Transportation Research Procedia
Volume 15, 2016, Pages 495–512
ISEHP 2016. International Symposium on Enhancing Highway Performance

Data Fusion for ITS: Techniques and Research Needs

Nour-Eddin El Faouzi[1] and Lawrence A. Klein[2*]
[1]*Université de Lyon, F-69000, Lyon, France*
IFSTTAR, LICIT, F-69500, Bron
ENTPE, LICIT, F-69518, Vaulx en Velin
[2]*Klein & Associates, Santa Ana, California, U.S.A.*
nour-eddin.elfaouzi@ifsttar.fr, larry@laklein.com

Abstract
Intelligent transportation system (ITS) infrastructures contain sensors, data processing, and communication technologies that assist in improving passenger safety, reducing travel time and fuel consumption, and decreasing incident detection time. Multisource data from Bluetooth® and IP-based (cellular and Wi-Fi) communications, global positioning system (GPS) devices, cell phones, probe vehicles, license plate readers, infrastructure-based traffic-flow sensors, and in the future, connected vehicles enable multisource data fusion to be exploited to produce an enhanced interpretation of the monitored or observed situation. This occurs by decreasing the uncertainty present in individual source data. Although demonstrated for more than two decades, data fusion (DF) is still an emergent field as related to day-to-day traffic management operations. Data fusion techniques applied to date include Bayesian inference, Dempster-Shafer evidential reasoning, artificial neural networks, fuzzy logic, and Kalman filtering. This paper provides a survey of ITS DF applications, including ramp metering, pedestrian crossing, automatic incident detection, travel time prediction, adaptive signal control, and crash analysis and prevention, and indicates directions for future research. The encouraging results so far should not conceal the challenges that remain before widespread operational deployment of DF in transportation management occurs.

Keywords: Sensor and data fusion, data fusion, information fusion, data fusion in ITS

1 Introduction

Timely and accurate information enable transportation systems to monitor and manage operations that maximize the safety and efficiency of the highway system. As connected and autonomous vehicles proliferate, the need to provide traffic flow, collision avoidance, and dangerous-condition warning information becomes both a major challenge and a major opportunity for the public agencies and private companies that support Intelligent Transportation Systems (ITS). Simultaneously, the spread of

[*] Corresponding author

Selection and peer-review under responsibility of the Scientific Programme Committee of ISEHP 2016

doi:10.1016/j.trpro.2016.06.042

Bluetooth® and Internet Protocol (IP)-based (cellular and Wi-Fi) communications technologies has increased travelers' proclivity for accurate road traffic information. Traffic sensors that monitor traffic flow at a given point are often ineffective in supplying the data required by modern transportation management systems. Therefore, other data sources, such as surveillance cameras, global positioning system (GPS), cell phone tracking, probe vehicles, license plate readers, and soon connected vehicles, increasingly supplement the information provided by conventional measurement systems. In addition, traffic management agencies normally archive traffic flow data by time-of-day, day-of-week, month, season, and recurring special events. This offline information, together with sensor real-time data, often is useful in predicting traffic trends.

Multisource data may be complementary in nature and, if this is the case, multisource data fusion can be applied to produce a better interpretation of the observed situation by decreasing the uncertainty present in individual source data, thus allowing traffic management centers and traffic information providers to achieve their goals more effectively (El Faouzi 2011). The objectives of this paper are to introduce readers to the basic tenants of data fusion (DF), acquaint them with the most significant applications of DF to ITS, and to indicate directions for future research.

The paper contains eight sections. Section 2 defines sensor and data fusion and describes one of the models utilized in developing its applications. Section 3 explores sensor and data fusion architectures suitable for ITS applications. Opportunities and challenges of ITS data fusion appear in Section 4, whereas Section 5 presents examples of data fusion applications to traffic management. Suggestions for selecting a data fusion algorithm for an ITS application are described in Section 6. Section 7 explores the ongoing need for data fusion research and Section 8 contains conclusions and suggestions for future research topics.

2 Sensor and Data Fusion Definitions and Models

Data fusion is concerned with:

1. The representation of information within a computational database, particularly the information gained through data fusion.
2. The presentation of this information in a manner that supports the required decision processes when a human operator or decision maker is involved.

Data fusion should not be the goal or end result of a transportation management strategy. Rather the goal is to provide a control system, in the form of a machine or a human, the information necessary to support making automated or semi-automated decisions where vehicle systems or operators may have to take corrective actions to ensure safety.

Several definitions of sensor and data fusion are found in the literature. The Joint Directors of Laboratories (JDL) model, perhaps the most widely cited, defines data fusion as "a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats and their significance" (Kessler 1991; Waltz 1990, p. 1). The Institute of Electrical and Electronics Engineers (IEEE) Geoscience and Remote Sensing Society's definition is "the process of combining spatially and temporally-indexed data provided by different instruments and sources in order to improve the processing and interpretation of these data." The University of Skövde provides a definition in terms of information fusion as "the study of efficient methods for automatically or semi-automatically transforming information from different sensors and different points in time into a representation that provides effective support for human or automated decision making" (Boström, Andler, Brohede, Johansson, Karlsson, van Laere, Niklasson, Nilsson, Persson, Ziemke 2007, p. 5). These definitions provide different insights into the role of sensor and data fusion. Their existence is a reflection of the diverse applications for sensor and data fusion

The terms *data fusion* and *sensor fusion* are often applied interchangeably. Strictly speaking, data fusion is defined as in the preceding text. Sensor fusion, then, describes the use of more than one sensor in a configuration that enables the gathering of more accurate or additional data about events or objects in the observation space of the sensors. The need for more than one sensor to completely and continually monitor the observation space may exist for a number of reasons. For instance, some objects may be detected by one sensor but not another because each sensor may respond to a different signature-generation phenomenology. The signature of an object may be masked or otherwise hidden with respect to one sensor but not another; or one sensor may be blocked from viewing objects because of the geometric relation of the sensor to the objects in the observation space, but another sensor located elsewhere in space may have an unimpeded view of the object. In this case, the data or tracks from the sensor with the unimpeded view may be combined with past information (i.e., data or tracks) from the other sensor to update the state estimate of the object (Klein 2012).

Many of the data fusion models and processing techniques originally developed by the U.S. Department of Defense, namely the JDL model, to support the identification and tracking of military objects can be used today to aid traffic management on streets and highways (Kessler 1991; White Jr. 1990; Steinberg 1999; Leung 2000; Lefebvre 2007). The JDL data fusion model consists of five processing levels with a potential sixth one.

Level 0 concerns the preprocessing of data from the contributing sources. It may normalize, format, order, batch, and compress input data (Hall 1992; Steinberg 1999). It may even identify sub-objects or features in the data that are used later in Level 1 processing. For traffic management, Level 1 processing refines the position and identity estimates of the objects by combining or fusing data from all appropriate sources, including real-time point and wide-area traffic flow sensors, transit system operators, toll data, cellular telephone calls, emergency call box reports, probe vehicle and roving tow truck messages, commercial vehicle transmissions, roadway-based weather sensors, and connected vehicles as these data become available (Klein 2001; El Faouzi 2003). Level 2 processing identifies the probable situation causing the observed data and events by combining the results of the Level 1 processing with information from other sources and databases. These sources may include highway patrol reports and databases, roadway configuration drawings, local and national weather reports, anticipated traffic mix, time-of-day traffic patterns, construction schedules, and special event schedules. Level 3 processing assesses the traffic flow patterns and other data with respect to the likely impact of a traffic event on traffic flow (e.g., duration of traffic congestion, incident, construction or other preplanned special event, fire, or police action). Level 4 processing seeks to improve the entire data fusion process by continuously refining predictions and assessments, and evaluating the need for additional sources of information. Sometimes a sixth level is added to address issues concerned with enabling a human to interpret and apply the results of the fusion process. The DF methods investigated in traffic literature involve basic operations such as temporal and spatial alignment of input data, data association, and data mining for knowledge extraction. The latter is also one of the potential objectives of multisource information fusion (Dasarathy 2003).

3 Sensor and Data Fusion Architectures for ITS Applications

An architecture is a structure of components, their relationships, and the principles and guidelines governing their design and evolution over time (C4ISR 1996). An architecture

- Identifies a focused purpose.
- Facilitates user understanding and communication.
- Permits comparison and integration.
- Promotes expandability, modularity, and reusability.
- Achieves most useful results with least development costs.
- Applies to the required range of situations.

The selection of a data fusion architecture requires an overall system perspective that simultaneously considers the viewpoints of four major participants (Klein 2012):

1. System users, whose concerns include system requirements, user constraints, and operations.
2. Numerical or statistical specialists, whose knowledge includes numerical techniques, statistical methods, and algorithm design.
3. Operations analysts concerned with the man/machine interface (MMI), transaction analysis, and operational concepts.
4. Systems engineers concerned with performance, interoperability with other systems, and system integrity. Traffic management personnel at a traffic management center frequently assume this role in traffic management applications.

There are several ways to classify sensor fusion architectures. One taxonomy utilizes the terms sensor-level or decision-level, central-level or centralized, and hybrid. In sensor-level and decision-level fusion, each sensor detects, classifies, identifies, and provides state estimates of the objects of interest before data entry into the fusion processor, which then combines the individual sensor information to improve the classification, identification, or state estimate of the objects. In central-level fusion, minimally processed sensor data are sent to a fusion processor that analyzes the data for object features or attributes that aid in identifying and tracking the objects. In pixel-level fusion, minimally processed data from each sensor are combined at the pixel or resolution-cell level of the sensors using a central-level fusion architecture. Little, if any, preprocessing of data occurs before reaching the fusion processor. Hybrid fusion architectures use sensor-level fusion for data coming from some sensors and centralized fusion for others, depending on the nature of the sensor outputs or data fusion processing resources available. The reader is referred to Dasarathy (1997), Durrant-Whyte (2008), Klein (2012), and El Faouzi and Klein (2015) for a further discussion of potential architecture frameworks.

4 Opportunities and Challenges of ITS Data Fusion

Technological advances in road telematics (such as on-board electronic systems, vehicle localization mechanisms, telecommunications, and data processing) have expanded and improved the means of traffic data collection. Some of these developments are the availability of new sensor technologies and new architectures found in on-board vehicle equipment, enhanced roadside-mounted sensors that provide new data types or improved spatial resolution, and multiform data collection. Basic traffic flow data (volume, occupancy, and speed) needed by traffic operations personnel are typically obtained from sensors embedded in the pavement. The predominant sensor of this type is the inductive loop detector (ILD) that measures temporal traffic flow characteristics at a given location. Sensors mounted above the roadway, such as acoustic and ultrasonic sensors, magnetometers, and Doppler microwave sensors, are also utilized to gather roadway network data at specific locations. While these devices provide point data, they fail in measuring the spatial behavior of traffic flow (Klein 1996, 2001). In addition, their deployment and maintenance costs may become prohibitive when large-area coverage of a roadway network is required. Other above-the-roadway mounted sensors with limited spatial capabilities have been developed and deployed to supplement loop detector data. These include visible and infrared spectrum video detection systems and surveillance cameras and multilane presence-detecting microwave radar sensors. The implementation of ITS applications and concurrent need for real-time and accurate data in support of various traffic management functions including incident detection, active travel and demand management, route guidance, and safety warnings found in connected vehicle applications, has shown the importance of having a complementary source of data for traffic flow parameter estimation.

One of these complementary data sources is probe vehicle data, also known as floating car data (FCD) and in its extended version as xFCD. With this technique, cars on the road shift from a passive attitude to an active one and act as moving sensors, continuously feeding information about traffic conditions to a traffic management center (TMC). Cooperative systems, where vehicles connect via continuous wireless communication with the road infrastructure, are capable of exchanging data and information to increase overall road safety and enable cooperative traffic management (RITA 2014). Automatic vehicle identification (AVI) systems, based on different technologies, can be used as detection devices. These technologies include automatic vehicle tag identification, automatic license plate matching techniques, and GPS tracking and identification. With the advances in wireless communications and the spread of cellular phones, technical improvements in cellular positioning provide the opportunity to track and utilize cell phone-equipped drivers as traffic probes (Ygnace 2001; Youngbin 2000).

This spectrum of data and heterogeneous sources of information are of potential use for addressing many problems of traffic engineering as a typical data fusion problem. The purpose of DF is to produce an improved model or estimate of system parameters or events from a set of independent data sources. For traffic applications, the desired model is the state vector of the traffic phenomenon. These estimates may include current or future vehicular speeds, mean speeds, travel time, vehicle classification, and similar parameters of interest to travelers and traffic operators.

Several data fusion algorithms are already prevalent in ITS applications. These include Bayesian inference, Dempster–Shafer evidential theory and some of its modifications, artificial neural networks, fuzzy logic, knowledge-based expert systems, and vehicle and pedestrian tracking based on the Kalman filter or extended Kalman filter (EKF), Monte Carlo techniques, and particle filters. The Bayesian and Dempster–Shafer approaches belong to the class of feature-based parametric algorithms. They directly map parametric data (e.g., features) into a declaration of identity. Physical models are not used. Artificial neural networks belong to the class of feature-based information theoretic techniques, which transform or map parametric data into an identity declaration. No attempt is made to directly model the stochastic aspects of the observables. Fuzzy logic and knowledge-based expert systems are examples of cognitive-based approaches that attempt to emulate and automate the decision-making processes used by human analysts. The Kalman filter and its nonlinear motion counterparts are examples of physical models since the kinematics of the objects being tracked are modeled. Physical models replicate object discriminators, in this case position, velocity, and sometimes acceleration that are easily observable or calculable. Detailed descriptions of these algorithms have been curtailed since the purpose of this paper is to show how DF is currently being applied to ITS. Descriptions of the algorithms may be found in Klein (2012) and El Faouzi and Klein (2015).

5 Current Applications of Data Fusion to ITS

El Faouzi and Lesort (1995) and Sethi, Bhandari, Koppelman, and Schofer (1995) published the first papers describing a practical traffic and transportation issue addressed by a data fusion framework. For the last 15 years, researchers have made significant contributions to the ripe set of DF applications and challenges in transportation systems (FHWA 2003; El Faouzi-INRETS 2000(a); El Faouzi 2000(b)). These include conventional transportation modeling problems that incorporate multisource processing, namely planning, demand estimation, and traffic estimation (Sussman 2000; Gordon 2010). Traffic mobility and safety issues addressed by ITS are also suitable DF candidates. Advanced transportation management systems (ATMS), automatic incident detection (AID) that is normally a part of ATMS, advanced traveler information systems (ATIS), advanced driver assistance systems (ADAS), and commercial vehicle operations (CVO) can gather information from different data sources. DF techniques can then be used to combine the information to yield a better decision or understanding of the situation at hand.

5.1 Advanced Transportation Management Systems

Advanced transportation management systems provide a systems approach for roadway management that incorporates ITS technology in the planning, programming, and evaluation of transportation facilities to better enable them to respond to recurring and non-recurring transportation demand and congestion.

These facilities include freeways (ramp metering, information dissemination, managed lanes, and active traffic management), arterials (traffic signals, transit and emergency vehicle signal priority, and parking guidance), integrated corridors, road-weather systems, and transportation management centers (USDOT 2014).

The first DF application to be discussed is a fuzzy ramp-metering algorithm due to Taylor, Meldrum, and Jacobson (1998) that provides metering rate control based on local occupancy and speed data. The input variables to the fuzzy control system are mainline and ramp occupancy and mainline speed computed from the previous 20-second period data, and ramp occupancy from older data samples. The output variable is the metering rate. Seventeen production rules were heuristically developed based on experience in operating the ramp metering system. The fuzzy centroid is used to defuzzify the fuzzy values represented by the logical products and consequent membership functions. The fuzzy ramp-metering algorithm was evaluated with FRESIM (FREway SIMulation) over a section of freeway that did not have many alternative diversion routes. The evaluation was against the other ramp meter controllers built into the FRESIM model, namely clock metering, demand/capacity metering, and speed metering. The performance criteria were to maintain a reasonable ramp queue, maximize distance traveled, minimize travel time (or equivalently maximize average system speed), and minimize the average delay/distance traveled per vehicle for all vehicles in the system. The more demand exceeded capacity, the greater was the ability of the fuzzy controller to balance the conflicting demands of mainline efficiency and minimum ramp queues as compared to the other controllers. The balance provided by the fuzzy controller was attributed to the ramp occupancy inputs available to this controller but not to the others. Generally, fuzzy control produced a modest improvement over the other metering controllers and when no metering was used at all.

Niittymaki and Kikuchi (1998) designed a fuzzy system to control pedestrian crossing at a signalized intersection in much the same manner as an experienced crossing guard who regulates the timing of pedestrian crossings. The objectives were to minimize pedestrian waiting time by accommodating the pedestrian as soon as possible, minimize the delay to vehicular movement by not stopping the vehicle flow for an unreasonably long period, and maximize vehicle and pedestrian safety by preserving and passing groups of approaching vehicles. In addition to the AID applications discussed in the next section, transportation management centers also apply DF to traffic state prediction and active traffic management (e.g., dynamic speed limits, hard shoulder running, and queue-end automatic detection).

5.2 Automatic Incident Detection

Incident detection algorithms for automatic recognition of incidents, accidents and other road events requiring emergency responses have existed for more than three decades. Most of the algorithms rely on loop detector data. However, these algorithms exhibit mixed success. Interest in incident detection algorithms has renewed partly because of the availability of new sensors and data sources. One of these sources is probe vehicles. Hence, AID belongs to the class of problems that can be solved by DF techniques.

Several data fusion techniques support incident detection and traffic management including Dempster–Shafer inference, Bayesian inference, and artificial neural networks. Most of these applications combine probe vehicle data with conventional traffic data. Such work includes that by Koppelman, Sethi, and Ivan (1994), Ivan, Schofer, Koppelman, and Massone (1995), and Ivan (1997), who developed an AID system using surveillance data from two different sources: fixed detectors (e.g., inductive loop detectors) and probe vehicles specially equipped to report link travel time. Different neural network representations were studied in Ivan where the results showed that probe and detector-based incident detection on arterial networks offered considerable promise for improved performance and reliability (Ivan 1997). Dempster–Shafer inference or evidential reasoning was also utilized to implement an operational AID system (Byun 1999).

Thomas (1996) investigated AID from a multiple attributes decision-making viewpoint with Bayesian scores. The author utilized combinations of probe travel times, number of probe reports, and ILD-reported occupancies and volumes as the inputs. The results demonstrated that models based solely on probe data lack in performance due to excessive overlaps in class distributions. On the other hand, models based on detector occupancies and vehicle counts by lane perform outstandingly. Using probe data also enhanced the performance of detector data-based models.

Klein (2000, 2002) studied the application of Dempster–Shafer inference to traffic management in support of incident detection and the identification of other events of concern to traffic managers. The application of the Dempster–Shafer inference algorithm to incident detection and verification is illustrated with an example consisting of three possible events, where data are supplied from three different types of sources. The available information is combined using Dempster's rule and the most probable event is identified.

Incident detection algorithm fusion is another area where classification accuracy requires improvement. Cohen's (2003) investigations applied three aggregation schemes: a logical aggregation, a neural network fusion, and a veto procedure. The validation step, which was based on real-world data, demonstrated that both logical aggregation and veto procedure outperform the single best algorithm.

5.3 Network-wide Control

Data fusion techniques were also applied to construct an adaptive online traffic control method for urban and freeway road networks. Mueck's (2002) model determines the queue length from vehicle counts produced by traffic flow sensors located close to the stop line and from signal timing information. Wang and Papageorgiou (2005) explored traffic state estimation on freeways using the extended Kalman filter. Friedrich and Minciardi (2003) introduced a new approach based on queuing theory models for real time queue length determination. In this latter method, Mueck's model serves as a quasi-measurement that utilizes Kalman filtering.

5.4 Advanced Traveler Information Systems

In Advanced Traveler Information Systems, a variety of automatic data collection techniques are employed to assist in understanding traffic conditions and derive relevant indicators to support traveler guidance (FHWA 2003). Traveler information is often presented as travel time. In this context, travel time is used as a measure of impedance (or cost) for route choice strategies. However, traffic sensors normally used to measure the prevailing traffic conditions on an urban road are almost ineffective. The proliferation of new data and information source devices (e.g., surveillance cameras, GPS, cell phone tracking, license plate readers, and connected vehicles) provides alternate sources to supplement information provided by conventional sensor measurements. These new sources also have the potential to improve the accuracy of travel-time estimates. As a result, travel-time estimation becomes a candidate DF problem.

Tarko (1993), Thakuriah (1993), and Berka (1995) discussed the requirements for data fusion in the ADVANCE program. ADVANCE was an in-vehicle application of ATIS that provided route guidance in real time in the northwestern portion of Chicago and its northwest suburbs. It used probe vehicles to generate dynamic travel-time information on expressways, arterials, and local streets. A general framework combined data from loop detectors and travel-time reports from probe vehicles using inference rules. Evaluations of the proposed algorithms found that probe data greatly improve static (archival average) link travel-time estimates by time of day. Dailey, Harn, and Linet (1996) describe the details of a data amalgamation (fusion) approach used with ITS projects and present a quantitative data fusion algorithm that estimates speed from volume and occupancy measurements.

El Faouzi and Lesort (1995) and El Faouzi (1997) proposed an estimation framework for real-time traffic condition characterization based on multisource data. As an illustrative example, multisource travel-time estimation was implemented using two data sources: data from conventional loop detectors that deliver Eulerian data and probe vehicles that collect Lagrangian data. Travel-time measurements collected by license plate matching were considered as a reference and were used for validation purposes only. The data from the loop detectors was of a statistical nature and can be viewed as a distributed estimation problem: each source derives an estimator of travel time and the individual estimates are then combined according to a weighted mean strategy. The weights were derived from variance–covariance estimation errors. Results show the need to improve the estimation accuracy of the proposed schemes. In another approach, evidence theory was used to solve the same problem (El Faouzi 2009; El Faouzi-Recherche 2000). Here travel time was separated into classes to formulate the estimation problem as a classification one. Various strategies for classifier fusion were proposed and their evaluation displayed some improvement in classification rate.

Abe (1997) advanced travel-time forecasting by using data from automatic vehicle identification devices to improve accuracy. Dynamic route guidance systems (DRGS) are also an area where DF has potential. Kühne (1997) proposed a framework for fusing information from various sources within DRGS. Once again, the objective is travel-time estimation and prediction. The data sources consist of loop detectors, probe vehicles, and a QoS indicator with some exogenous information: information on road works and incidents. The proposed solution is based on a weighted mean scheme. The weights are derived according to the source reliability. Choi (1997) and Choi and Chung (2001) addressed the problem of generating travel time from loop detectors, probe vehicles, and video-camera sources.

5.5 Advanced Driver Assistance

Passenger safety is a primary function of ITS. The increased availability of ADAS and collision avoidance systems (CAS) is indicative of the growth in active safety devices that complement the traditional passive ones such as seat belts and air bags. These systems provide a more reliable description of traffic and other hazards surrounding the vehicle in pre-crash situations. Their input data frequently come from a variety of sensors including radar and lidar. Fusion is used to combine these data to alert the driver to potentially dangerous situations. Simultaneous localization and mapping is a complementary technique that provides a static map of the environment and the vehicle position on the map (Durrant-Whyte 2006).

Connected vehicles and automated highways are the other research topics where DF is important. Connected and Automated versus Autonomous vehicles are gaining importance due to their near-future deployment and their development for personnel highway driving. In these applications, the vehicle needs to sense its environment with an array of sensors and the sensory information needs to provide effective decision support. Challenges involved are the heterogeneous nature of the data and extracting relevant features in real time from the measurements that can be used in DF algorithms.

Fusion of data from complementary and independent sources incorporates the data into a single description. The problem to solve here is data association and data assimilation, a process that matches sensor data with an environment description that requires synchronization of the sensor data and the associated object state (e.g., position and velocity). Whenever there are multiple sensors that detect multiple objects, there is a need to associate the measurements with the individual objects (Hall 1992). Once the sensor measurements are associated with appropriate objects, the next step is to remove sensor bias through a sensor registration process. Finally, the state of the object is estimated using fused sensor measurements. The Kalman filter, its variants, and particle filtering become an essential tool to perform this step (Bar-Shalom 2001). For example, Murphy (1998) discussed the role of sensor fusion in vehicle guidance and navigation, and proposed general methods for fusing data, and sensor-fusion activities within a robot architecture. Stiller, Hipp, Rossig, and Ewald (1998) reported a DF framework for obstacle detection and tracking.

5.6 Traffic Demand Estimation

One of the most important problems in the field of transportation planning and control is the problem of origin-destination (OD) estimation from link counts. To decrease the cost of passenger surveys, traffic counts are undertaken on specific links of the transportation network. An estimation of a most likely OD matrix is then derived from the counts. Some of the proposed schemes derive the OD matrices by combining data from different sources. An illustration of this class of problems is the dynamic OD estimation initiated by Cremer and Keller (1981) and Cremer (1983). Further development along the same lines was pursued by Okutani (1987) and Ashok (1993). Kalman filtering is commonly applied in this class of problems. Ben Akiva and Morikawa (1987) explored OD estimation methods that combine different data sources (stated preference data and traffic measurements) and Lundgren, Peterson, and Tengroth (2003) described a method for adjusting time-dependent travel demand information by incorporating link flow observations. They utilized the structure of the given OD matrix, which is developed from different sources, to make simple overall adjustments.

5.7 Traffic Forecasting and Traffic Monitoring

Traffic flow forecasting is of increasing importance to traffic surveillance and management. Many traffic flow prediction schemes were based on classic autoregressive models, especially time series techniques. Harrison and Stevens (1971) approached this problem in the context of a Bayesian framework. Others used Kalman filtering techniques (Okutani 1984), neural networks and system identification (Vythoulkas 1993), and a nonparametric paradigm that incorporated kernel techniques (El Faouzi 1996). None of these methods allows one to achieve highly accurate predictions except in some special situations (for some network configurations and/or with high sensor coverage). This is caused to some extent by traffic dynamics that cannot be formalized by a single procedure. Therefore, in the context of traffic operations where highly accurate forecasts are needed, one can obtain different forecasts of the same quantity from different methods (the important assumption here is that different predictors are measures of the same quantity or various aspects of the same item). Often the approach used is to find the single “best” predictor in some sense (most accurate values, most appropriate models of the underlying process, most cost-effective, etc.) among the available forecasting methods. Another approach consists of combining these individual forecasts. Bates (1969) and Granger (1989) demonstrated that the linear combination of several predictors from a single data set can outperform the individual predictors.

El Faouzi (1999) provided a methodological framework to combine various forecasts of the same quantity. He derived two predictors based on nonparametric traffic flow using a kernel estimator and predicting scheme founded on a propagation of a lagged upstream traffic flow. Data integration and data fusion were applied in other traffic flow forecasting research. Cremer and Schrieber (1996) studied the integration of in-vehicle information and loop detector data using the extended Kalman filter. Sau, et al. (2007) and Canaud et al. (2013) investigated traffic monitoring and prediction with multisource data by applying a particle filter as the estimation technique. Choi (1989) examined the problem of missing data estimation and proposed a framework for missing data inference based on evidential reasoning.

5.8 Accurate Position Estimation

Modern transportation systems require accurate information concerning the position and orientation of the vehicle. Inertial navigation systems (INS) that determine the location of a vehicle rely on dead-reckoning. The problem with these systems is that of integration drift caused by the accumulation of small errors in the measurement of acceleration and angular velocity into progressively larger errors in the position estimate. In the last few decades, GPS, initially developed as a military navigation aid, has gained a wide acceptance in civilian navigation systems (Grewal 2004). When the satellite signals are blocked by tall buildings or degraded by electromagnetic interference, GPS outage occurs. In such situations, due to the lack of reference signals, the estimation of position is impossible and the device ceases to work. DF offers an approach to combat the drawbacks of both techniques. The benefits of using GPS with an INS are that the INS may be calibrated by the GPS signals and that the INS can provide position and angle updates at a quicker rate than GPS. For highly dynamic vehicles such as missiles and aircraft, INS fills in the gaps between GPS positions. In addition, GPS may lose its signal while the INS continues to compute the position and angle during the period of lost GPS signal. Thus, the two systems are complementary and are often employed together.

The Kalman filter was among the earliest approaches in GPS–INS integration. For instance, Wei (1990) utilized a decentralized filtering strategy by applying a Kalman smoother to integrate the GPS differential range and phase measurements with the INS data. Variants of the Kalman filter are often employed to improve integration. A constrained unscented Kalman filter algorithm was proposed by Li (2003) to fuse differential GPS, INS (gyro and accelerometer), and digital maps to localize vehicles for ITS applications. For the Kalman filter to operate, accurate stochastic models of the sensors are required. Such requirements are often difficult to achieve and result in the application of artificial intelligence techniques for GPS–INS integration. Different types of artificial neural networks are used to combine the GPS and INS information. For example, multilayer perception and radial basis function neural networks are successfully applied for GPS–INS integration (El-Sheimy 2006; Sharaf 2005).

Table 1 presents a summary of the data fusion algorithms and architectures used to date to support ITS applications or strategies.

Application	***Data Fusion Algorithm***	***Architecture***
Ramp metering	Fuzzy logic	Sensor level
Pedestrian crossing time	Fuzzy logic	Central-level
Automatic incident detection	Artificial neural network	Sensor level
Automatic incident detection	Bayesian inference	Sensor level
Automatic incident detection	Dempster-Shafer	Sensor level or decision level
Travel time estimation	Inference rules	Sensor level
Travel time estimation	Dempster-Shafer	Sensor level
Travel time estimation	Weighted mean of several travel-time estimators. Weights are a function of the variance or covariance of the estimators.	Sensor level
Travel time estimation	Weighted mean where the weights are a function of the data source reliability.	Sensor level
Travel time estimation	Fuzzy logic	Sensor level
Vehicle and object tracking	Kalman filter	Central level
Lane departure warning	Image processing using edge detection and extraction of other features.	Pixel level
Traffic state estimation	Extended Kalman filter	Central level
Crash analysis and prevention	*k*-means algorithm	Sensor level or decision level
Traffic forecasting and monitoring	Bayesian inference	Sensor level
Traffic forecasting and monitoring	Artificial neural network	Sensor level
Traffic forecasting and monitoring	Kalman filter	Central level
Traffic forecasting and monitoring	Extended Kalman filter	Central level
Traffic forecasting and monitoring	Kernel estimator	Central level
Traffic forecasting and monitoring	Particle filter	Central level
Vehicle position estimation	Unscented Kalman filter	Central level
Vehicle position estimation	Artificial neural network	Central level

Table 1: Data fusion algorithms and architectures currently applied to ITS

6 Data Fusion Algorithm Selection

How does one know which data fusion algorithm or technique to use in a given application? A starting point is to evaluate the choice of algorithm and its performance based on the degree to which the technique makes correct inferences and the availability of required computer resources and algorithm input parameters (Klein 2012). The selection process also seeks to identify algorithms that meet the following goals:

1. Maximum effectiveness: Algorithms are sought that make inferences with maximum specificity in the presence of uncertain or missing data. Required a priori data such as probability density distributions (required for Bayesian inference DF) and probability masses (required for Dempster–Shafer DF) are often unavailable for a particular scenario and must be estimated within time and budget constraints.
2. Operational constraints: The selection process should consider the constraints and perspectives of both automatic data processing and the analyst's desire for tools and useful products that are executable within the time constraints posed by the application. If more than one decision maker examines the output products, then multiple sets of user expectations must be addressed.
3. Resource efficiency: Algorithm operation should minimize the use of computer resources (when they are scarce or in demand by other processes), for example, CPU time and required input and output devices.
4. Operational flexibility: Evaluation of algorithms should include the potential for different operational needs or system applications, particularly for data driven algorithms versus alternative logic approaches. The ability to accommodate different sensors or sensor types may also be a requirement in some systems.
5. Functional growth: Data flow, interfaces, and algorithms must accommodate increased functionality as the system evolves.

Many of the Level 1 object refinement data fusion algorithms are mature in the context of mathematical development. They encompass a broad range from numerical techniques to heuristic approaches such as knowledge-based expert systems. Practical real-world implementations of specific procedures (e.g., Kalman filters and Bayesian inference) exist. Algorithm selection criteria and the requisite a priori data are still major challenges however. Applying classical inference, Bayesian inference, Dempster–Shafer evidential theory, artificial neural networks, fuzzy logic, and Kalman filtering data fusion algorithms to vehicle and event detection, classification, identification, and state estimation requires expert knowledge, probabilities, or other information from the analyst or data fusion specialist in the form of a priori probabilities and likelihood functions (Bayesian inference), probability mass (Dempster-Shafer), neural-network type, numbers of hidden layers and weights, and training data sets (artificial neural networks), fuzzy set identification, membership functions, production rules, and defuzzification method (fuzzy logic) or object kinematic and measurement models, process noise, and model transition probabilities when multiple state models are utilized (Kalman filtering). Thus, the choice of which data fusion algorithm to use frequently depends on the availability or ease of computing the input data in the form required by the algorithm. Klein (2012) provides more detailed examples of the prerequisite information typically required to utilize Bayesian inference, Dempster–Shafer evidential theory, artificial neural network, fuzzy logic, and Kalman filtering algorithms.

7 Ongoing Need for Data Fusion Research

There are ongoing needs for data fusion research in many areas, including:

- Reliability and credibility of fusion system input data. Approaches should calculate the degree of confidence in the data in terms of reliability and credibility (Cholvy 2004 and Nimier 2009). The most notable work in this area combines a measurement of the reliability of the source of information with a measurement of its credibility, where both measures are evaluated using existing knowledge (NATO 1992). A proposed evaluation formalism relies on three notions: the number of independent sources supporting the information, their reliability, and knowledge that the information may conflict with some available or prior information. Degree of conflict, in contrast to merely conflicting or nonconflicting information has also been incorporated as an assessment factor (Cholvy 2007). Nonetheless, the current formalism is still not complete as some notions, such as total ignorance about the reliability of the information source, are not considered. Another important aspect of input information quality is the rate at which information enters the fusion system. The effect of the information rate is particularly important in decentralized fusion settings where imperfect communication is common.

- Assessing the fusion system using measures of performance. Performance evaluation has different and possibly conflicting dimensions that may be difficult to capture in one comprehensive and unified measure. One can argue that performance assessment should be multifaceted accounting for not only the measurement of the extent of achieving the fusion goals, but also the amount of effort and resources spent to accomplish this task. Therefore, a comprehensive measurement of performance (MOP) might become too abstract and properly fail to reveal all system performance dimensions. The alternative is to deploy a set of MOPs suited to the application (Khaleghi et al., 2013).
  - Adaptive nature of MOPs. A fair indicator of fusion performance may require MOPs that are adapted over time or according to the given context and situation. Thus, the more difficult the evaluation scenario, the more challenging it becomes for the fusion system to maintain the desired performance level.
  - Dependency of MOPs on the data fusion scenario. A multitarget system consisting of a finite set of vectors is fundamentally different from a single target system consisting of a single vector. This is due to the appearance and disappearance of targets (e.g., vehicles and pedestrians) over time, which causes the number of states to vary with time. Likewise, multiple sensor systems have more parameters to evaluate than single sensor systems. Metrics can be computed for individual targets or over an ensemble of targets. Individual target metrics include track accuracy, track covariance consistency, track jitter, track estimate bias, and track continuity. Ensemble target metrics include average number of missed targets, average number of extra targets average track initiation time, completeness history, and cross-platform commonality history (Khaleghi et al., 2013).
  - Ground truth. Adequate ground truth is still another factor that enters into the assessment of fusion system performance. Yet it is not usually known and many of the currently used MOPs require knowledge of the ground truth. This is the most common and serious issue that still needs attention. A potential solution is to develop objective performance measures, that is, those that are independent of ground truth or human subjective evaluation.
- Commercial operating system and database management. Commercial operating systems (OS) and database management systems (DBMS) may be ill suited to ITS real-time requirements for sensor data processing and control of critical safety-related functions. A restriction of commercial database management systems is that they are designed for flexibility of application rather than real-time or fast-time processing (McDaniel and Schaefer 2003). Accordingly, database management for data fusion is still difficult to implement for the following reasons:
  - Existence of large and varied databases with numerous records and record formats.
  - Lack of support for rapid updates for incoming sensor data and fusion results.
  - Lack of support for rapid data retrieval for human analysts and automated fusion processes such as data association.
  - Need to provide flexible and user-friendly interfaces.
  - Need for maintenance of data integrity in real-time under rapid receipt of sensor data, intense human interactions, and asynchronous, out-of-sequence, and false sensor reports.

  - Need to accept both fixed format and free-text message formats under multiple protocols.
- Design for worst-case scenarios. An example is to design for automated driving applications where delays at critical times are unacceptable. Rapid prototyping is the best solution for estimating data-processing requirements. Guidelines for rapid prototyping include using the target machine if possible, using prototype software in the required language, and driving the analysis with the worst-case load (Klein 2012).

8 Conclusions and Recommendations

The application of data fusion to various transportation management functions has been ongoing for at least two decades and has given rise to a still maturing resource. This paper described the state-of-the-art and practice of sensor and data fusion to traffic data. For the applications reported, DF techniques appear promising. However, these encouraging results should not conceal the challenges that still remain before any operational widespread deployment of DF in the transportation field occurs. These include obtaining data with the necessary accuracy to make the application effective, dynamic and real-time issues associated with data quality as traffic flow changes, the need to process the data in real time, and the development of methods to combine sensor or hard data with human-generated or soft data (El Faouzi 2011; Khaleghi et al. 2013). The benefits of DF will become more apparent as the number of successful and practical DF applications increases in the transportation field. Real opportunities do exist for additional DF applications in road transportation systems. Prospects include the increased collection of useable data from sources other than roadside sensors installed for traffic management and surveillance. Wireless technologies, which offer (1) the potential of easier reporting and access to customized information (e.g., cooperative systems such as vehicle-to-vehicle, vehicle-to-infrastructure, and infrastructure-to-vehicle communications) and (2) the ability of tracking individual vehicles and obtaining information collected by FCD and xFCD, will enrich the data sources that characterize the traffic situation, and will certainly accelerate the need for operational data fusion systems.

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