A Sensor Fault Controller Scheme to Achieve High Measurement Fidelity for Intelligent Vehicles, with Applications to Headway Maintenance

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ABSTRACT

Intelligent Vehicle (IV) systems is a key research area, rooted in the development of safer and more efficient means of public transportation. Extensive knowledge about the environment, typically obtained from externally mounted sensors, is often necessary for IV systems to operate. A common problem is the reliability and accuracy of the data received from such sensors, given the harsh conditions they must operate in. This report focuses on the development of a SFCS to achieve high measurement fidelity for IV systems.

Methods for data validation, multi-sensor fusion, and fault detection, isolation, and tolerance are contained within the SFCS framework. These processes are grouped into modules that comprise the four tiers of the SFCS framework. The framework itself is modular, easily placed into any given system requiring high measurement fidelity.

The SFCS framework is applied to the problem of headway maintenance in Advanced Cruise Control systems, using data obtained from the automated vehicles at The Ohio State University. These vehicles were displayed during the National Automated Highway Systems Consortium's (NAHSC) *Technical Feasibility Demonstration* (Demo97). For headway maintenance, there are two forward measuring devices, a laser-radar and a microwave-radar. These two sensors offer redundancy in relative distance and velocity measures for targets in the forward path of motion.

In the application of the SFCS framework to ACC, an analytical method for data validation and fault detection is used. This process focuses on the biases of the residuals produced by a Kalman filter and the development of fault signatures. Prior to entering the validation process, the sensor data is first filtered to eliminate undesirous measurements. A rule-base approach is used for the initial sensor data filtering, which uses knowledge of the current vehicle operating state. The optimal fused measurements are found using Bayesian estimation. All validated sensor data to be fused must be in consensus prior to the fusion process. Experimental results are presented, demonstrating the manipulation of actual sensory data through the developed SFCS framework.

INTRODUCTION

Intelligent Vehicle and Highway Systems (IVHS) research has been spurred by the mass congestion of the Nation's highway systems and concerns over passenger safety (1). A core technology in IVHS is the development of intelligent vehicles, as witnessed at the NAHSC Demo97 during the summer of 1997. Through the advancements in computer, sensor, communication, and control technologies over the last two decades, major strides have been made in intelligent vehicle technology.

The interaction between intelligent vehicles and their environment is becoming increasingly more sophisticated, including autonomous lane changes, obstacle avoidance, and car following. With the emergence of intelligent vehicle technologies into public transportation, more emphasis is being placed on the quantity and quality of environmental information available. Today, the amount of reliable, real-time data able to be extracted from the surroundings is becoming the limiting factor, not the control systems. Another obstacle to the actual implementation of intelligent vehicle systems onto public roadways is the public acceptance of such technologies as being safe and reliable. In a recent published report, a majority of drivers found current freeway conditions stressful, congested, and only moderately safe. However, they remain fairly uncomfortable with active automated systems in automobiles such as automatic steering and adaptive cruise control (2).

Despite the current concerns and skepticism over the deployment of intelligent vehicle systems, the possibility of increased automobile density on the highways, increased safety, and reduction in pollution all help support the further development of Intelligent Vehicle (IV) systems. A leading area for development is in sensor fusion, data validation and in fault detection and isolation. These areas of research will help provide the safety and robustness required of IV systems to gain public acceptance and real-world implementation.

The reliability of the information acquired from the many environmental sensors is essential in creating a robust control system. Accommodating noise in measurements is a common problem in dealing with sensors, especially in noisy environments. An automobile where there exists very harsh operating conditions, such as extremes in temperatures, moisture, and vibrations is one such environment. Aside from the noise introduced from the environment of the sensor and its operating conditions, there is also the possibility of processing noise and sensor failure. IV systems needs to accommodate all of these possibilities for signal corruption. This introduces the need for techniques to validate the information from the sensors, fuse data from like sensors and trace failures to the problematic sensor(s) in real-time operations, not hindering the progress of the high-level control processes. This paper proposes a framework for addressing these issues, the SFCS. This framework is applied to the problem of headway maintenance in Advanced Cruise Control (ACC), with an example using the automated vehicles developed at The Ohio State University.

DEVELOPING THE SFCS FRAMEWORK

Reliable and accurate data from external measurement sources is essential for automated travel. Along with the overriding issue of safety in an IV, cost also plays an important role in the actual implementation of IV technology, as does the response rate of the given systems (associated to the safety issue). To achieve a higher level of measurement fidelity, in light of the above stipulations, a real-time fault monitoring and adapting procedure is necessary. The SFCS is developed to accommodate this need.

The proposed SFCS framework is comprised of four tiers, each containing individual modules that pertain to separate tasks. The complete SFCS framework is itself modular, providing a closed-loop control path around the sensors and providing a concise, common data type to all high-level control and computation routines. Each module of the SFCS framework is associated with a given task. The processes selected to perform these assignments are specific to the implementation of the framework.

Review of Common Methodologies

An attempt is made to provide an accurate representation of the most commonly used methods for data fusion and validation, and fault detection and isolation. Several other less common methods exist than those presented here. This review focuses on methods found most suitable for IV applications given the developed SFCS framework.

Methods for Data Fusion

Data fusion is the process of combining like information from many sources into one representative form. The fusion process is comprised of two main problems, the theoretical design and the implementation of this design without reducing the performance below the optimum level (3). The fused data can be obtained temporally from a single device queried over a set time span or from several sensors, models, or databases with like measurement information. Using fusion techniques with redundant sensors, the effects of measurement noise are diminished.

There exists several common data fusion techniques, including weighted averaging, the use of Kalman filters, Bayesian estimation methods, and the Shafer-Dempster evidential reasoning scheme. Other common fusion methods include multi-Bayesian statistical decision theory, fuzzy logic, production rules, and neural networks. While all these fusion techniques are applicable to IV systems, the first set contains those that would best fit into the SFCS framework.

Methods for Data Validation and Fault Detection

A key component of the SFCS framework is the data validation module. The process of data validation is concerned with the certification of data. In order to validate data, there needs to be some sort of reference or model for comparison. This method of comparison is the main determining factor in the selection of a validation scheme.

Fault detection is commonly associated with the process of data validation, hence the two tasks are presented together here, and are closely linked in the SFCS framework. A fault can be formally classified as an uncommon event, often related to a physical failure or undesirous change in the data source. The main difference between the validation process and that of fault detection is that data validation is a more general search, mainly for outlying data points. Fault detection techniques classify outlying data points based upon system knowledge. The classification of invalid data according to known faults also allows for the isolation of the fault source, which is a key stipulation for fault tolerance.

Similar to data fusion, there are numerous methods for the comparison of data in the validation process. The most common of these techniques include comparisons based upon spatial redundancies in measurement value, temporal redundancies through repetitive measurements of a data element, and analytical redundancies obtained from functional relationships among the measurement devices.

Methods for Fault Tolerance

The majority of techniques for the fusion of data, the validation of data, and for fault detection account for faulty measurement devices and data. However, they do not present ways to ramify the problems once detected. Fault tolerance, as the name suggests, presents methods for tolerating a fault, and providing correction procedures to hinder the development of similar faults. The ability to tolerate faults is often addressed in the development of the system control algorithms. Likewise, in dealing with faults in sensor measurements, the ability to control the sensor operations is often necessary. Rule bases are often invoked for the sensor control decisions.

Proposed SFCS Framework

Figure 1 contains a block diagram of the SFCS framework. Process flow in this hierarchical structure proceeds from the sensors upwards to the high-level control and computation routines. This structure is not constrained to operating in an intelligent vehicle, but is designed flexible enough for implementation in any control system requiring high data fidelity from external sensing devices. The SFCS is an application-oriented design, relevant to any control environment where there exist multiple environmental sensors with redundant or related measurements. The specific algorithms and processes developed in this paper for use in the SFCS framework are focused on IV systems, namely headway maintenance for ACC.

The SFCS framework can handle multiple tasks related to a common set of sensors. However, given that multiple SFCS frameworks can coexist using a common set of sensors, it is preferable to apply multiple frameworks rather than a single multi-tasking instance of the framework. This dispersion of tasks reduces the complexity of the inter-module process channels, which, under a multi-task load, can cause a noticeable increase in the computational time of the framework. Computational speed is a key stipulation in IVHS design.

The four separate tiers to the developed Sensor Fault Controller Scheme framework, shown in Figure 2, are: *Physical Sensor*, *Data Pre-Processing*, *Data Processing*, and *Control and Computation*. The individual modules that comprise each tier are described below, including the associated processes selected for implementation in IVHS.

SFCS Physical Sensor Tier

The actual physical sensors reside at this level. This tier constitutes the 'real-world' in the SFCS framework. No decisions are performed here, however, the optional sensor control algorithms for the Fault Tolerance (FT) module reside at this level. The minimal computations at this level are those required to initialize and invoke the sensor devices.

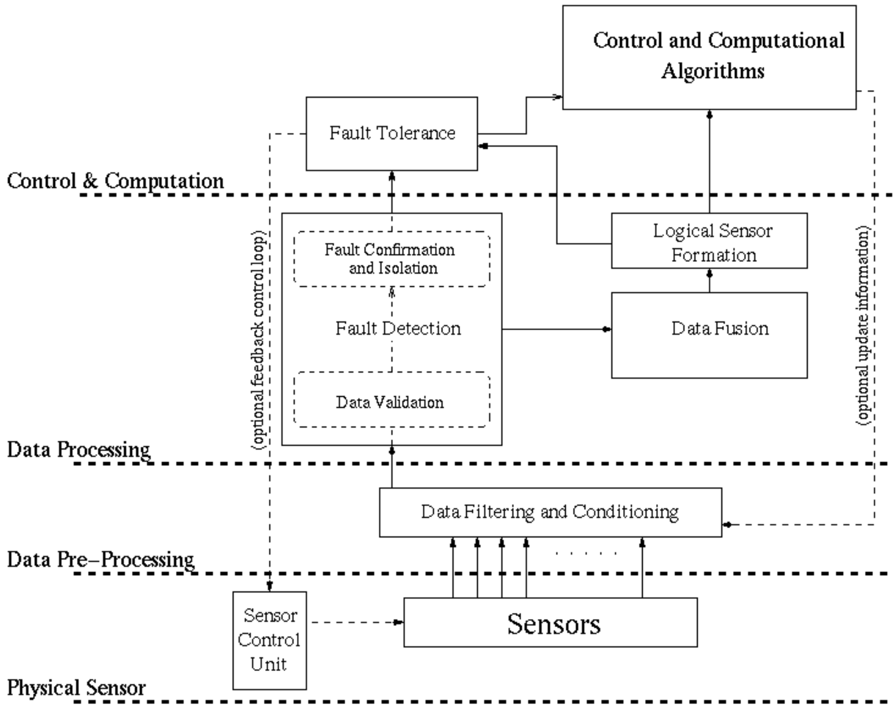

Figure 1: Structural diagram of the developed SFCS for IV systems

<u>SFCS Data Pre-Processing Tier</u>

The barrier between the real-world and the SFCS framework lies between the *Physical Sensor* and *Data Pre-Processing* tiers. The raw data transmitted by the sensors is received by the Data Filtering and Conditioning (DFC) module. All initial filtering and conditioning of the incoming sensor data is performed here.

Each incoming data element from the sensors is analyzed and subsequently filtered using a rule-based routine. For IV applications, this routine utilizes information about the current state of the vehicle to make informed decisions on what data is desirous, and all outlying information is subsequently removed from further consideration. The rule-base used can be constant or dynamic, depending on the application. The vehicle states change over time, thus for IV applications the rule-base is dynamic, receiving updated information from the high-level control and computation algorithms.

After the data has been screened, it is then conditioned for further transmission. The data is packaged in a common packet format that is used for all inter-module communications. This packet format, shown in Figure 2, contains a central backbone in which the sensors in the framework attach, using nodes. Information concerning the status and available data from each sensor is accessible from these nodes. The final fused measurements and their associated statuses are also accessible in the packet structure. Maintaining a common data structure for inter-tier and inter-module communications enhances the robustness of the SFCS, avoiding errors arising from framework communications.

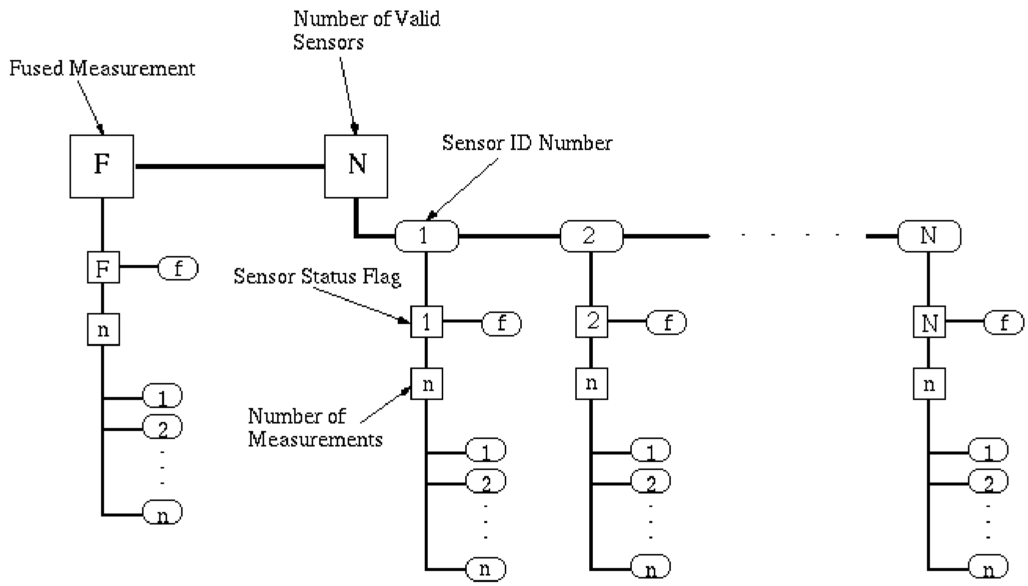

Figure 2: The format for inter-module data transmission in the SFCS framework

Note that the transmission rate from the *Data Pre-Processing* tier to the *Data Processing* tier is dependent upon the sensing device with the slowest update rate. To decrease the duration between updates, an observer can be placed in the *Data Pre-Processing* tier to provide estimated sensor measurement values for the sensor(s) with the slowest update rate. Another manner in which to accommodate this problem is to operate the framework at the slowest sensor update rate, and place an observer at the output of the Logical Sensor Formation (LSF) module to estimate the fused measurements.

SFCS Data Processing Tier

Most of the SFCS processes reside within the *Data Processing* tier. The Fault Detection (FD) module is comprised of two sub-modules, the Data Validation (DV) and the Fault Confirmation and Isolation (FCI) sub-modules. Here, incoming data from the *Data Pre-Processing* tier is processed sequentially: the data is first validated, then any questionable data elements are passed through the fault confirmation and isolation phase. The division of the FD module into smaller components allows for the transmission of validated data information to the data fusion module in a more timely manner. A graphical representation of the inter-connections in the *Data Processing* tier is shown in Figure 3.

The actual process that the FD module performs is application dependent, where the differences lie in the comparison technique imposed on the data. The process selected for comparing the incoming data for ACC is an analytical comparison technique using residual biases from a Kalman filter.

Prescribed sensor models are used by the Kalman filter in the validation process of the filtered measurement data, as shown in Figure 3. Data validation is computed using the residuals and error covariance matrices from the Kalman filters, in a likelihood function. A Mahalanobis distance measure is found from the likelihood function, and is defined as

$$d(k+1)^2 = E(k+1)^T S(k+1)^{-1} E(k+1), \tag{1}$$

where *E(k+1)* is the residual from the Kalman filter and *S(k+1)* is the error covariance matrix of the given sensor. The Mahalanobis distance measure has a chi-squared distribution, which allows for the development of a gate, or valid region, where the measurements should fall from the Kalman estimated values. The validation gate, *G*, represents a predetermined confidence level necessary for the measurement data to be valid, and is implemented as a threshold where if

$$G \geq d(k+1)^2 \tag{2}$$

the new measurement lies within the gate and is valid.

The outcome of the validation process is transmitted to the DF module and the FCI module simultaneously. Any suspect data elements from the DV sub-module are scanned in the FCI sub-module to determine the type and severity of the fault encountered. The fault detection process is concerned with monitoring the residuals of the Kalman filter, looking at their biases. Temporal results are used, based on the time stamp of the given data, to monitor the biases for latent faults. The biases are then compared to known fault signatures for classification. Associated with each invalid measurement is then a fault code that is indicative of a known fault. Such classifications allow the source of the invalid data to be isolated and possibly corrected if the optional feedback loop from the FT module is implemented.

The fusion process selected for this project is the Bayesian consensus sensor method. The data fusion process is not sub-divided like the fault detection process, namely because no data transmissions are required until after the process is completed. Furthermore, the Bayesian method chosen is a fairly homogeneous process. The fused data element is sent to the LSF module, as seen in Figure 3.

The Bayesian Consensus Sensor method, as defined in (5,6), is used to fuse the laser and radar data together. This estimation technique consists of two stages: the determination of the largest group of consensus sensors, and the calculation of the fused value. Each sensor is assumed to have a normal distribution and is assigned a probability density function. Using the conditional probability between two consensus sensors, a confidence distance measure is calculated for each unique sensor pairing *{ij}*,

$$d_{ij} = 2\left|\int_{x_i}^{x_j} P_i(x|x_i)P_i(x_i)dx\right|, \tag{3}$$

where $P_i(x|x_i)$ is the conditional probability and d_{ij} defines the area between the readings from sensor *i* and *j* under the probability distribution curve $P_i(x_i)$. The individual confidence distances are grouped together into a distance matrix which is then translated into a relations matrix. The relations matrix is then represented as a directed graph, in which the largest connected group determines those sensors in consensus.

Since the sensor measurements used in the fusion process are known to be in consensus, static Bayesian estimation can be used to achieve an optimal estimated measurement. Using standard Bayesian state estimation, the estimated measurement states are defined as

$$\hat{x} = m_x + \Psi H^T[H\Psi H^T + R]^{-1}[z - Hm_x], \tag{4}$$

where m_x is the mean value of the measurement, Ψ is the covariance matrix of the measurement, *H* is a relations matrix, *R* is the unknown measurement disturbance and *z* is the measurement being estimated. Equation 4 can be expanded to produce an estimate based on m consensus sensor measurements,

$$\hat{x}_f = \left[\sum_{i=1}^{m} \Gamma_i^{-1} + \Psi^{-1} \right]^{-1} \sum_{i=1}^{m} \left[\Gamma_i^{-1} \hat{x}_i + \frac{\Psi^{-1}}{m} \hat{x}_i \right]^{-1}, \tag{5}$$

where $\hat{x}_f$ is the final estimated measurement states, and Γ_i is covariance matrix for the i^{th} sensor,

$$\Gamma_i = (H_i^T R^{-1} H_i)^{-1}. \tag{6}$$

The final module located in the *Data Processing* tier is the LSF module. The only task of the LSF module is to take the final fused and validated sensor data and place it into a common data structure for the high-level control and computational algorithms to interpret. This is similar to the data packets used for inter-modular communications inside the SFCS framework, however, this data structure is for transmission to processes lying outside the SFCS framework. This common data type is selected to enhance the modularity of the SFCS framework, and minimizes the modification necessary to accommodate it.

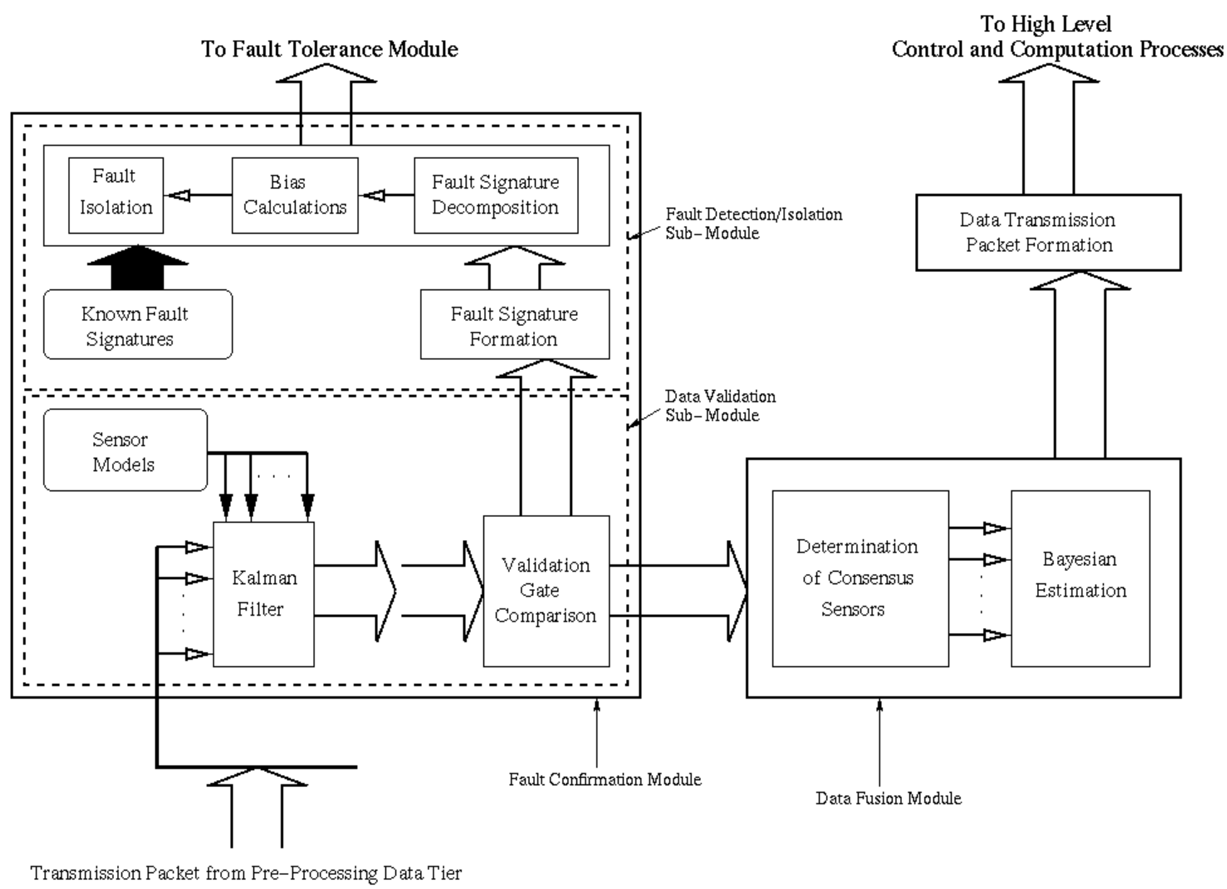

Figure 3: The inter-connections within the *Data Processing* tier

SFCS Control and Computation Tier

The highest tier in the SFCS framework is really not a part of the developed framework, but terminal for the data flow. Modifications are required on the high-level processes to accommodate the new data structure from the LSF module. The only SFCS related module in this tier is the FT module. This module has no interactions with the existent processes in this level, however, it is placed here upon its operation mode (being a control process).

The FT module makes sensor control decision based upon the outcome of the fusion and fault detection processes. This control decision is rule-based, and dependent upon the application of the SFCS framework.

SFCS IMPLEMENTATION IN AN IV

The selection of the processes outlined for use in the SFCS has revolved around IV applications, namely headway maintenance for Advanced Cruise Control (ACC) systems. Headway maintenance refers to the control of a vehicle such that a set minimum following distance to targets detected in its forward path of travel is maintained. ACC systems provide de-acceleration capabilities to conventional cruise control systems found in public transportation, to accomplish headway maintenance.

Obstacle avoidance and ACC are often used synonymously, though these two processes are different. ACC is concerned with the ability to monitor for and accommodate slower moving vehicles in its projected trajectory. Obstacle avoidance focuses on non-moving or slowly moving obstacles or obstructions found in the path of motion. While these routines are similar in their environmental focus and objective, their subsequent control and sensor algorithms are quite different. Using two SFCS frameworks, both obstacle detection and ACC can be accommodated, though this report is only concerned with ACC. Figure 4 depicts the constraints placed upon the relative distance and velocity measurements of a target for the ACC system demonstrated.

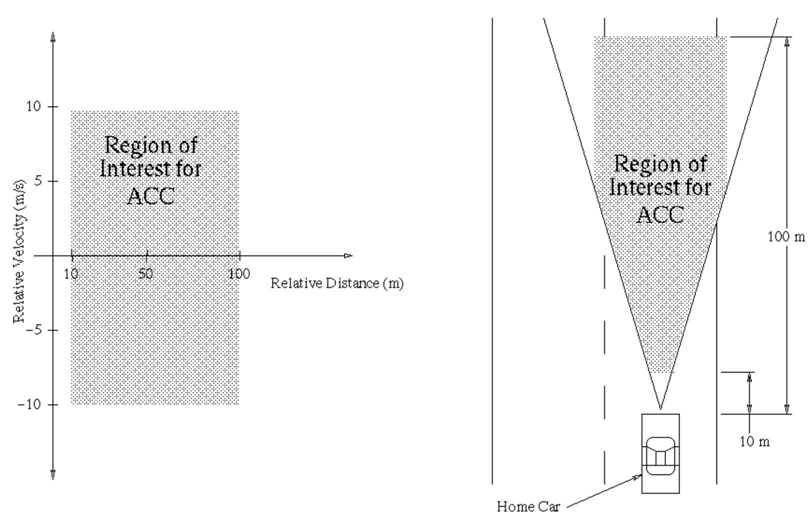

Figure 4: Graphical representation of specified ACC constraints

There are two major issues for implementing ACC, the perfect detection of all obstacles in the present line of travel, and the elimination of false obstacle detection. To accommodate this, the sensory data must be both sensitive and highly selective. The SFCS framework coupled with the forward-looking sensors is capable of achieving these goals.

The ACC process requires a forward distance monitoring sensor, and throttle and brake actuation with proper control algorithms for each. This report uses data acquired from the automated vehicles developed at The Ohio State University's Center for Intelligent Transportation Research (OSU-CITR) for the Demo97 project.

The OSU Automated Vehicle

The three automated vehicles developed by OSU-CITR are 1996 Honda Accords that have been outfitted with a drive-by-wire system by Honda, including electronic control of throttle, brake, and steering. A block diagram of the OSU-CITR vehicle is presented in (4). Though this vehicle is capable of automating both the longitudinal and lateral fields of vehicle motion, only the longitudinal components are examined here.

The OSU-CITR vehicles are equipped with a 5 Hz scanning laser-radar, provided by Honda. This laser system stores 6 targets from each sweep, sequentially placing them based upon an internal rule-based methodology. The data is passed to the central processing system via a serial connection. The laser has a maximum experimental distance rage of 120 meters, and a sweep angle of roughly $\pm 20°$. The update rate from the laser is 10Hz, and the data transmitted includes the measured target distance, relative speed, width, and lateral offset. The forward sensing experimental microwave-radar operates at 10 GHz and is only capable of monitoring a single target. The radar has a maximum experimental distance range of 35 meters, with a $\pm 20°$ field of view at closer proximities. The radar provides the distance to the target at a 100 Hz update rate.

The control algorithms used for ACC are executed during a 100 Hz loop on the central processor. The SFCS framework must therefore provide the necessary sensor data to the control and computation routines at this rate. Since the data process will be limited by the update rate of the laser-radar, a Kalman-observer is used to provide estimated laser measurements with a 10 Hz update rate.

Experimental Results

The first tier in the SFCS framework filters the incoming sensor data using a dynamically changing rule-based system dependent upon the operating state of the vehicle. A flowchart of the vehicle states is presented in (4). The state-machine selections are based upon conditional data received by the many sensors and algorithms on the vehicle, and the developed scenario for the Demo97 project.

For this application a rule-base is used to determine when the measured targets from the laser and radar are within the preset ACC operating constraints. This criteria focuses on the relative distance and velocity of the targets, the target width and lateral offset for the laser measurements, and the signal strength of the radar measurements.

Data is taken from an OSU automated vehicle traveling at 45 mph while closing in upon a slower moving vehicle. The laser-radar and microwave radar measurements for this scenario are displayed in Figures 5 and 6 after being initially filtered and along with the Kalman estimated values. The radar measurements are shown to be noisier than the comparable laser measurements. Using validation gate defined in Equation 2, the radar measurement presented in Figure 6 is found to be invalid at the very beginning and ending of the data string, where the radar measurement contains large amounts of noise. The fault detection routine classifies these instances as being poor measurements, not sensor faults. There are no invalid measurement points in the laser data shown in Figure 5. All validated measurement are provided to the DF module for fusion.

The Bayesian consensus sensor fusion process defined in Equation 5 is applied to the sensor data found in Figures 5 and 6, and the results are depicted in Figure 7. Notice that since this fusion process utilizes statistical information about the sensors, the measurements recorded from the laser tend to be favored over those from the radar.

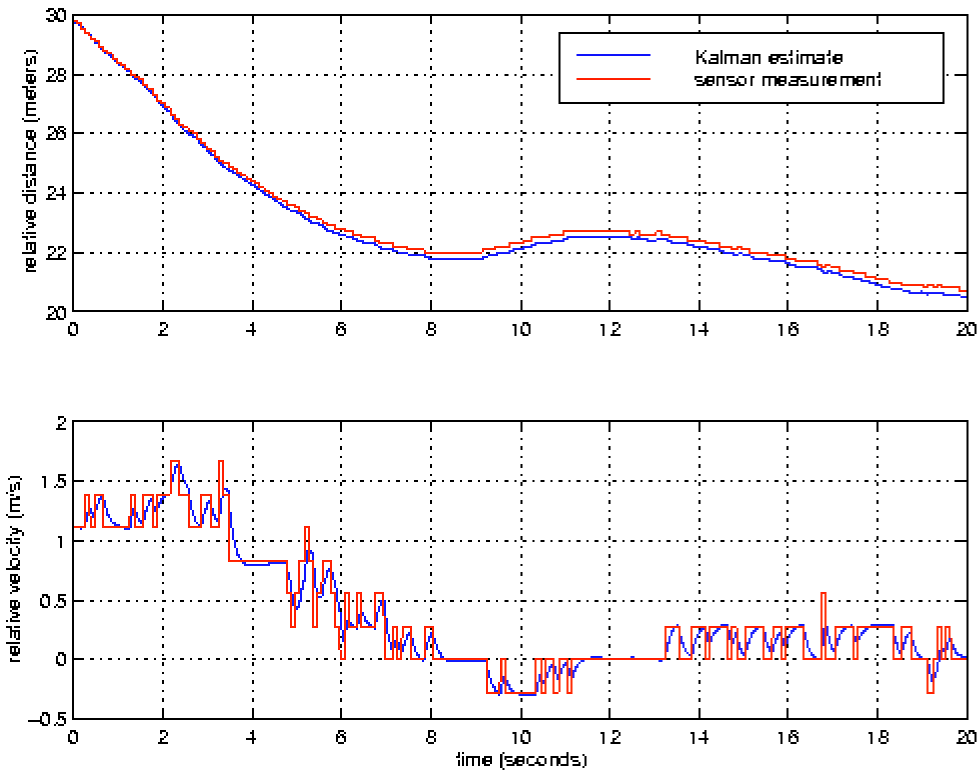

Figure 5: Relative distance and velocity measurements from laser with Kalman estimate

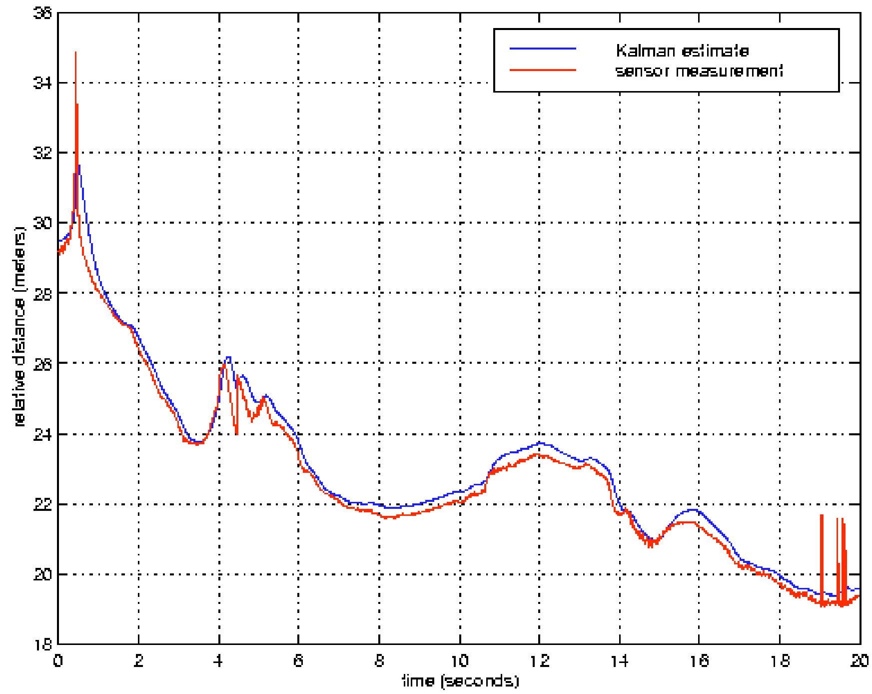

Figure 6: Relative distance measurement from radar with Kalman estimate

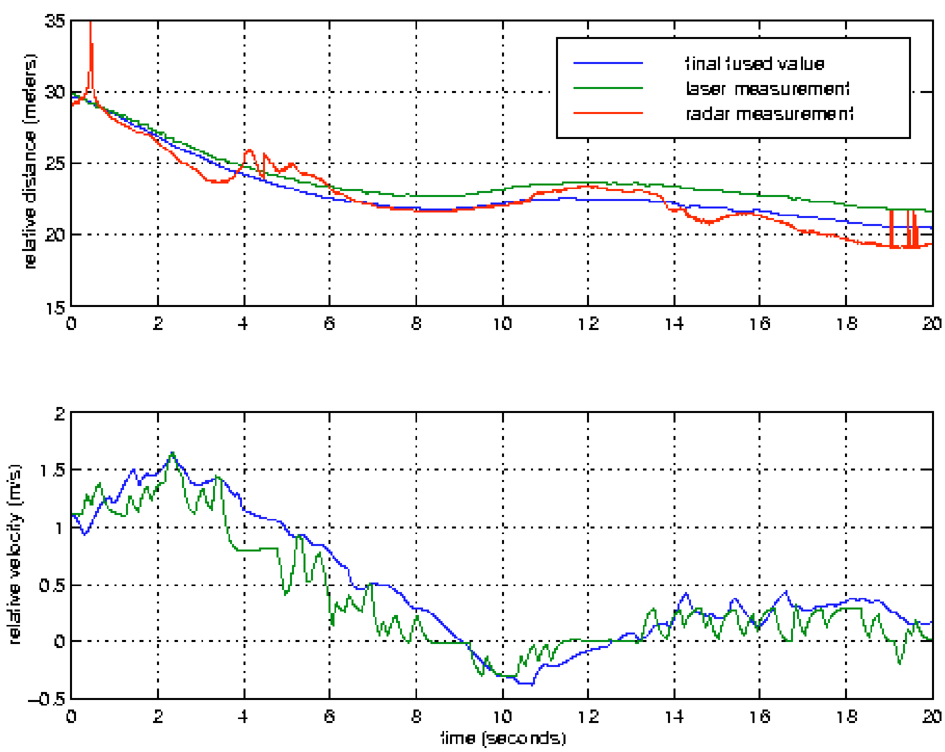

Figure 7: Fused relative distance and velocity measurements from SFCS framework

CONCLUSION

This paper has shown the development of a framework for real-time sensor validation and fusion, and fault detection and tolerance. While this system is applicable to many systems, the internal processes have been selected relevant to IV systems. The short example demonstrates the sensor data manipulation within the SFCS for an Adaptive Cruise Control system. Further research is underway in the implementation of this framework for obstacle detection, and lateral control issues in automated vehicles.

ACKNOWLEDGMENT

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ENDNOTES

1. Petros A. Ioannou, Automated Highway Systems (city, ST: Plenum Press, 1997).
2. Avraham Horowitz, “User Needs for Automated Highway Systems (AHS),” Internet Survey for Societal and Institutional Issues Team of the National AHS Consortium, 1995.
3. John M. Richardson and Kenneth A. Marsh, “Fusion of Multisensor Data,” The International Journal of Robotics Research (1988): 78-96.
4. Keith A. Redmill and Umit Ozguner, “The Ohio State University Automated Highway Systems Demonstration Vehicle,” SAE 1998 World Congress (Detroit, MI, 1998), paper #980855.
5. R. C. Luo and M. G. Kay, “Multisensor Integration and Fusion in Intelligent Systems,” IEEE Transactions on Systems, Man, and Cybernetics 19(5) (September-October 1989).
6. Ren C. Luo and Min-Hsiung Lin, “Robot Multi-Sensor Fusion and Integration: Optimum Estimation of Fused Data,” Proceedings of the IEEE conference on Robotics and Automation (Philadelphia, PA, 1988): 1076-1081.