Multisensor Architecture for an Intersection Management System

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Chapter 1

Introduction

Chapter 2

Multisensor Data Fusion and Intersection Management Systems

An intersection is a highly-dynamic scenario that can be monitored using a wide range of sensors. For this reason, an efficient and accurate fusion of the information is needed. This chapter is divided into two sections. In the first section a brief overview of multisensor data fusion is presented, remarking in different architectures proposed in the literature and different approaches used for laser and video data fusion are described. The second section contains a short review on intelligent transportation systems and intersection management systems, including current research on this topic. Finally, some projects that include fusion of laser and video data for intersection managing applications are presented.

2.1 Multisensor Data Fusion

Data fusion, also referred as mutisensor data fusion, information fusion or sensor fusion, has received several definitions from different authors in the literature. For example, Joint Directors of Laboratories defined data fusion as "multi-level, multifaceted process handling the automatic detection, association, correlation, estimation, and combination of data and information from several sources"[37]. Luo refers to multisensor fusion and integration as "synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information"[25] and "to achieve inferences that are not feasible from each individual sensor operating separately"[27]. Elmenreich states that sensor fusion is "the combining of sensory data or data derived from sensory data such that the resulting information is in some sense better than would be possible when these sources were used individually"[14]. In [6] there is a compilation of more definitions of information fusion and the author summarize in his own statement as follows: "Information fusion is the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making".

All of previous definitions can be seen as a way to answer these three questions about data fusion:

- What is involved in data fusion?
  Combine, merge or integrate homogeneous or heterogeneous data.
- What is the aim of data fusion?
  Get a better representation of a process or the environment, infer underlying information, improve quality of the data.
- How to apply data fusion?
  Data fusion is a multi-level task, depending of the nature of the sensors, the final application and the environment.

It is clear, now, that multisensor data fusion is a multidisciplinary field, because information in a typical process, flows from sensors to applications, passing through stages of filtering, data enhancement and data extraction. It is for this that knowledge in a wide range of fields are required, e.g. signal processing, machine learning, probability and statistics, etc. Also, it would be pointless to try to define a general method, technique or architecture that fits the requirements of any system, for applying data fusion in it.

2.1.1 Data Fusion Architectures and Models

Although there is not a general rule of how to design or implement a sensor fusion system, many authors have proposed some models, architectures and guidelines for this task. Three well-known models are Waterfall model, JDL fusion model and Multisensor integration fusion model.

Waterfall model

Harris and Markin in [21] and CITE, proposed a model named Waterfall, in which they describe the fusion process as an information flow through sensing to decision-making. They describe 3 levels of processing with 2 inner stages each ((2.1). The first level is about transform the raw data from sensor to a better representation of the measured phenomena through signal processing and having in mind sensor models and nature of the process itself. The second level objective is to find a meaningful description of the data, reducing its volume while maximising information. This is done using feature extraction and pattern recognition techniques. The third level is the high level of the process in which situation assessment and decision making are performed, based on data available, configuration parameters, database information or human interaction. Finally, a feedback from high-level to low-level (sensor) is done, advising the whole system for re-calibration or reconfiguration.

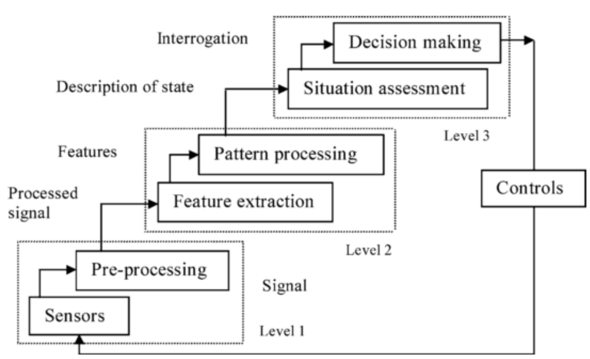

Figure 2.1: Waterfall model. (from [16]).

JDL fusion model

One of the first proposals of fusion architecture, and probably one of the most widely used, is the JDL fusion model, originated from the US Joint Directors of Laboratories and described by Hall and Llinas in [20] and [24]. The JDL fusion model was conceived to aid the developments of military applications and comprises 5 levels of data processing at which data fusion could be done. These levels and a database are connected by a bus (2.2), and are not meant to be execute sequentially and can also be executed concurrently.

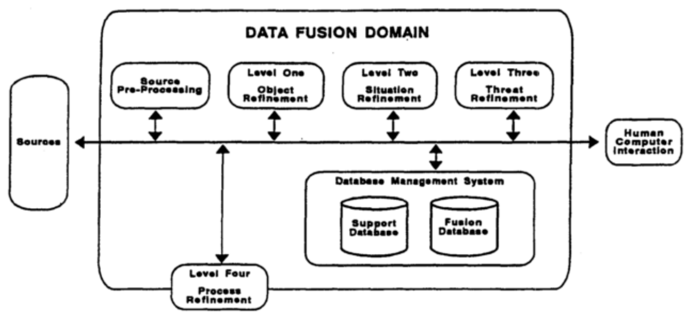

Figure 2.2: JDL fusion model. (from [20]).

The first stage, referred as level-0 is the source preprocessing in which raw data is handled to concentrate the more pertinent data for the current situation. The level-1 is for object refinement, starting with the alignment of the data in a commonly space-time reference frame. Then, performs identification and tracking of objects using different techniques. Situation refinement is at level-2, which takes observed and partially-observed object from level-1 and tries to find a contextual description between them. Level-3, threat refinement, is the level in which results from level-2 are interpreted looking for possible advantages and disadvantages for the system to operate, based on previous knowledge and predictions about executing an action.

Multisensor Fusion Integration model

Luo and Kai, in [28, 26], proposed a full integration model for data fusion in which they define a three-level hierarchy for sensor fusion: data-fusion, feature-fusion and decision-fusion. This model separate MFI in five classes, based on Input/Output pair: Data in-data out fusion, data in-feature out fusion, feature in-feature out fusion, feature in-decision out fusion, and decision in-decision out fusion [27] (figure 2.3).

Also, they made a clear distinction between multisensor fusion and multisensor integration, being the former the process in which information provided by a set of sensors is combined in any of the three levels aforementioned, and the latter is how sensor fusion could be integrated in a full system in order to assist

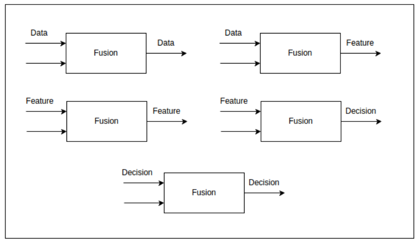

Figure 2.3: Five classes of Multisensor Fusion.

in a particular task. As is depicted in figure 2.4, sensor fusion is an element of the whole MFI architecture, which also includes block for sensor managing tasks, like control, selection and registration of sensors, previously to the fusion process. A sensor processing stage and a system controlling module are also included after the sensor fusion stage.

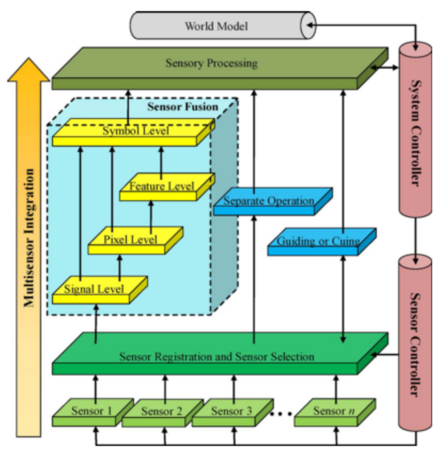

Figure 2.4: Multisensor Fusion Integration architecture (from [27]).

2.1.2 Classification of Data Fusion Architectures

Elmenreich in [14] classify fusion models in three categories: Abstract models, generic architectures and rigid architectures. Abstract model are not intended to show how to implement a sensor fusion system, but to explain which processes are done in it. Generic architectures gives an outline on how a system could be implemented in an application, but do not specify what type of hardware, database or communication system could be used. Finally, rigid architectures, are a good guide for implementation of data fusion in certain applications, at the cost that several design decisions have been already taken, making expensive

Category	**Data Fusion Model**
Abstract Model	Waterfall Model [21] Boyd Loop [7]
Generic Architecture	JDL Model [37] Multisensor Fusion Integration Model [28] Omnibus model [5]
Rigid Architecture	LAAS Architecture [1] DFuse Architecture [23] Time-triggered Model [15]

Table 2.1: Classification of data fusion models

Low level fusion		Medium level fusion	High level fusion
Estimation methods		Classification methods	Inference methods
Recursive: $leftmargin = .07in]itemizeClustering$ KL Transform Markov Chains Kalman Filtering AdaBoost	Covariance based:	Parametric templates	Bayesian inference

Table 2.2: Classification of fusion algorithms

the migration to another architecture.

In addition to models previously mentioned, there exists more proposal for data fusion architectures in literature, as can be viewed in table 2.1.

2.1.3 Algorithms in Data Fusion

Different types of algorithms have been used in implementing data fusion systems, depending on a variety of conditions like, level of fusion, type of the data, nature of environment, etc. Constrains like processing and memory limitations, centralised or distributed schemes, human-interactive or completely autonomous process, also determine which algorithms should be used in fusion process.

Luo in [27] propose a classification for fusion algorithms based on the level of fusion. Low-level fusion refers to the merge of raw data or signals, mid-level fusion refers to the fusion of features and High-level fusion refers to the process of fuse decisions.

Khaleghi in [22] describes a classification for fusion algorithms based on challenging problems that arise from the data to be fused, due to the variety of sensors and the nature of the application environment. This classification is not on the algorithms directly, but on the theory or framework in which they originate. Four types of data are enumerated: Imperfect data, correlated data, inconsistent data and disparate data. For thi

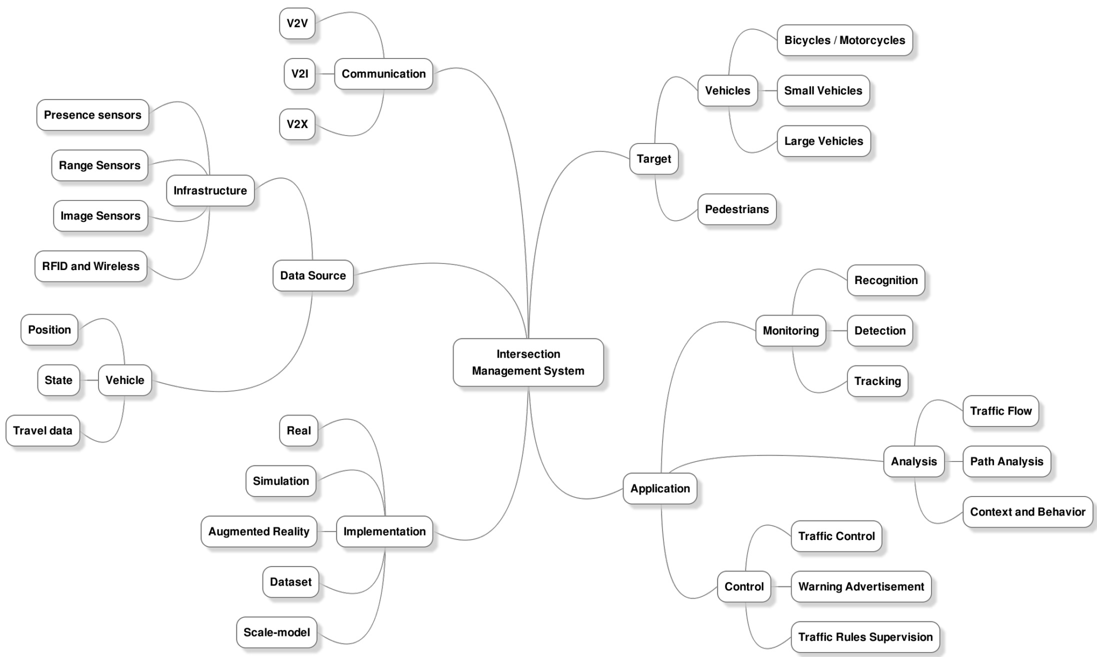

Figure 2.5: Fusion algorithms based on level of fusion. (from [27])

2.2 Intersection Management Systems

Intelligent Transportation Systems includes a wide range of applications and services transversal to many knowledge areas. For classifying those services, some taxonomies have been proposed like the ones presented in [36, Ch.1] and [38]. From described categories and classes, Advanced Traffic Management Systems have to be considered when an intelligent handling of traffic needs to be deployed.

One of the most desirable scenarios to improve efficiency and safety is an intersection. This because intersections are places where vehicles arrive from different directions at different velocities, increasing the chances for incidents and crashes. Choi [10] states that 40% of reported traffic accidents in the US, were intersection related. Also, in [12], is reported that for Colombia in 2011, most of the accidents in the main cities were at intersections.

Different types of applications and systems are conceived to address these issues. Some tasks those systems realize are intersection monitoring, vehicles detection, incident warning, collision avoidance, among others. Communication approaches in these systems are based in the interaction between vehicles and infrastructure, commonly divided in three groups: Vehicle-to-vehicle communication (V2V) , Vehicle-to-infrastructure communication (V2I) and the combination of both of them (V2X).

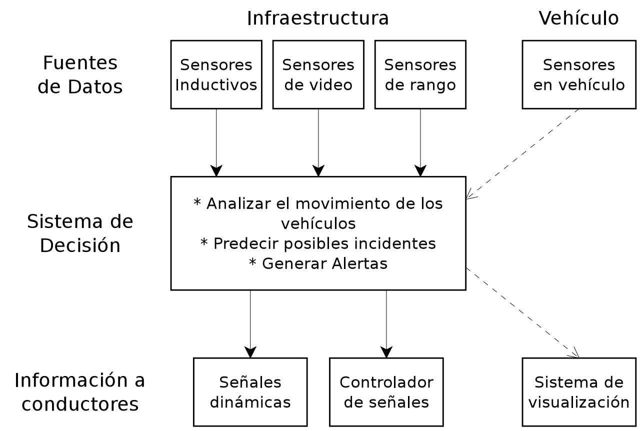

Figure 2.6: Generic block diagram of an Intersection Management System (from [9]).

Figure 2.6, presents a generic block diagram of an Intersection Management System composed by three main components: (a) Data source, that could be infrastructure sensors, like inductive loops, range sensors or cameras, and also could be vehicle sensors. (b) Decision system, which is the core of the whole system, is in charge of analyse and process information provided by infrastructure, vehicles and environment in order to predict future incidents, control traffic and generate safe decisions and warnings alerts. Finally, (c) is the presentation and displaying of the output of decision system. It could be at the infrastructure using dynamic signals, semaphore controlling, or vehicle-directed through on-board visualization/notification system.

2.2.1 Applications in IMS

Intersection monitoring is a required task to be done within intelligent transportation systems for high-level applications as traffic analysis, counting and classification of vehicles or pedestrians, events and incident detection, accidents prevention and security and surveillance applications.

To complete these tasks, many approaches have been proposed for information capture stage, both taking data from vehicle or from the infrastructure. For example, monitoring mobile wireless network like Bluetooth [17], detecting vehicle presence using inductive loops or RFID tags, identifying vehicles and pedestrian using cameras [8, 35], single or multiple laser-scanners [29, 30, 42, 40, 41], and multi-sensor integrated systems [31, 33, 32, 18, 39].

Other application are traffic-control oriented, rather than to sensing and data-processing stage. The aim of these applications are to maximise vehicle flow, reduce accidents and improve safety. Many works have been done and although their objective is the same, are diverse between them regarding its communication approach (V2V, V2I or V2X), sensors and information that are used, the execution scenario (simulation, real implementation or augmented reality) and the nature of vehicle driving (Human driver or autonomous vehicles).

In [3] and [2], intervehicular-communication based architectures are proposed. In these, each vehicle send to the others its own information about position, velocity, destination and more, and then they coordinate how the access to the intersection should be done. In [19], is presented a system capable of work in V2I mode, additional to V2V, using inductive loops and RFID information for detecting vehicles. The information is gathered by an intersection controller which manage the access to the crossroad. Another V2I based systems is presented in [4], where wireless magnetic nodes are used to detect presence and to send data to a base station, which determines possible collisions and warns driver through a visualisation system in infrastructure. Furthermore, in [13] and [11], are presented simulation-based systems for traffic controlling, using agents and applied to autonomous vehicles. In [34], an augmented reality implementation of the system proposed in [13] is done. In this work, approaching vehicles request to an intersection manager for authorisation to cross and is the manager which decides if it is safe to cross or not, depending on the defined traffic policies.

2.3 Conclusions

Multisensor data fusion can be defined as the process of combine, merge or integrate data from homogeneous or heterogeneous set of sensors in order to get a better representation of a process, the environment or a situation, through the inference of underlying information and the improve of quality of data. Depending of the nature of the sensors and the source of information, fusion can be done in several manners, i.e., sensor-level fusion, feature-level fusion or decision-level fusion.

Several models, architectures and frameworks have been proposed in literature; some of them to show how a data fusion system should work and some other providing guidelines on how to implement it in a given application.

Chapter 3

Architecture Description and System Specification

Appendices

Appendix A

Vehicular Environment Simulators

Bibliography

[1] R. Alami, R. Chatila, S. Fleury, M. Ghallab, and F. Ingrand. An Architecture for Autonomy, 1998.

[2] R. Azimi, G. Bhatia, R. Rajkumar, and P. Mudalige. Intersection Management using Vehicular Networks. pages 1–13, Apr. 2012.

[3] R. Ball and N. Dulay. Enhancing Traffic Intersection Control with Intelligent Objects. *Urban IOT 2010 Urban Internet of Things Towards Programmable Realtime Cities*, 2010.

[4] F. Basma, Y. Tachwali, and H. H. Refai. Intersection collision avoidance system using infrastructure communication. *2011 14th International IEEE Conference on Intelligent Transportation Systems ITSC*, pages 422–427, 2011.

[5] M. Bedworth and J. O'Brien. The Omnibus model: A new model of data fusion? *IEEE Aerospace and Electronic Systems Magazine*, 15:30–36, 2000.

[6] H. Boström, S. Andler, and M. Brohede. On the definition of information fusion as a field of research. Technical report, University of Skövde, 2007.

[7] J. R. Boyd. A discourse on winning and losing. 1987.

[8] N. Buch, S. a. Velastin, and J. Orwell. A Review of Computer Vision Techniques for the Analysis of Urban Traffic. *IEEE Transactions on Intelligent Transportation Systems*, 12(3):920–939, Sept. 2011.

[9] C.-Y. Chan and B. Bougler. Evaluation of cooperative roadside and vehicle-based data collection for assessing intersection conflicts. In *IEEE Proceedings. Intelligent Vehicles Symposium, 2005.*, pages 165–170. IEEE, 2005.

[10] E.-H. Choi. Crash Factors in Intersection-Related Crashes: An On-Scene Perspective. Technical Report September, U.S. Departament of Transportation, Springfield, VA, 2010.

[11] L. Conde Bento, R. Parafita, and U. Nunes. Intelligent traffic management at intersections supported by V2V and V2I communications. In *2012 15th International IEEE Conference on Intelligent Transportation Systems*, pages 1495–1502, Anchorage, Alaska, USA, 2012.

[12] Corporación Fondo de Prevención Vial. Anuario Estadístico de Accidentalidad Vial. Technical report, Bogotá, Colombia, 2010.

[13] K. Dresner and P. Stone. A Multiagent Approach to Autonomous Intersection Management. *Journal of Artificial Intelligence Research*, 31:591–656, 2008.

[14] W. Elmenreich. A Review on System Architectures for Sensor Fusion Applications. In *Software Technologies for Embedded and Ubiquitous Systems Lecture Notes in Computer Science Volume 4761, 2007,*, pages 547–559, 2007.

[15] W. Elmenreich and S. Pitzek. Using sensor fusion in a time-triggered network. *IECON'01. 27th Annual Conference of the IEEE Industrial Electronics Society (Cat. No.37243)*, 1, 2001.

[16] J. Esteban, A. Starr, R. Willetts, P. Hannah, P. Bryanston-Cross, and N. Comput. A Review of data fusion models and architectures: towards engineering guidelines. *Neural Computing and Applications*, 14(4):273–281, June 2005.

[17] M. Friesen, R. Jacob, P. Grestoni, T. Mailey, and R. McLeod. VEHICULAR TRAFFIC MONITORING USING BLUETOOTH. In *2013 26th IEEE Canadian Conference Of Electrical And Computer Engineering (CCECE)*, 2013.

[18] M. Goldhammer, E. Strigel, D. Meissner, U. Brunsmann, K. Doll, and K. Dietmayer. Cooperative multi sensor network for traffic safety applications at intersections. In *2012 15th International IEEE Conference on Intelligent Transportation Systems*, pages 1178–1183. IEEE, Sept. 2012.

[19] J. A. Guerrero-Ibañez, C. Flores-Cortés, J. M. Ramírez-Alcaraz, P. Santana, T. Mendoza-Robles, H. A. Vizcaíno-Anaya, E. Peña Cárdenas, and A. Anguiano-Mancilla. Sistema Inteligente basado en comunicación V2X para prevención de colisiones en intersecciones viales. In *Décima Segunda Conferencia Iberoamericana en Sistemas, Cibernética e Informática. CISCI 2013*, Orlando, FL, 2013.

[20] D. L. Hall and J. Llinas. An Introduction to Multisensor Data Fusion. *Proceedings of the IEEE*, 85(1):6–23, 1997.

[21] C. J. Harris, A. Bailey, and T. J. Dodd. Multi-sensor data fusion in defence and aerospace. *Aeronautical Journal*, 102:229–244, 1998.

[22] B. Khaleghi, A. Khamis, F. O. Karray, and S. N. Razavi. Multisensor data fusion: A review of the state-of-the-art. *Information Fusion*, 14(1):28–44, Jan. 2013.

[23] R. Kumar, M. Wolenetz, B. Agarwalla, J. Shin, P. Hutto, A. Paul, and U. Ramachandran. DFuse: a framework for distributed data fusion. *Conference On Embedded Networked Sensor Systems*, 2003.

[24] J. Llinas and D. L. Hall. An introduction to multi-sensor data fusion. *ISCAS '98. Proceedings of the 1998 IEEE International Symposium on Circuits and Systems (Cat. No.98CH36187)*, 6:537–540, 1998.

[25] R. Luo. Multisensor fusion and integration: approaches, applications, and future research directions. *IEEE Sensors Journal*, 2(2):107–119, Apr. 2002.

[26] R. Luo and M. Kay. A tutorial on multisensor integration and fusion. In *[Proceedings] IECON '90: 16th Annual Conference of IEEE Industrial Electronics Society*, pages 707–722. IEEE, 1990.

[27] R. C. Luo, C. C. Chang, and C. C. Lai. Multisensor Fusion and Integration: Theories, Applications, and its Perspectives. *IEEE Sensors Journal*, 11(12):3122–3138, Dec. 2011.

[28] R. C. Luo and M. G. Kay. Multisensor integration and fusion in intelligent systems. *IEEE Transactions on Systems, Man and Cybernetics*, 19:901–931, 1989.

[29] D. Meissner and K. Dietmayer. Simulation and calibration of infrastructure based laser scanner networks at intersections. *2010 IEEE Intelligent Vehicles Symposium*, pages 670–675, June 2010.

[30] D. Meissner, S. Reuter, and K. Dietmayer. Real-time detection and tracking of pedestrians at intersections using a network of laserscanners. *2012 IEEE Intelligent Vehicles Symposium*, pages 630–635, June 2012.

[31] D. Meissner, S. Reuter, and K. Dietmayer. Combining the 2D and 3D world: a new approach for point cloud based object detection. In *IET Intelligent Signal Processing Conference 2013 (ISP 2013)*, pages 4.1–4.1. Institution of Engineering and Technology, 2013.

[32] D. Meissner, S. Reuter, E. Strigel, and K. Dietmayer. Intersection-Based Road User Tracking Using a Classifying Multiple-Model PHD Filter. *IEEE Intelligent Transportation Systems Magazine*, 6(April 2014):21–33, Jan. 2014.

[33] D. Meissner, S. Reuter, B. Wilking, and K. Dietmayer. Road user tracking using a Dempster-Shafer based classifying multiple-model PHD filter. In *Information Fusion (FUSION), 2013 16th International Conference on*, volume 32, pages 1236–1242, Nov. 2013.

[34] M. Quinlan, T.-C. A. T.-C. Au, J. Zhu, N. Stiurca, and P. Stone. Bringing simulation to life: A mixed reality autonomous intersection. *Intelligent Robots and Systems IROS 2010 IEEERSJ International Conference on*, (October):6083–6088, 2010.

[35] E. Strigel, D. Meissner, and K. Dietmayer. Vehicle detection and tracking at intersections by fusing multiple camera views. In *2013 IEEE Intelligent Vehicles Symposium (IV)*, pages 882–887. IEEE, June 2013.

[36] J. M. Sussman. *Perspectives on Intelligent Transportation Systems (ITS)*. Springer US, Boston, MA, 2005.

[37] F. E. White. Data Fusion Lexicon. In *The Data Fusion Subpanel of the Joint Directors of Laboratories, Technical Panel for C3*, volume 15, page 15, 1991.

[38] B. Williams. *Intelligent Transport Systems Standards*. Artech House, INC., 2008.

[39] H. Zhao, J. Cui, and H. Zha. Sensing an Intersection Using a Network of Laser Scanners and Video Cameras. *IEEE Intelligent Transportation Systems Magazine*, pages 31–37, 2009.

[40] H. Zhao, J. Cui, H. Zha, K. Katabira, X. Shao, and R. Shibasaki. Monitoring an intersection using a network of laser scanners. In *Proceedings of the11th International IEEE Conference on Intelligent Transportation Systems*, pages 428–433, Beijing, China, 2008. Ieee.

[41] H. Zhao, J. Sha, Y. Zhao, J. Xi, J. Cui, H. Zha, and R. Shibasaki. Detection and Tracking of Moving Objects at Intersections Using a Network of Laser Scanners. *IEEE Transactions on Intelligent Transportation Systems*, 13(2):1–16, 2012.

[42] H. Zhao and R. Shibasaki. Joint tracking and classification of moving objects at intersection using a single-row laser range scanner. In *Proceedings of the IEEE Intelligent Transportation Systems Conference*, pages 287–294, Toronto, Canada, 2006.