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Role of Data Fusion in Intelligent Transportation System: A Survey

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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. With the advent of modern communication and computational devices and inexpensive sensors, it is possible to collect and process data from a number of sources. Data fusion (DF) is collection of techniques by which information from multiple sources are combined in order to reach a better inference. DF is an inevitable tool for ITS. 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 includes Bayesian inference, artificial neural networks, fuzzy logic, and Kalman filtering. This paper provides a survey of how DF is used in different areas of ITS and indicates directions for future research.

Keywords:- Sensor and data fusion, information fusion, ITS, collision avoidance systems (CAS), Incident Detection, commercial vehicle operations (CVO).

I. INTRODUCTION

Providing accurate traffic information is becoming a major challenge for the public institutions and private companies leading to the rapid growth of intelligent transportation system (ITS) [2]. At the same time, the emergence of new information technologies and the transformation that has occurred in road traffic management has both increased a need for very accurate road traffic information. The spread of Bluetooth and Internet Protocol (IP)-based (cellular and Wi-Fi) communications technologies has increased travelers' proclivity for accurate road traffic information. In order to provide an accurate and more comprehensive traffic state on a road network, other sources of data (such as cameras, GPS, cell phone tracking, and probe vehicles) are increasingly used to supplement the information provided by the conventional measurement systems. 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 effective. 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.

II. DATA FUSION BACKGROUND

Several methodologies have been proposed in the literature for the purpose of multi-sensor fusion and aggregation under heterogeneous data configurations. Due to the different types of sensors that are used and the heterogeneous nature of information that needs to be combined, different data fusion techniques are being developed to suit the applications and data. These techniques were drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and other areas. Traffic engineering field has naturally benefited from this abundant literature. 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. Many of the data fusion models and processing techniques originally developed by the U.S.Department of Defence, 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. The JDL data fusion model consists of five processing levels with a potential sixth one.

Level 0 concerns the pre-processing of data from the contributing sources. It may normalize, format, order, batch, and compress input data.

Level 1 processing concerns the gathering of 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, commercial vehicle transmissions, and roadway-based weather sensors .

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 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 occurrence of a traffic event (e.g., traffic congestion incident, construction or other pre-planned special event, fire, or police action) that impacts traffic flow**.**

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

III. CURRENT APPLICATIONS OF DATA FUSION TO ITS

Practical traffic and transportation issue addressed by a data fusion framework deal with conventional transportation modeling problems that incorporate multisource processing, namely planning, demand estimation, and traffic estimation (Advanced transportation management systems (ATMS), automatic incident detection (AID) that is normally a part of ATMS, advanced traveller 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.

A. 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. 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. 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.

B. 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. 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.

C. 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 (2008) 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.

D. 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. 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. 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 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 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.

E. 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 approached this problem in the context of a Bayesian framework. Others used Kalman filtering techniques neural networks and system identification and a nonparametric paradigm that incorporated kernel techniques (El Faouzi 1996).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. 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.

F. 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.

IV. 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.

V. 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 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.

VI. ONGOING NEEDS FOR DATA FUSION RESEARCH

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

1. Reliability and credibility of fusion system input data: Approaches should calculate the degree of confidence in the data in terms of reliability and credibility

2. 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.

3. 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.

VII. 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 .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.

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