4 million vehicles at the beginning of 2010 and added another 800 000 in that year. Congestion can lead to an increase in fuel consumption, air pollution, and difficulties in implementing plans for public transportation [1]. It can also increase the risk of heart attack, as indicated by a medical report [2]. Second, accident risks increase with the expansion of transportation systems, particularly in several developing countries. Zheng *et al.* [3] showed that in China, there were 104 373 fatalities in 2003 and 67 759 fatalities in 2009. It was pointed out by Malta *et al.* [4] that almost three fourths of all traffic accidents can be attributed to human error. The reports published by the U.S. Federal Highway Administration indicated that traffic accidents that happened in cities account for about 50%–60% of all congestion delays [5]. Undoubtedly, there is a need to reduce traffic accidents and to detect accidents once they have occurred to minimize their impact. Third, land resources are often limited in several countries. It is thus difficult to build new infrastructure such as highways and freeways. After the terrorist attacks in New York City on September 11, 2001, the effectiveness of transportation systems is increasingly tied to a country's capability to handle emergency situations (e.g., mass evacuation and security enhancement) [6]–[8]. The competitiveness of a country, its economic strength, and productivity heavily depend on the performance of its transportation systems [9].

Some of the aforementioned problems can be solved by implementing new transportation policies. For example, during the 2008 Beijing Olympics, the city government of Beijing, China, imposed a restriction on car owners based on odd/even license plate numbers to keep 50% of private cars off the road. This approach has certainly alleviated congestion and the air pollution problem to some extent. In general, the approach works for special events but may not be appropriate under nominal circumstances. Another strategy is to add additional infrastructure by constructing new roads and/or to improve the existing infrastructure such as widening the roads. This approach, however, can be costly and demanding for the use of already very limited land resources. The third strategy is to optimize the use of the existing transportation system by analyzing the data that are collected from a large amount of auxiliary instruments, e.g., cameras, inductive-loop detectors, Global Positioning System (GPS)-based receivers, and microwave detectors. Ideally, these three approaches should be complementary to each other.

Manuscript received April 28, 2010; revised March 21, 2011; accepted May 9, 2011. Date of publication July 22, 2011; date of current version December 5, 2011. This work was supported in part by the National Natural Science Foundation of China under Grant 60975044, Grant 70890084, and Grant 60921061, the 973 Program under Grant 2010CB327900, and the Chinese Academy of Sciences under Grant 2F09N06. The Associate Editor for this paper was N. Zheng.

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Digital Object Identifier 10.1109/TITS.2011.2158001

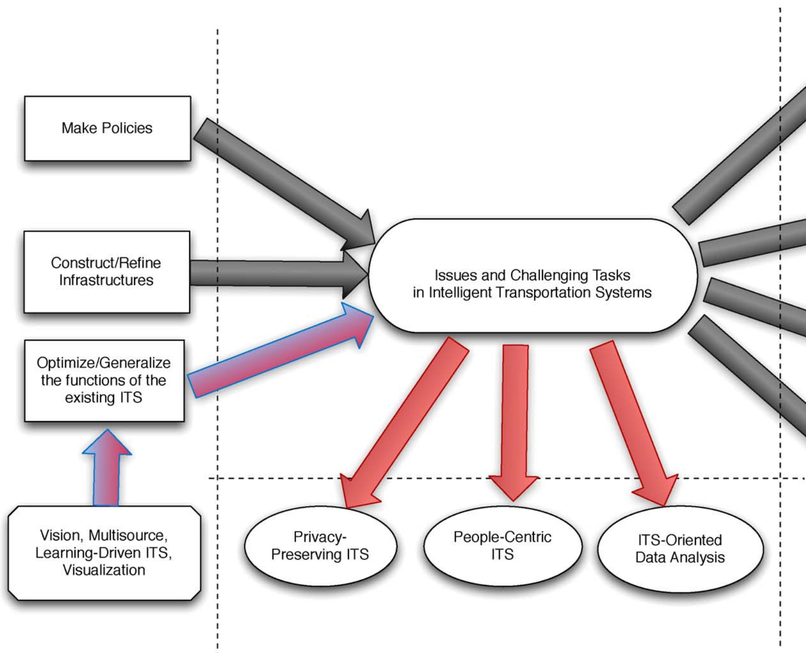

Fig. 1. Schematic of D^{2}ITS. The right side in the rightmost dotted line displays some practical issues in the ITS. Several new directions are plotted in the lowest horizontal dotted line. The left side in the leftmost dotted line shows some potential strategies for addressing the issues and challenging tasks in ITS. Each arrow reflects the direction that a module would affect the other module. For example, a bidirectional arrow means that there is an interactive influence between two modules.

Note that, currently, data can not only be processed into useful information but can also be used to generate new functions and services in intelligent transportation systems (ITS). For example, GPS data can be utilized to analyze and predict the behavior of traffic users, which is a function that is not fully utilized in conventional ITS. We envision that the conventional ITS will eventually evolve into a data-driven intelligent transportation system (D^{2}ITS) in which data that are collected from multiple sources will play a key role in ITS. It is necessary to examine, in more detail, the pros and cons of D^{2}ITS. It is also important to build a strong theoretical basis to establish a data-driven approach to improve the performance of D^{2}ITS. The system structure of D^{2}ITS that we envisioned is illustrated in Fig. 1.

This paper focuses on some of the key components of D^{2}ITS. The remainder of this paper is organized as follows. In Section II, we define the D^{2}ITS and provide a survey on its recent development. In Section III, we discuss its potential issues and future directions, followed by the final conclusion in Section IV.

II. Data-Driven Intelligent Transportation System

There are six fundamental components in ITS [9] as follows:

1) advanced transportation management systems;
2) advanced traveler information systems;
3) advanced vehicle control systems;
4) business vehicle management;
5) advanced public transportation systems;
6) advanced urban transportation systems.

Whether the functions of these components can fully be realized depends on how data are collected and processed into useful information. D^{2}ITS can be summarized as follows.

D^{2}ITS, which are supported by a large amount of data that are collected from various resources, are systems that would allow users to interactively utilize data resources that pertain to transportation systems, access and employ data through more convenient and reliable services to improve the performance of transportation systems, and realize and extend the functions of the six fundamental components of ITS.

Clearly, D^{2}ITS directly interfaces with people or users of transportation systems. For D^{2}ITS to widely be accepted, first, it should be privacy aware and people centric. Unlike the data-driven model proposed by van Lint [10], in which models are designed to directly learn the complex traffic dynamics from traffic data, the concept of D^{2}ITS considered here covers the current state of ITS and prescribes a possible framework for futuristic ITS. Furthermore, the work of van Lint [10], [11] and van Lint *et al.* [12] focused on a specific ITS application, i.e., the short-term prediction of travel time on freeway. The distinction between D^{2}ITS and conventional technology-driven ITS is that conventional ITS mainly depend on historical and human experiences and place less emphasis on the utilization of real-time ITS data or information. For example, Lin and Liu [13] improved the existing linear-programming-based analytical system-optimal dynamic traffic assignment model to enhance realism in modeling merge junctions. Zhao *et al.* [14] used linear program to achieve fast signal timing for individual oversaturated intersections. Alonso-Ayuso *et al.* [15] applied a mixed 0–1 linear optimization model for collision avoidance between an arbitrary number of aircraft in the airspace. Mulder *et al.* [16] investigated the car-following kinematics to design a haptic feedback algorithm to achieve "safely promoting comfort" in active support systems for drivers. Shieh *et al.* [17] employed unidirectional cosine functions to approximate the irregular radiation pattern. These models are

Fig. 2. Some examples of traffic-related objects. From left to right and from top to bottom. Vehicle [19], pedestrian [21], license plate [23], traffic sign [25], lane [27], pedestrian counting [33], and vehicle trajectory [34].

built based on historical or human experiences. Furthermore, data that are used in conventional ITS are collected from limited sources, e.g., inductive loops, floating cars, and video monitoring and recording.

According to the type of data used, the way that data are processed, and the specific D^2ITS applications, a full D^2ITS can be classified into several major categories, as discussed in the following sections.

A. Vision-Driven ITS

As a main component of D^2ITS, vision-based devices have broadly been employed in several other areas and generated unprecedented quantity of data in recent years for the following four reasons.

1) In a perceptual sense, people are more used to visual information than to other forms of perceptual information (e.g., voices).
2) Video sequences cover a broad range of information that can reflect, in the most direct way, the status of transportation systems and can be employed to detect some time-varying trends, e.g., the collision of vehicles, an important feature for ITS.
3) Video sensors can easily be installed, operated, and maintained [18].
4) The price-to-performance ratio of a vision-based device has greatly been improved.

Consequently, a large number of applications in ITS are implemented with vision-driven technologies, where input data are collected from video sensors, and output is used for ITS-related applications. Several representative vision-driven applications are listed as follows:

1) traffic object detection, tracking, and recognition [Methodologies have been developed to detect such traffic-related objects, including vehicle detection [19], [20], pedestrian detection [21], [22], license plate recognition [23], traffic sign detection [24]–[26], and lane tracking [27] (see Fig. 2 for a few examples).];
2) traffic behavior analysis, e.g., detecting irregular vehicle behavior and the concealment of intent in transportation systems [28], [29], and automatic incident detection [30];
3) vehicle density [31] and pedestrian density estimation [32], [33] (see Fig. 2);
4) construction of vehicle trajectories [34];
5) statistical traffic data analysis [20].

The detection, recognition, and tracking of the traffic-related objects have broad applications in ITS. In particular, vehicle detection and identification are commonly used for identifying cases for traffic violation (e.g., speeding and red light running), which is important for reducing traffic accidents. In addition, vehicle identification is complementary to the license plate recognition approach in several ITS applications, e.g., parking lot access control, easy-pass toll collection, and stolen vehicle recovery [19], [35]. Several research on vision-driven technologies for ITS development focuses on these applications. The following five main issues are listed as follows [35].

1) Vehicles greatly vary in shape, size, and color.
2) The appearance of a vehicle always changes with its poses change.
3) Complex outdoor environments can add difficulties to the design of a general vehicle detection and identification system.
4) The computing power is often very demanding due to the rapid movement of on-road vehicles.
5) It is difficult to design a system that is robust to a vehicle's movements and drifts.

To address these issues, Wang and Lien [19] proposed a vehicle detection method by extracting local features from subregions in each frame. This approach will enable the performance of vehicle detection that is less susceptible to the geometrical variance [19]. Vehicle detection is also a critical step toward the intelligent vehicle research. Effective car-following and lane-changing control measures can be implemented for a vehicle if the position of its neighboring vehicles can be captured precisely. Sivaraman and Trivedi [36] built an on-road vehicle detection system by integrating active-learning-based vehicle recognition with particle filter tracking. Cherng *et al.* [37] proposed a dynamic visual model that performs visual analysis of video sequences to detect critical motions of nearby moving vehicles while driving on a highway (see [35] for a complete review of on-road vehicle detection systems).

Similarly, an effective pedestrian detection can help reduce the occurrence of pedestrian-vehicle-related injuries. If a system can issue a warning in time and start some proactive measures once a pedestrian has been discovered in a risky region, then the pedestrian-vehicle-related accident can be mitigated and even avoided. Obviously, the detection of the sign of such potential risks from both the frontal and lateral views should be a prerequisite of an effective pedestrian detection system (PDS). The main issues are given as follows: 1) It is not an easy task to separate pedestrians from background in an image or video sequences in the computer vision domain [38], and 2) the pedestrian appearances vary in clothing, hairstyles, and bags [39]. To solve the aforementioned issues, Broggi *et al.* [40] studied the use of in-vehicle cameras to detect pedestrians who have a high risk of subjecting themselves to traffic incidents. With a single camera, Cao *et al.* employed a cascade classifier to detect the candidate risky region and estimate the distance between each pedestrian and the vehicle [41]. Munder *et al.* utilized a Bayesian multicue approach to combine the extracted shape, texture, and depth information to detect and track pedestrians in a clutter urban environment [21]. For a more comprehensive review of research on pedestrian detection and protection, see [38], [42], and [43].

License plate recognition is a core module for intelligent infrastructure systems and intelligent vehicle management useful for a variety of applications, ranging from vehicle behavior monitoring to travel-time estimation. Typical license plate recognition software consists of the following three key parts: 1) license plate detection; 2) character segmentation; and 3) character recognition. Similar to vehicle and pedestrian detection, we have the following two ways of identifying a license plate: 1) from still images or 2) from video sequences [23]. Although commercialized products have been developed for this application and are available on the market, the problem itself remains to be challenging. The major challenges remain to be the design of a robust license plate detection and recognition system that can work under a variety of complex conditions with the movement of multiple objects. Furthermore, the detection should be less sensitive to the angle variation between the ground and the license plate installed in the bumper. A detailed review on license plate recognition is given in [23].

Traffic-related object recognition can also be useful for refining the performance of driver assistant systems (DASs), in which the used video devices are mobile, whereas in several other cases, the devices are static [41]. In addition to the aforementioned vehicle and pedestrian detection, lane detection and tracking in real time is very important to the development of a collision-warning system in DASs. However, the lane detection and tracking system usually suffers from a wide variety of lane markings and lane surfaces, as well as weather conditions and time of days. McCall and Trivedi [44] gave a comprehensive survey on the detection and tracking from five aspects, including road modeling, road marking extraction, preprocessing, vehicle modeling, position tracking, and common assumptions and comparative analysis. The authors pointed out [44] the following four cases.

1) Lane recognition can have better performance at night and dawn than during day and dusk, because there are larger contrasts between road and road markings and the lack of complex shadows at night, and a morning fog can help eliminate shadows at dawn.
2) Lanes with solid and segmented line markings are recognized better than with other markings.
3) A lane departure warning system should pay more attention to the recognition of the edge of the lane, whereas a lane-keeping system should focus on the location near the center of the lane.
4) Lane recognition will suffer from some special scenarios such as tunnel and complex shadows.

They also proposed a steerable filter for robust and accurate lane marking detection. In real-time lane tracking under various challenging scenarios, Kim employed several machine-learning algorithms, e.g., neural networks and support vector machines, to learn the lane mark from a collection of image patches, followed by utilizing particle-filtering-based tracking algorithm to track the lanes [27]. By modeling a road with varying curvature as a hyperbola function with some nonlinear terms, Wang *et al.* estimated the parameters of the model and employed a condensation model to track the road in real time [45].

Vehicle speeding can significantly increase the chance of fatal crashes. Speeding sometimes occurs due to drivers' failure in spotting the speed sign. Laboratory experiments revealed that distraction is a main source that can result in an increase in the failure to detect simulated traffic signals. To address this issue, Barnes *et al.* introduced a fast symmetry detector to detect the speed limit sign under a broad range of lighting conditions. One additional advantage of using the detector is that, as the authors pointed out, it can well combine with the subsequent speed sign recognition [24]. Baró proposed an evolutionary version of AdaBoost to detect the sign by employing the error-correcting output code framework to achieve an effective traffic sign classification [25]. Khan *et al.* [26] utilized two basic geometric properties—the relationship between the area and the perimeter, and the number of sides of a given shape—to analyze different shapes and achieved an automatic road-sign recognition based on image segmentation and joint transformation correlation. Recently, Gómez-Moreno *et al.* [46] have evaluated the influence of image segmentation algorithms for traffic sign recognition. To obtain better recognition on low-quality sign images, Ruta *et al.* [47] developed a robust sign similarity measure based on the domain-specific traffic sign images. To reduce traffic accidents that result from the distraction of drivers, e.g., drunk or drowsy driving, Chang *et al.* developed the following two vision-based modules: 1) an unexpected lane departure avoidance module for preventing lateral collisions and 2) a rear-end collision avoidance module for avoiding longitudinal accidents [28]. Within the two modules, radial basis probability networks are employed to distinguish between the normal lane change and the abnormal lane departure. Neural networks and fuzzy membership functions have been used for raising a warning to the potential longitudinal accidents.

Note that one disadvantage of these algorithms is that they only work during daylight. To construct an effective vision-driven system for nighttime, one way is to use an infrared camera, which is less sensitive to the lighting conditions of the surrounding environment. Based on detecting images of specific size and aspect ratio in far infrared (FIR), Bertozzi *et al.* [48] implemented a PDS with night vision. Ge *et al.* [49] combined a monocular near-infrared (NIR) camera with illumination from full-beam headlights to achieve a real-time pedestrian detection and tracking systems during nighttime driving. With this method, the cost of purchasing expensive FIR cameras can greatly be saved without compromising the desired recognition rate. Using image-based metrics, Bi *et al.* modeled pedestrian detection performance with night-vision systems. In particular, they described a model of the probability of pedestrian detection as a function of distance and image-based clutter, contrast, and pedestrian size metrics [22]. More recently, Lim *et al.* [50], [51] have studied the influence of human factor to driver performance with night-vision systems. They pointed out the following two cases: 1) FIR night-vision systems can produce less cluttered images than NIR systems [50], and 2) compared with NIR systems, FIR night-vision-enhancement systems can help drivers shorten search times and pay more glances to the scenes that have pedestrians in it [51].

Pedestrian counting is useful for emergency evacuation. In general, evacuation strategies can be divided into static and dynamic approaches. The former approach can utilize geographical information systems (GISs) to provide information on surface transportation, whereas the latter approach heavily depends on the availability of real-time traffic and pedestrian information [6]. Compared with other technologies, video sequence is a cost-effective way of collecting such information. However, the performance of a pedestrian-counting system significantly suffers from occlusion in the scenes when the density of the pedestrian crowd increases. Furthermore, its performance is influenced by large variances in pedestrian appearances, including height, clothing, and accessories [32], [33]. To address the issues, research has been performed to extracting a collection of high-dimensional statistical features from the pedestrian image sequences, followed by employing the supervised dimension reduction technique, a technique that makes use of the counting label of each sample in the training set to guide the reduction in selecting the representative features. Experiments that have been conducted showed promise of this approach compared with several existing algorithms [32]. By utilizing temporal relationships between each frame and its neighboring frames as the constraint term, Tan *et al.* [33] developed a semisupervised elastic net to achieve pedestrian counting. Another important application of vision-driven ITS is to analyze the vehicle/pedestrian trajectories from video sequences, because trajectories can be useful for planning applications, emission modeling, and abnormal behavior detection. For example, Atev *et al.* [34] studied the vehicle trajectories by proposing a trajectory-similarity measure based on the Hausdorff distance.

Flow, occupancy, and speed are, so far, the most used indices for characterizing traffic conditions. They are routinely generated for traffic control and transportation system management. These indices remain to be the key input to ITS. For several years, these data have been collected with inductive-loop detectors that are embedded in the road's surface. One of the major disadvantages with the loop detectors is their high installation and maintenance costs. In recent years, video devices have been utilized to generate these measures. For example, Morris and Trivedi developed a visual vehicle classifier and traffic flow analyzer (VECTOR) module to obtain traffic flow measures from video sequences. Furthermore, they constructed a probabilistic scene motion model to perform activity analysis so that some potential traffic abnormality that results from accidents or special events can be detected in time [20]. Chitturi *et al.* [52] evaluated the effect of shadows and time of day on the performance of three video detection systems (Autoscope, Peek, and Iteris) at a signalized intersection. There is a trend that commercial roadside or overhead video detectors have gained much more market share in detecting traffic.

B. Multisource-Driven ITS

D^2ITS can be supported by data from multiple sources, e.g., inductive-loop detectors, laser radar, and GPSs. To a certain extent, multisensor-driven systems play a complementary role for vision-driven systems, which are often easily subject to environmental constraints as aforementioned [53]. Although vision-driven automatic incident detection (AID) systems can provide an effective and automatic way of detecting incidents without a need for human operators, for example, its performance suffers from the change of outdoor environments, e.g., snow, static or dynamic shadows, rain, and glare [18], [30].

In recent years, GPSs have much more frequently been used in ITS, because they provide real-time positioning information that would allow us to trace the movement of vehicles, a feature that is particularly useful to ITS.

Clanton *et al.* [53] developed a lane departure warning system through estimating GPS bias measurement by treating an automative-grade navigation GPS as an auxiliary element of vision-based systems. Huang and Tan applied a differential Global Positioning System (DGPS) and intervehicle communication device to build a future-trajectory-based cooperative collision warning system (CCWS) [54] in which the time-dependent location of a vehicle and its neighboring vehicles are measured and processed through a GPS platform. To reduce the errors that result from measurements and to enhance the robustness of the proposed CCWS, the authors used the Kalman filter technique to estimate the magnitude of errors so that proactive actions can be taken based on the probability of collision [55]. By clustering the GPS-derived speed pattern, Kianfar and Edara [56] attempted to optimize freeway traffic sensor locations for better estimating travel times. Chen *et al.* [57] proposed a GPS-based data reduction algorithm to remove redundant GPS location data and preserve some key points for the Qinghai–Tibet railway system.

The main issues with GPS the following three conditions:

1) the multipath issue, i.e., a place may receive multiple GPS positioning information, particularly in an urban area with high-rise buildings, where signals from the satellite can be blocked, resulting in potential errors in vehicle positioning data;
2) the missing data issue, e.g., during the time that a vehicle goes through a tunnel;
3) few visible satellites.

Due to these disadvantages of GPS, the performance of some GPS-based traffic applications can be degraded. To address the problem, Schleischer *et al.* [58] considered visual information as a complementary data source for GPS data. Their research fused these two heterogeneous data sets to generate the vehicle positioning information with high precision by estimating the fingerprint of each vehicle (or vehicle poses) with stereovision and then refining the vehicle orientation estimation with a low-cost GPS. Experiments show that the proposed method is much more robust for tracing vehicles in an urban environment. To reduce possible errors, Meguro *et al.* [59] proposed to mount on a car an omnidirectional infrared camera, which is less sensitive to its surrounding environment.

There are other types of detectors that are used for ITS, e.g., laser radar detectors and ultrasound detectors. Although very costly at the present time, radar detectors can successfully be used in a parking-aid system, whereas other conventional methods, e.g., the ultrasonic-based method and the graphical-user-interface-based method will fail [60]. Jung *et al.* further introduced scanning laser radar to a parking-aid system to position vehicles with high accuracy [60]. To avoid the strong sensitivity to atmospheric conditions and the impossibility of obtaining direct and accurate information with regard to depth, Gidel *et al.* [61] used a multilayer laser scanner that is mounted onboard a vehicle to detect pedestrians. With the combination of traffic features and meteorological features, e.g., wind speed and wind direction, Zito *et al.* studied the prediction of real-time roadside carbon monoxide (CO) and nitrogen oxide concentrations by using neural networks. Extensive experiments indicate that the proposed neural network models have a good transferability, which can easily be adapted to data sets collected from other areas [62]. This research can bring benefits to the improvement of the near-road air quality and, in some sense, the influence of the performance of vision-driven tasks, because most such tasks depend on the imaging quality.

There is an interesting trend toward the utilization of some unconventional transportation sensors that enable us to collect and analyze traffic information in a more cost-effective way. Sohn and Hwang studied the feasibility of utilizing the already-installed mobile cellular networks for automatic vehicle identification (AVI) [63]. One major focus of their work is to employ a probe phone to estimate the vehicle passage time on a freeway and investigate the factors that may affect the accuracy of such estimates. Compared with the known surveillance systems, the proposed cell phone probing systems play a complementary role in enhancing the quality of traffic information. Calabrese *et al.* [64] used the real-time data collected from mobile phones to monitor the vehicular traffic status and the movements of pedestrians in Rome, Italy. Gandhi and Trivedi employed omnidirectional cameras mounted on an automobile to achieve a 360° surrounding view map [65]. Gandhi *et al.* [66] designed a multisensory testbed for the collection, synchronization, and analysis of multimodal data for monitoring the status of transportation infrastructures. In the testbed, the video and seismic sensors supply information about vehicles and can be used together with other data sources to improve the reliability of vehicle classification [66]. Ehlgen *et al.* utilized catadioptric cameras—a combination of cameras and mirrors—to view the surrounding area of vehicles, potentially reducing the accidents resulting from blind spots of trucks and trailers [67].

When multiple sensors are installed on a vehicle, one issue is that they would communicate with each other. For example, it was shown that, when multiple ultrasonic sensors are installed in front of a vehicle, crosstalk will happen [68]. This condition is one of the major sources that would lead to a failure of the short-range collision-warning systems in congested traffic environment and parking-assistance system. The authors proposed to use a microcontroller to produce a pseudorandom number of sinusoidal pulses to reduce the occurrence of crosstalk.

Finally, one of the challenging issues in data fusion is how we can build a universal similarity measure to align images from different sources. When motion vehicles are present on a road, the condition will become more difficult, because in general, such a motion will bring a detrimental effect to the performance of image alignment [69]. Jwa *et al.* [69] presented an effective image registration to align images from different sources, e.g., unmanned aerial vehicles (UAVs) or conventional cameras. The contents of multisource-driven ITS are summarized in Fig. 3.

C. Learning-Driven ITS

Although video devices and multiple sources can generate data of transportation systems for a broad scope of applications in ITS, it is not sufficient to rely on only these devices to generate data to serve as input used for traffic control, particularly for real-time traffic control and transportation system analysis. Furthermore, the latest development in ITS exhibits a new trend toward proactive control as opposed to conventional passive control and management [70]. For example, the effective prediction of the occurrence of accidents can enhance the safety of pedestrians by reducing the impact of vehicle collision. Thus, there is a need to learn the intrinsic mechanism of the transportation system using both real-time and historical data. Several major learning-driven approaches are summarized in the following sections.

1) Online Learning: As an example, one typical application that is related to the learning-driven ITS is the prediction of trip travel time or vehicle passage time in a transportation network, an important input for several ITS components [10]. The difficulty for this case is that the travel time depends on traffic conditions that are highly dynamic and nonlinear in nature, changing over time and space. As a result, it is not easy to accurately estimate the trip time of a driver when the driver starts the trip. To solve the problem, van Lint proposed

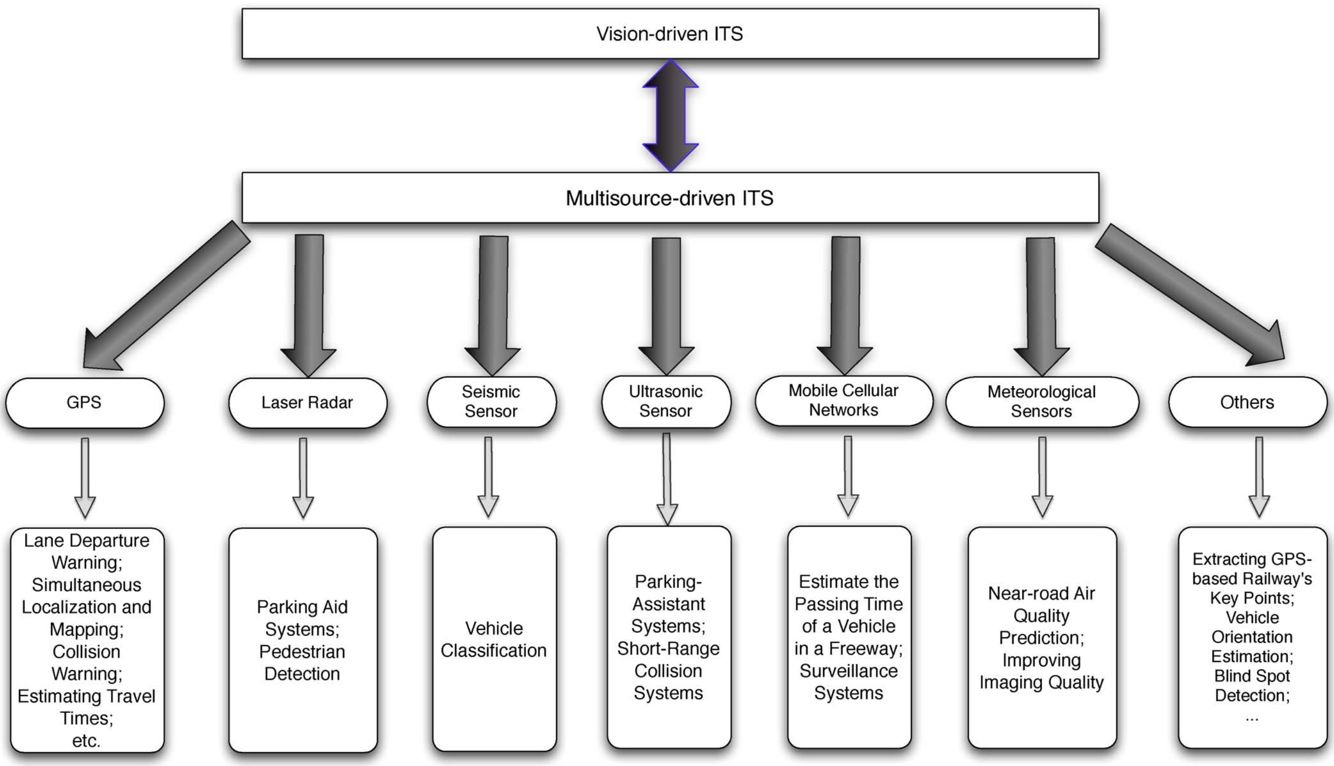

Fig. 3. Schematic of the multisource-driven ITS. Here, the bidirectional arrow means that vision- and multisource-driven ITS are complementary in D^2ITS.

to employ the state-space neural network, which is an online learning algorithm, to achieve the short-term prediction of travel time on freeways [10]. By adopting the node-arc network representation, with arcs representing the roadway segments and nodes representing the junctions or intersections, Jula *et al.* proposed a real-time Kalman filter model to predict travel time at the arc level and estimate the arrival time at the node of the stochastic traffic networks by combining historical data with real-time measurements of travel times along the arcs [71]. Linda and Manic [72] proposed to evaluate the spatiotemporal risk based on the combination of online nearest neighbor and fuzzy inference.

Furthermore, the vehicle or pedestrians' trajectory/motion pattern analysis is a crucial goal of autonomous navigation in different regions, e.g., cities and parking lots. However, it is difficult for most offline trajectory/motion pattern analysis algorithms to predict or identify a real-time-basis new pattern with high accuracy. To address the issue, Vasquez *et al.* [73] proposed a growing hidden Markov model where the structure and parameter of the model is through online learning so that the new motion patterns can effectively be identified. Aiming at automatically learning models of vehicle activities with minimal human training, Veeraraghavan and Papanikolopoulos [74] transformed the observed trajectories into an action sequence and presented a semisupervised learning algorithm that can learn activities as complete stochastic context-free grammars. Angkititrakul *et al.* [75] employed Gaussian mixture models to model stochastic driver behavior, e.g., lane-cross events and intentional driver correction events, and then used the online observed driving signals to achieve a lane departure warning system.

Another application of online learning is to develop effective evacuation strategies. Chiu and Mirchandani utilized feedback information to achieve an online behavior-robust routing strategy for mass evacuation [6]. Compared with the open-loop-based approaches, the proposed approach is more effective in guiding vehicles to some prespecified safe location by regularly providing frequently updated evacuation route information [6].

2) Data Fusion: In general, it is insufficient, in most cases, to use a single model to attain good performance in ITS. To address the issue, Tan *et al.* [76] fitted three models using three traffic flow sets and utilized neural network as a data aggregation model to combine the prediction results of the three models. Here, two of the three data sets—daily time series data and weekly time series data—are generated from the conventional traffic flow data. Considering the fact that vehicles tend to practice different maneuvers under different traffic scenarios. Toledo-Moreo and Zamora-Izquierdo proposed an interactive multiple model to better predict lane changing for different traffic conditions [77]. Malta *et al.* combined a brake-pedal force model and a speech model to better capture the driver behavior [4]. Fusion strategy can effectively utilize multisource-driven ITS to better analyze and predict traveler behavior and traffic dynamics [1]. The fusion of data from multisources can provide us with holistic and comprehensive information and can thus improve the performance of ITS, e.g., guiding emergency evacuation and congestion control. Jwa *et al.* [69] attempted to detect and track vehicles using multiple UAVs. They aligned images that are collected from different UAVs based on their proposed robust alignment algorithm and tracked vehicles with their proposed outlier rejection algorithm. Masini *et al.* surveyed several fusion techniques that are used to fuse video streams in the long- and short-wave infrared bands, e.g., the fusion of coefficients in the two Laplacian pyramids, and evaluated their performance by examining frame-by-frame images that are extracted from the video streams [78]. Considering the pros and cons of the loop detectors and GPS receivers, Kong *et al.* fused data that are collected from these two sensors based on the evidence theory [79], leading to improved estimates of traffic state information. Polychronopoulos *et al.* designed a hierarchical structure to fuse environmental data and vehicle dynamics data for predicting the trajectories of moving vehicles [80]. Sun and Zhang proposed a new selective random subspace predictor to deal with the prediction of traffic flow under incomplete data. They presented a data fusion algorithm to improve the accuracy of the prediction based on the fusion of multiple outputs [81]. Based on the complementary properties of infrared receivers and ultrasonic barriers, García *et al.* [82] utilized a set of diverse techniques of data fusion and proposed a multisensory system for obstacle detection on railways with high reliability.

3) Rule Extraction: Another function of learning-driven ITS is to gain insight into some useful patterns, trends, and correlation between different traffic data sets. This function is conventionally realized through the use of association rules. Barai [83] employed the association rule to explore the relationship between the type of roads and specific types of traffic accidents. Gong and Liu [70] combined association rules with association analysis to predict the traffic network flow. Furthermore, with association rules, Haluzová discovered that the number of traffic accidents influences the delay rate in the affected areas [84].

One alternative strategy for obtaining insight is to use the rough set theory proposed by Pawlak [85]. The theory can derive some important attributes through the attribute reduction without utilizing any *a priori* information outside the data set. Chang *et al.* [86] extracted a reduction of pavement maintenance and rehabilitation based on the rough set theory. Wong and Chung [87] employed the rough set theory to model the mechanism of traffic accidents as factor chains, including driver properties, travel properties, driver behaviors, and environmental factors. In addition, they also discovered a relationship between the bump-into-facility accidents and humid road.

4) ADP-Based Learning Control: One of the major problems for D^2ITS is how we can realize learning-based performance optimization of ITS in an uncertain dynamic environment. This problem is usually difficult, if not impossible, to handle with the traditional mathematical programming approach. One promising way is to develop adaptive dynamic programming (ADP) and reinforcement learning (RL) methods [88] for the performance optimization of complex dynamic systems, because ADP and RL have been shown to be powerful in solving Markov decision processes with large or continuous state and action spaces. RL and ADP can be utilized here to provide a framework for solving the learning control problem. In the last decade, research on ADP-based learning control and optimization of ITS has received much more attention in the literature. For example, Ling *et al.* [89] studied automate streetcar bunching control through multiple RL agents that act on a series of successive signalized intersections. Abdulhai *et al.* [90] proposed a Q-learning algorithm, which is a type of simple yet powerful RL algorithm, for traffic signal control. Salkham *et al.* [91] developed a collaborative reinforcement learning approach for optimal traffic control in an urban setting. Although much research needs to be done in the future, it can be expected that ADP-based learning control will provide a basic tool for realizing D^2ITS with online learning and performance optimization in dynamic uncertain conditions.

5) ITS-Oriented Learning: ITS have their unique characteristics and properties that should be considered when it comes to the development of learning-driven algorithms. For roadway transportation, the spatial–temporal relationship between traffic data and the corresponding geographical information of the roadway infrastructure should be considered when performing a learning-driven ITS. For example, in the data collection, traffic data from a roadway segment should be distinguished by the direction of traffic for spatial clustering. Otherwise, two data points from different lanes with different driving directions may incorrectly be clustered into the same group [92]. Furthermore, the occurrence of traffic accidents will usually generate traffic patterns that are different from traffic patterns that result from recurrent congestion [93]. The occupancy upstream the incident site will usually increase, and the occupancy downstream will decrease. Such traffic patterns should be incorporated into the learning-driven ITS. The framework of a learning-driven ITS is shown in Fig. 4.

D. Visualization-Driven ITS

From a perceptual viewpoint, visualization, as a specific application of D^2ITS, is the most intuitive way of helping people understand and analyze traffic data. Compared with computers, human beings have a stronger judgment ability to analyze visualized data when the dimension of the data space is less than three. Therefore, it is not surprising that visualization has become a substantial and ubiquitous tool in ITS. For example, changeable/variable message signs provide a simple and intuitive way of visualizing the congestion information on the freeways in real time. As a result, travelers can better plan their travel routes in response to the change in traffic conditions. For traffic management, visualization can help decision makers quickly identify abnormal traffic patterns and accordingly take necessary measures to bring the system back on track [94].

The following four approaches are the commonly used visualization techniques [67]:

1) line charts;
2) bidirectional bar charts;
3) rose diagrams;
4) data images.

For example, line charts are used to illustrate the variation of traffic flow in some phase or some region. The bidirectional bar chart can effectively describe the directional difference of traffic flows. By encoding data with color, a data image can be used to evaluate traffic conditions, detect irregular traffic patterns, and identify the trend. Details on the introduction of these visualization methods are discussed in [95].

Lee *et al.* [96] visualized the relationship between headway, speed, and occupancy by using a 5-D stack bar chart, which

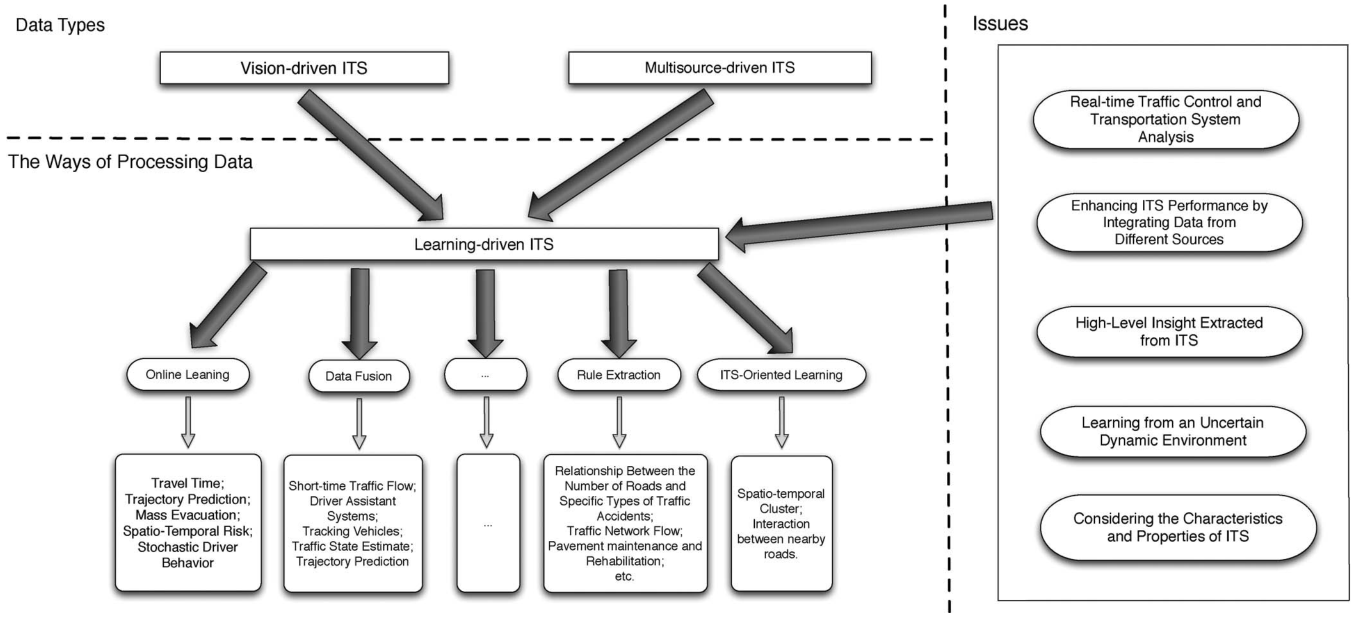

Fig. 4. Schematic of the learning-driven ITS. The top side in the topmost dotted line displays the types of data that can be used for the learning-driven ITS. The right side in the rightmost dotted line displays some practical issues that lead to the learning-driven ITS.

allowed them to identify irregularities in traffic associated with accidents. Lu *et al.* [94], [97] developed a web-based visualization package, named CubeView, to aggregate data for identifying major traffic trends.

III. Roadmap and Future Directions of Data-Driven Intelligent Transportation System

The previous section discussed the technology side of the development in D^{2}ITS. In the following sections, we will discuss some issues related to the deployment of D^{2}ITS and identify areas that are worth in-depth research in the future.

A. Learning Issues

Data play a key role in the effectiveness and efficiency of the D^{2}ITS. As Barai [83] pointed out, a large amount of data that can be used for ITS are, in fact, highly irregular, heterogeneous, and high dimensional in ITS. Because most data are sampled from either vision or multisource devices and are transmitted with various ways, it leads to the following four challenging tasks.

1) Data Cleansing and Imputing: It is well known that traffic data are full of noise due to various known and unknown factors. For example, during a study performed on freeway traffic flow in the third ring of the City of Beijing, it was observed that the speed data that were collected contained samples with vehicle speeds much higher than the speed limit posted on the road [98]. The reason for this is that the detector that was used always autochecks its working status by sending a pseudospeed signal with fixed-time intervals. Obviously, it is necessary to perform data cleansing to remove the noisy and/or abnormal data in D^{2}ITS. However, the development of an automatic data-cleansing process is very challenging. Wu and Zhu attempted to fuse data cleansing with data analysis and proposed a noise-aware data-mining algorithm to detect and remove noise. Meanwhile, they refined the data-mining performance by estimating the statistical information of different types of noise [99]. One major disadvantage of their approach is that they assume noise to be of some known form, whereas noise in data in the real world in D^{2}ITS is often random and hard to be characterized with a single well-defined probability distribution function.

Detector malfunction can also lead to the loss of data package during transmission [100]. Because the cause of missing data could vary, Qu *et al.* [100] introduced probabilistic principal component analysis (PPCA)-based missing data imputation, where PPCA is used to capture the main structure, and maximum-likelihood estimation is used to estimate the missing value. The advantage is that the method considers not only local information such as the traffic flow data of each day but the global information as well, including neighboring relationships between historical data. One major disadvantage of this approach is that the underlying linear assumption used in the method does not always hold.

2) Dimension Reduction: In the ITS domain, most data are high dimensional. For example, when one pixel is regarded as one dimension, then a vehicle image has multiple dimensions. The "curse of dimensionality" issue would arise, i.e., as the dimension increases, the number of samples must exponentially be increased. Consequently, the learning problem can be highly complex. Fortunately, one common viewpoint is that data can be generated from a set of intrinsic low-dimensional variables. Several dimension reduction methods have been proposed in recent years. Several newly developed and representative theories include manifold learning [101], [102], nonnegative matrix factorization (NMF) [103], and kernel dimension reduction [104].

Manifold learning discovers the underlying low-dimensional manifold embedded in the high-dimensional Euclidean space. When projecting data onto a low-dimensional space, for example, isometric mapping [101] preserves approximated geodesic distances of any two points, and locally linear embedding [102] keeps the local topology between a sample and its neighboring samples. A survey on the recent development of manifold learning is shown in [105].

The initial motivation of NMF is to extract the nonnegative part from data, e.g., extracting the eyebrows and mouth of a face image. Ding *et al.* [106] generalized the method of applying to areas such as clustering and enhanced its interpretability.

Kernel dimension reduction utilizes supervised information to guide the dimension reduction to maximize statistical independence. The statistical independence means that a projection subspace of data space will have the same contribution as the original space, and the corresponding orthogonal complement subspace of a subspace will contribute nothing to the inference of response variable and is thus redundant [82]. The kernel dimension reduction method was adopted for pedestrian counting with promising performance, as discussed in [32].

The aforementioned three methods can help us uncover insightful information for ITS data, enabling us to improve the performance of learning-driven tasks under a reduced dimensional space.

3) Sparsity Learning: Unlike dimension reduction, which intends to discover some underlying low-dimensional structure, sparse learning directly removes some redundant features from the original feature space but preserves the interpretability of the remaining features. One classical sparse learning algorithm is Lasso, which is proposed by Tibshirani [107], [108]. In this algorithm, features that are not related to response variables will be weighted by zeros and are thus naturally removed from the original feature space. To obtain higher sparsity, several refinements have been proposed for the last decade. Yuan and Lin proposed Group-Lasso to group variables of higher order interactions and emphasize the main effect of these variables [109]. Qi *et al.* exploited the sparsity nature of high-dimensional feature space and utilized an L_1-penalized log-determinant regularization to develop an efficient sparse metric-learning algorithm in the high-dimensional space [110]. Duchi and Singer incorporated sparsity penalization into the boosting algorithms to achieve better performance with high sparsity [111]. Huang *et al.* employed coding complexity associated with the structure to study the structure sparsity of a featured set, which is a generalization of the group sparsity idea [112]. Traffic data consist of several redundant features that need to be removed. It is also important to have a good assessment of features that are crucial to the performance of D^{2}ITS.

Another branch of sparse learning is compressive sensing (CS) [113]–[115]. CS assumes that most data are sparse, which can be sampled at a lower rate than the Shannon–Nyquist sampling rate.[1] If the coherence between the original measurement and the proposed measurement is low, then it is possible to consider a form of sparse learning with a high probability. In particular, the proposed measurements can be nonadaptive and thus be universal for all the data. A CS resource can be accessed at http://dsp.rice.edu/cs. Because D^{2}ITS heavily depends on vision and multiple sensors, it would be interesting to study how CS can be incorporated into D^{2}ITS. In addition, CS techniques can save costs incurred that result from installing expensive devices with a high sampling rate for ITS.

4) Heterogeneous Learning: Multiple sensors for improving the performance of ITS would generate data from different sources. As a result, data sets that are collected for transportation management, accident analysis, and traffic signal analysis demonstrate a strong heterogeneous property, with remarkably different features. Although heterogeneous data can uncover different facets of tasks, how we can compare and fuse the data is still a challenging task.

The problem can be considered with machine learning. There are two major areas in machine learning to deal with heterogeneous learning issues. One method is to search a common space for the heterogeneous data sets. For example, both canonical correlation [116] and Procrustes analyses [117] are devoted to aligning two heterogeneous data into a common space. These two methods assume that transformation between two heterogeneous data sets is linear. One natural generalization from linear to nonlinear transformation is to use a kernel trick that implicitly maps the data into some higher dimensional inner product space through the kernel canonical correlation analysis [116]. The other method is to utilize transfer learning [118], which aims at generalizing the regularity learned from one or more data sets into other heterogeneous data sets. A survey of transfer learning theories is given in [118].

B. Cost Issues

Although new technologies for ITS have rapidly been developed for the last two decades, cost is still a major concern for deployment at the system level. In the vision-driven ITS, for example, it is impractical and highly expensive to replace all low-resolution video devices with high-resolution video devices.

One way of addressing the cost issue is to enhance the capability of data analysis by designing an effective and reliable classifier for traffic object recognition [41] or to improve the quality of image or video sequences [39], [119]. Cao *et al.* developed a strong classifier to detect pedestrian with only a single optical camera [41]. Zhang *et al.* [39] utilized machine-learning techniques to learn the high-resolution gait images of the low-resolution counterparts from a collection of high/low-resolution training gait image pairs. As a result, it is possible to recognize pedestrians at a larger distance between pedestrians and a camcorder without the need of purchasing high-resolution camcorders.

The cost issue can also be resolved by identifying alternative devices and developing algorithms for improving their performance. For example, low-cost DGPS receivers with a positioning accuracy of approximate 2–3 m are regarded as a major tool for next-generation automated vehicle location systems [70]. However, it is still difficult to employ such receivers to position the vehicle location, because base stations, which are necessary for ensuring the performance of DGPS receivers, are quite expensive. Therefore, one alternative way is

[1] To avoid the loss of information, sampling frequency should be at least two times faster than the signal bandwidth [113].

to learn such accuracy from data collected from low-precision GPS receivers. Zhang *et al.* employed a refined principal-curve algorithm, which fits a curve to the data cloud, to learn the performance of a high-precision GPS device from a collection of low-precision data points [98]. Experiments indicate that the maximum difference between the ground-truth and the modified GPS data is reduced to 1.279 m, making it possible to position moving vehicles at the lane level.

Another way is to make use of the existing instruments or systems currently used for other applications [53], [63]. Claton *et al.* developed a low-cost lane departure warning system by combining the well-built high-accuracy map and automative-grade navigation system [53], obviating the need to purchase high-cost DGPS receivers. Sohn and Hwang claimed that, with the mobile cellular networks, vehicle passage times between two points can be estimated based on a probe cell phone. One advantage is that cellular networks have been installed worldwide, even in regions where it is hard to install transportation sensors. Thus, the proposed strategy can reduce the cost of D^2ITS to a certain extent [63].

C. Multimodal Evaluation Criteria

To assess the effectiveness of D^2ITS, we need to develop performance measures to evaluate each application. It may not be appropriate to evaluate the performance of some applications in ITS with a single criterion. For example, in planning our itinerary for a trip, we usually consider several factors, including the total travel time, the number of transfers, and the total walking and waiting times [120]. Furthermore, the status of transportation systems may change over time. It is thus necessary to construct multimodal evaluation criteria to optimize the itinerary and make a compromise between different requirements [120].

Several algorithms have been developed for the pedestrian detection problem, adopting different criteria in dealing with the problem. Hussein *et al.* evaluated algorithms with a set of detection error tradeoff (DET) curves [121]. They claimed that the detection performance is less influenced by the use of different types of sensors, e.g., NIR and visible bands, but is more tied to the window size that is chosen for modeling the classifiers.

To better understand the performance of a typical red light camera (RLC), Hobeika and Yaungyai [122] evaluated the Fairfax County RLC Program. They concluded that the RLC system has a positive effect on reducing the violation rate but does not necessarily reduce accident rates. The performance of the RLC system can be attributed to a large number of different factors, including the amber time, average daily traffic, speed limit, geometric configuration, and operation period [122]. Establishing multimodal evaluation criteria would help identify the root cause of the problem and design a system that explicitly addresses the key issues associated with the problem.

D. Other Issues

In the aforementioned sections, we consider the future directions for some of the core components of D^2ITS. In the following discussion, we consider some additional issues for future research that are important for the development of D^2ITS.

First, an ideal way for traffic object recognition is to install as many sensors as possible to capture the detail from all different angles. This approach, however, would generate much redundant data and is extremely costly. In addition, the level of detail is only relevant in the context of specific applications. D^2ITS should be scenario oriented. Broggi *et al.* [40] employed a laser scanner to narrow the search scope and proposed to detect and track appearing pedestrian for avoiding the potential accidents. One advantage of this approach is that we can save much cost for installing irrelative sensors and give more prompt reflection to the (potential) accidents, which is a key factor in ITS.

Second, the interaction between system suppliers (e.g., traffic engineers) and systems users (e.g., travelers) is less considered in traditional ITS. As the use of mobile phones with a variety of sensors has rapidly increased in recent years, several new ways of interactions have emerged, e.g., the people-participation or the microblog way [123], [124]. Assume that each individual phone is a “virtual lens.” A microblog can provide a high-resolution view of the world by integrating several short audios, embedded videos, or messages on the fly (i.e., multimedia microblogs) recorded by several active mobile phone users [123], [124]. People can share information about the event in which they participate or the environment they are in with a microblog. Naturally, sooner or later, such ways will influence several aspects of ITS, e.g., traveler routes, and the visualization of congestion. With the emergence of microblogs, it is not surprising that D^2ITS will become a people-centric ITS in the years to come.

Visual analytics is also an approach that can be incorporated into D^2ITS. Unlike the aforementioned visualization techniques, it emphasizes the maximal utilization of the capability of human judgment to process complex information received through visual channels, resulting in shortening the response time to the emergency events, making more effective decisions, and gaining better insight [125]. As shown in [125], the approach, which involves the fusion of data supported by a powerful visualization technique, can be utilized to integrate traffic information into traffic control for improving the real-time decision-making component in D^2ITS.

Furthermore, a virtual environment plays an important role in D^2ITS because of its low cost in providing a safe simulation for traffic simulators to simulate a variety of transportation events. For example, Zhang *et al.* [126] collected data from a driving simulator to simulate the driver’s behavior and the vehicle response. To deal with critical scenarios that may appear in the intersection of railroads and roadways, Huang *et al.* [127] utilized deterministic and stochastic Petri nets to simulate a parallel railroad-level crossing traffic control system. Recently, some researchers have attempted to utilize the practical ITS data to enhance the microsimulation of virtual environment, e.g., mass evacuation [128]. The recent development in parallel control and management for ITS [129], which explicitly incorporates engineering and social complexities into the modeling and decision making of a large-scale system, has also provided an ideal platform for deploying D^2ITS.

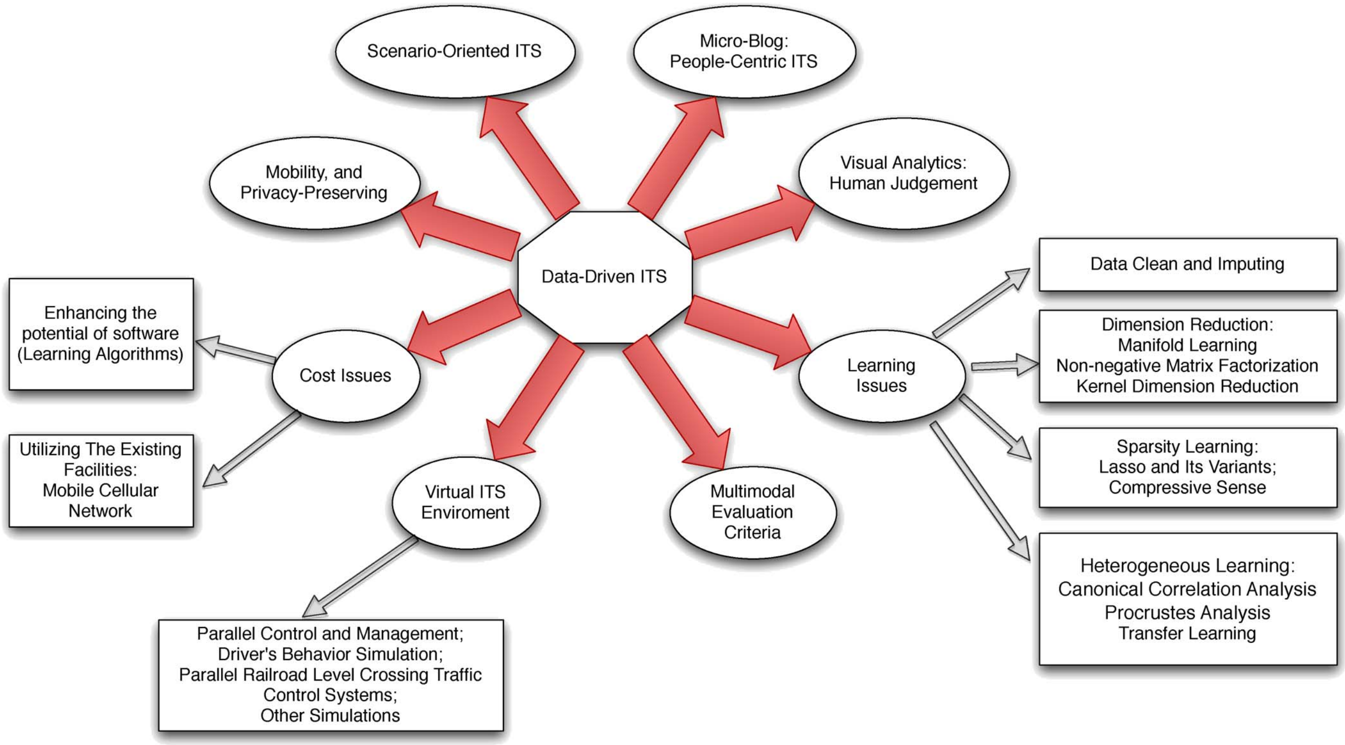

Fig. 5. Some potential directions in D^2ITS.

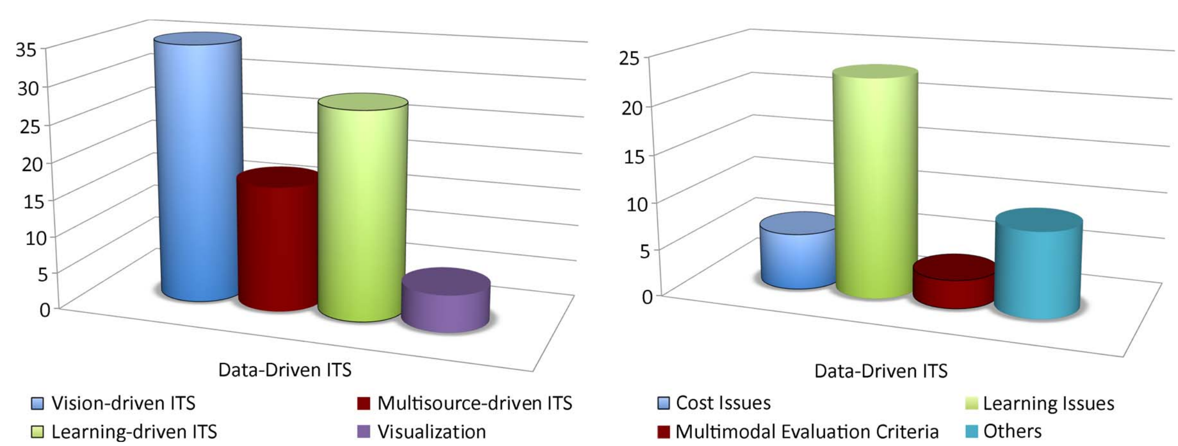

Fig. 6. Statistical analysis of the number of papers related to the D^2ITS. (Left) Number of papers related to several major directions in D^2ITS. (Right) Number of papers related to some potential directions in D^2ITS.

Finally, traffic objects represented in D^2ITS are dynamic in nature. It is possible to represent the degree of mobility with an unprecedented quantity of data at a very low cost. Therefore, a potential application of D^2ITS is how we can address mobility in an efficient way [130]. The advantages of studying mobility are described as follows. First, it generalizes the functions of D^2ITS. For example, we analyze the mobility of vehicles to design a better non first-in–first-out (FIFO) queue strategy (i.e., imposing different speeds on different lanes) on freeways. Experimentally, this strategy is proven to be more effective than the FIFO queue strategy in alleviating congestion [131]. Furthermore, the migrant behavior of travelers can help transportation system managers make better plans on the infrastructures and physical communication networks, e.g., roads and freeways. Second, the enforcement of mobility can reveal some traffic-related phenomena, e.g., traffic accidents. Third, it can provide novel services of great societal and economic impact to citizens after extracting the knowledge from mobility data. Note that most movement data are sensitive to the privacy issue. For example, information about vehicle trajectories obtained from a traveler's GPS device can reveal the traveler's travel habits, home, and workplace. Therefore, one potential direction in D^2ITS is to make tradeoffs between maximizing the use of individual vehicles data and minimizing the invasion of privacy [130]. The potential research directions in D^2ITS are summarized in Fig. 5.

E. Summary of the Papers Surveyed

Finally, we would like to provide a summary of the papers cited in this paper. We classify the papers according to the categories described in this paper and count the number of papers in each category. The results are shown in Fig. 6. The result shows the following three observations: 1) Vision- and learning-driven ITS have received much attention from researchers in the ITS community; 2) although the number of papers related to learning issues is 23, only four of these papers are closely related to the development of ITS, leaving more room for further research for directly addressing issues in D^2ITS; and 3) several directions, e.g., multimodal evaluation criteria, visual analytics, and microblogs, have yet to received enough attention from ITS researchers.

IV. Conclusion

In this paper, we have discussed the development of D^2ITS and introduced several important components of D^2ITS, including vision-, multisource-, and learning-driven ITS. A roadmap for future directions for the development and deployment of D^2ITS is described, emphasizing the privacy-preserving people-centric scenario-oriented aspects of the system components in D^2ITS. Several D^2ITS related issues have been identified for further research, including the learning issues for missing values, data cleansing, dimension reduction, sparse learning, and heterogeneous learning. We also identified some special issues that would affect the development of D^2ITS, including the cost issues and multimodal evaluation criteria. Overall, D^2ITS is a very promising field that can provide more functions and services to further improve our transportation systems.

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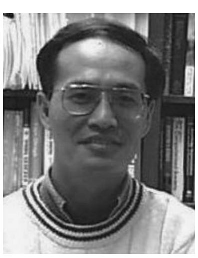

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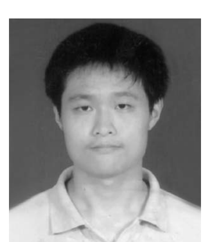

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