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Validation and Fusion of Longitudinal Positioning Sensors in AVCS[*] [**]

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ABSTRACT

Advanced Vehicle Control Systems (AVCS) require a large number of sensors for control at different levels. Whereas all sensors contains uncertainty to some degree, different sensors are particularly useful in different situations. Therefore, sensor redundancy is essential to achieve high sensor data fidelity. In this work, sensor validation and fusion of a positioning sensor system which includes Global Positioning System (GPS) receivers, a RADAR sensor and a linear transducer are performed. A synchronization method is suggested for the scenario in which sensors output at different frequencies and time delays. Two types of validation and fusion algorithms --- Probabilistic Data Association Filter (PDAF) and Fuzzy Sensor Validation and Fusion (FUSVAF) --- are implemented for the open loop test data from field tests performed in cooperation with SRI International in Oct.1997. A closed loop simulation has been performed using a simple PID controller for the follower control law within a platoon.

1. Introduction

In the Partners for Advanced Transit and Highways (PATH) AVCS program, reliability and safety are of paramount concern. High performance of the control system in AVCS relies heavily on the accuracy of information obtained from sensors. All sensor readings are corrupted by noise to some degree. Different types of sensor failure occur under different circumstances. A single sensor could never be expected to work reliably under all conditions. Therefore, sensor redundancy is essential to achieve high sensor data fidelity. Two types of redundancy are appropriate for a sensor system, functional redundancy and physical redundancy. Whereas physical redundancy is obtained by using multiple sensors to measure the same quantity. Functional redundancy can be implemented through a functional and logical relationship among the parameter values measured by different sensors. Both redundancies are used in AVCS; in this work we focus on physical redundancy. Noise characteristics of three different sensors are investigated in Wang (1998).

Positioning systems give information about the absolute or relative position of vehicles. In AVCS, the platoon model is utilized to increase highway capacity. Vehicles within one platoon are of two types: the leader (the first vehicle in the platoon) and the followers (all the following vehicles). For followers in steady state motion, the goal of the control system is simply to follow the vehicle ahead and keep a relative distance of two meters. Since the whole platoon is moving at a very high speed, it is very important to accurately control the intervehicle space. The motivation of this research is to increase the accuracy of the intervehicle spacing measurement.

The Berkeley Expert System Technology (BEST) Lab of UC Berkeley has performed a number of studies on sensor fusion and validation. Two major approaches were developed. A Bayesian based approach, the Probabilistic Data Association Filter (PDAF), was modified and implemented in AVCS by Alag (1996) as part of his Ph.D research. In addition, a fuzzy based approach, Fuzzy Sensor Validation and Fusion (FUSVAF), was developed and implemented in AVCS by Kai Goebel (Goebel, 1996) in his Ph.D research. The two schemes are used in parallel and both have advantages and disadvantages. Several sensors have been studied and their test data have been applied to the two fusion schemes by previous BEST lab researchers. These sensors include RADAR, SONAR, optical and others. In this paper, GPS sensors are integrated into the sensor system and the performance of the fusion schemes for this new sensor is studied.

The purpose of this paper is to: 1). integrate the GPS sensor with other sensors to perform sensor validation and fusion using the PDAF and FUSVAF algorithms 2). use the sensor models developed in Wang (1998) to perform a closed loop simulation of tracking within a platoon.

2. Sensors and synchronization

Three types of positioning sensors --- GPS receivers, RADAR, and the Rayelco transducer are used in this validation and fusion scheme. Their noise characteristics

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and noise models are investigated and developed in Farrell (1997), Grewal (1996) and Wang (1998). Before we apply the fusion algorithms, we first need to synchronize the outputs of the three sensors since GPS outputs are at a different frequency (4Hz) from the other two sensors (10Hz).

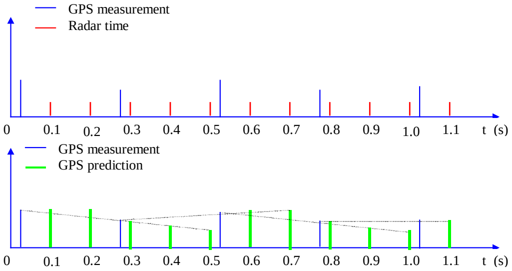

Figure 1 Sensor Output Synchronization Scheme

In our test, since GPS outputs were updated at a lower frequency than the other two sensors, we took the time stamps of the other two sensors as reference time and interpolated GPS data of 4 Hz into these time stamps. A simple way to synchronize is at each time stamp, taking the closest value of the GPS data as the predicted GPS output at that time stamp. Since we need to do the synchronization online, and we only have access to past data, the most recent GPS output could be used as the current GPS output prediction. However, a delay would be introduced by this way of synchronization, which is undesirable for most dynamic cases. Considering the dynamic cases, a linear predictor is used here to synchronize the GPS outputs with the other two sensors using the past two GPS readings. Suppose $x(n)$ and $x(n-1)$ are the two most recent GPS measurements; the predicted value for GPS output at time t is just

$$x(t) = x(n) + \frac{x(n) - x(n-1)}{t_n - t_{n-1}}(t - t_n) \quad .$$

The geometry of the synchronization scheme is shown in Figure 1. While perhaps suboptimal, this solution is easy and straightforward. It will be used in the following sections.

3. Brief overview of two kinds of fusion algorithms---PDAF and FUSVAF

Two types of validation and fusion schemes were developed by Alag (1996), Goebel (1996) and Agogino (1995). The flow chart is shown in Figure 2.

Suppose we are using a number of sensors measuring the same quantity. All of the original sensor readings are uncertain to some degree. The purpose of sensor validation is to remove most of the noise from the sensor readings and increase the sensor system’s robustness in the event of single sensor failure. The validated values are evaluated by passing through validation gates. The validation gates are designed based on the prediction of current state value using past information. Those validated values which are not too far from the predicted value (within the gates) are considered to be valid sensor measurements, while those outside of the gates are considered to be invalid sensor measurements and are rejected. Each valid sensor measurement is then assigned a confidence (or probability) value indicating to what degree they can be believed according to how far they are from the predicted value. In the fusion block, we calculate the fused value by taking a weighted average of all the valid sensor measurements using their confidence values as the weights. Note that the weighted average should also include the predicted value (therefore it needs a confidence value as well), so that if none of the sensor measurements are valid at a time, the predicted value can be taken as the current fused value.

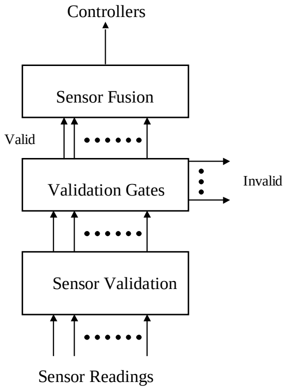

Figure 2 Sensor Validation and Fusion Scheme

In the PDAF implementation, a rule-based system is used first to determine the operating state of the vehicle, and then the proper system model is chosen. The model could be of the first, second or third order according to the operating states (Alag 1996). Then a Kalman filter based validation and fusion algorithm is used and a fixed validation gate is utilized for all the sensors. Probabilities are assigned to each sensor based on a Gaussian validation curve. PDAF works well for zero mean, white, Gaussian noise since it is based on a Kalman filter, but is not as ideal for other types of noise.

In the FUSVAF (Goebel 1996) implementation, a Fuzzy Exponential Weighted Moving Average (FEWMA) time series predictor is used for validation, fuzzy validation gates are designed for each sensor, and a weighted average scheme is used for fusion. Different non-symmetric dynamic validation gates can be designed for different sensors according to their characteristics based on the measurements, predicted value and current system state. Confidence values are assigned corresponding to the validation curves. FUSVAF is acceptable for both Gaussian and non-Gaussian noise. It does not require a priori knowledge about the noise (essential for the PDAF). And it is flexible in the choice of validation gates.

4. Comparison of the fusion results by the two algorithms --- PDAF and FUSVAF

Figure 3 shows the fusion of the three sensors using one set of the static test data (4 m test). The true distance between the centers of the two GPS receivers measured by a tape is about 4.06 m. Millimeter level accuracy could not be achieved by a tape. While the mean value of the GPS and transducer data are both approximately 4.057 m, we took 4.057 m as the true distance. The Sum of Square Errors (SSE) of 1000 data samples are calculated for each sensor and the PDAF issued to fuse output. According to the SSE values, RADAR is the noisiest sensor among the three. The linear transducer has noise with magnitude within 1 cm, which is quite accurate as expected. The GPS data are extremely accurate, with a SSE value smaller than that of the fused output.

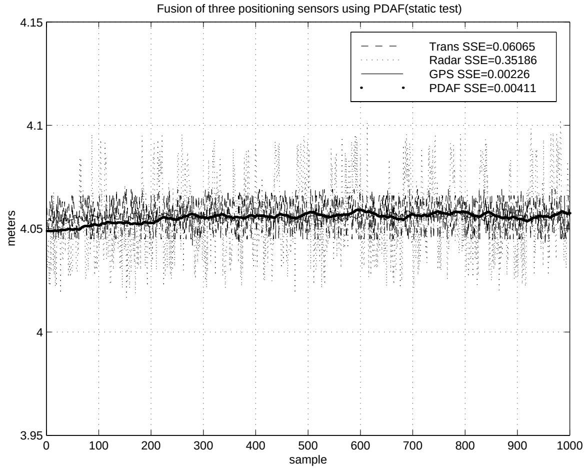

Figure 3 Fusion of three positioning sensors using PDAF (static test)

Figure 4 shows the fusion of two sensors using exactly the same RADAR and transducer data as in Figure 3. Comparing Figure 3 and 4, observe that without GPS outputs, the fusion results worsen slightly. The PDAF fusion SSE value increases from 0.00411 m^2 to 0.00826 m^2. This indicates that fusion of the RADAR and transducer outputs using PDAF results in accurate results, integration of the GPS outputs in addition adds to the accuracy.

Figure 5 shows the fusion of three sensors using one set of dynamic test data. We did not use SSE to evaluate the performance of the sensors and the fused outputs since we do not know the true distance for the dynamic case. As expected, however, both the GPS and transducer data are close in accuracy. RADAR readings are by contrast noisy. The fused outputs are quite close to the GPS and transducer outputs, which is good, although at sometimes is corrupted slightly by noisy RADAR outputs.

Figure 6 shows the fusion of three sensors using the FUSVAF. The data used here are exactly the same as those in Figure 3. Results from implementation of FUSVAF appear to be slightly more accurate than the PDAF in the sense of SSE.

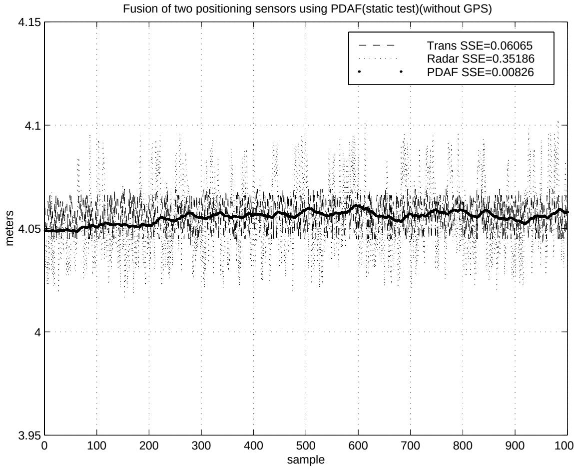

Figure 4 Fusion of two positioning sensors using PDAF (static test; without GPS)

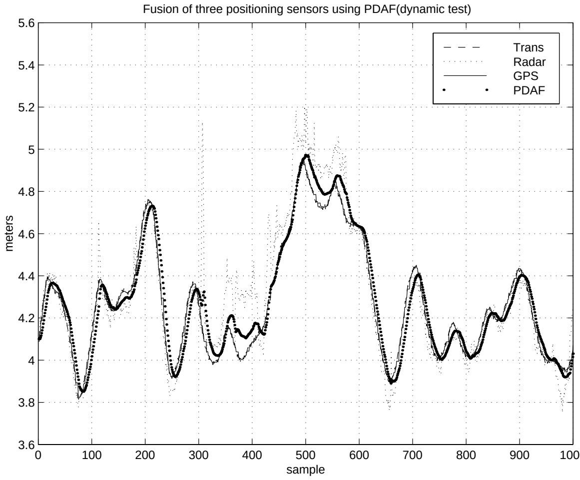

Figure 5 Fusion of three positioning sensors using PDAF (dynamic open loop test)

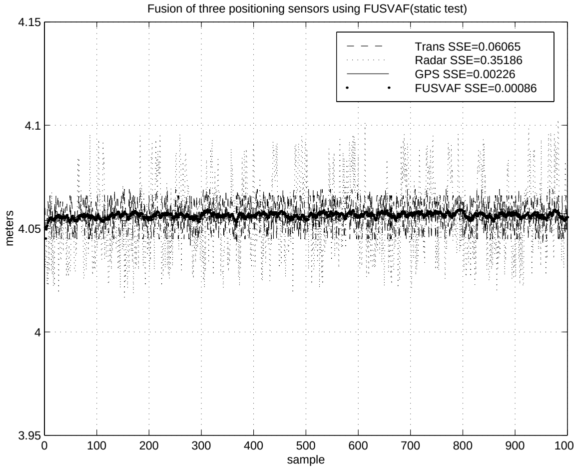

Figure 6 Fusion of three positioning sensors using FUSVAF (static test)

Figure 7 shows how the FUSVAF behaves without GPS readings. Compared with Figure 4, which use exactly the same sensor test data, FUSVAF performs worse than the PDAF under the same conditions.

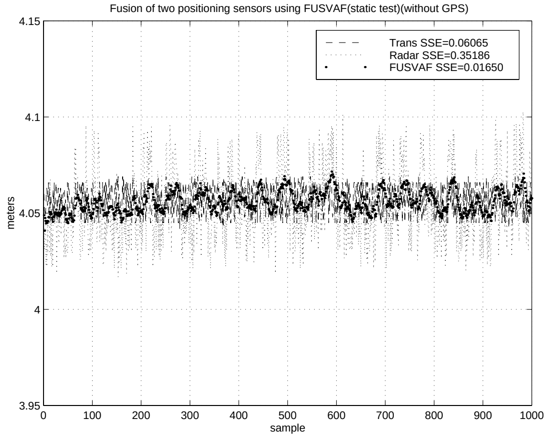

Figure 7 Fusion of two positioning sensors using FUSVAF (static test) (without GPS)

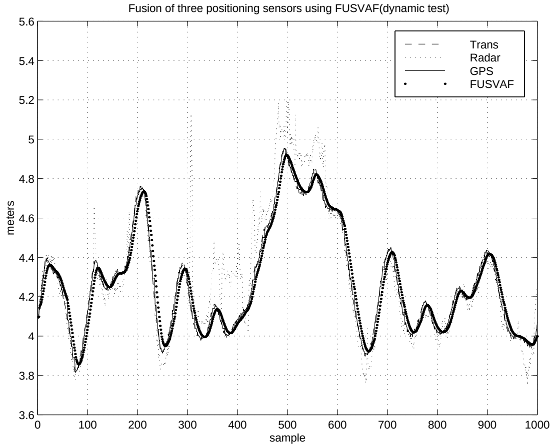

Figure 8 Fusion of three positioning sensors using FUSVAF (dynamic open loop test)

Comparing Figures 8 and 5, the fused output of the FUSVAF is closer to the GPS and transducer outputs than the PDAF. We can interpret this to mean that the FUSVAF results are more accurate since the GPS and transducer are supposed to be more accurate than RADAR.

5. Closed Loop Simulation

So far we have implemented the two fusion algorithms using open loop test data. Next we would like to show how the fusion schemes work in closed loop when GPS sensors are integrated. Since we only consider steady-state, straight following motion of two cars, a simple PID can be used here as the follower control law. The control goal is to track the lead car to keep an desired intervehicle spacing of D = 2 m. Then the spacing error is

$$e(i) = d(i) - D = x(i-1) - x(i) - D$$

where index i refers to the follower and $i-1$ refers to the lead car. Variable $d(i)$ is the distance between car $i-1$ and car i; in other words, this is the quantity being measured using our positioning sensors. Variable $x(i-1)$ is the position of car $i-1$, and $x(i)$ is the position of car i. The desired spacing is $D = 2$ m. All the above quantities are measured in meters.

Using the concepts suggested by Godbole and Lygeros (1993), the follower PID controller can be developed easily:

$$\ddot{x}(i) = c_p e(i) + c_v \dot{e}(i) + c_a \ddot{e}(i) \cdot$$

Under this control law the closed loop transfer function relating the spacing error experienced by car $i-1$ to the spacing error experienced by car i is:

$$H(s) = \frac{e(i)(s)}{e(i-1)(s)} = \frac{N(s)}{D(s)}$$

where $N(s) = c_a s^2 + c_v s + c_p$,

$D(s) = s^3 + c_a s^2 + c_v s + c_p$.

In this simulation the parameter values are: $c_p = 210.0, c_v = 140.0, c_a = 15.0 \cdot$

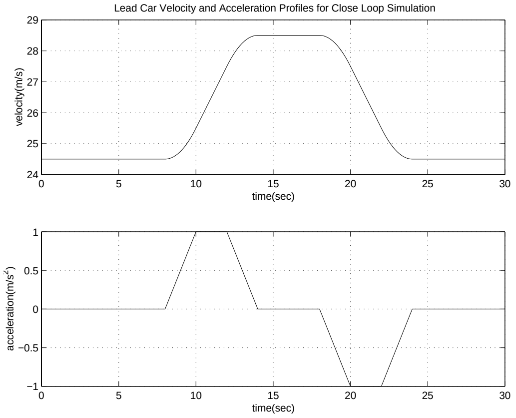

Figure 9 Lead car Velocity and Acceleration Profiles for Closed Loop Simulation

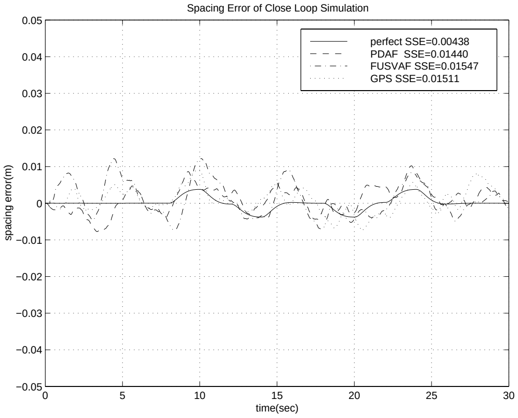

Figure 10 Simulated Spacing Error using different sensor fusion schemes

Figure 9 shows the velocity and acceleration profiles of the lead car in the simulation. Figure 10 shows the simulated spacing error using different sensor fusion schemes. Note that the “perfect” label indicates that no noise has been added, simulating ideal sensors. Both the PDAF and FUSVAF use the three sensor models (for GPS, the complex model is used) developed by Wang (1998). The RADAR and transducer models generate model based data at 50 Hz. GPS models generate data at 4 Hz. GPS model based data are synchronized with the other sensor models using the linear predictor introduced previously, prior to the fusion algorithms. The GPS plot includes the GPS model based noise, with no sensor fusion schemes involved. The SSE is the sum of squared spacing error for a 30 seconds simulation. Figure 10 shows SSE values for one run. The SSE values may change slightly during each simulation run. For the perfect case, SSE is 0.00438 m^2. For the PDAF, SSE varies from 0.0120 m^2 to 0.0155 m^2. For the FUSVAF, SSE varies from 0.013 m^2 to 0.017 m^2. For GPS-only, SSE changes from 0.013 m^2 to 0.0165 m^2. Generally speaking, in the sense of the SSE, the PDAF performs a little bit better than FUSVAF and GPS-only case. FUSVAF and GPS-only perform almost the same.

6. Conclusions and future work

The results of the open loop fusion and closed loop simulation show that both the PDAF and FUSVAF fusion schemes behave as expected and are consistent with previous research (Agogino, 1995, 1996). In the presence of GPS, RADAR and linear transducer noise (noise models for simulation), both algorithms filter out noise to varying degrees, and fuse multiple sensor readings.

One recommendation is to use the GPS position readings as the sole position sensor, and only use the fused results as reference (or backup) when there is a question about the GPS integrity (e.g., travel in blind spots under tunnels, overpasses). On the other hand, when GPS does not work well, switch to the fused results as the primary position sensor.

In the future, more complicated closed loop simulation schemes need to be implemented. PDAF and FUSVAF both have their advantages and disadvantages. A combined validation and fusion scheme needs to be developed exploiting the desirable properties while rejecting their shortcomings.

Acknowledgments

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