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Aggregation of Direct and Indirect Positioning Sensors for Vehicle Guidance

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11. Keywords

Sensor Modeling, Sensor Validation, Sensor Fusion, Data Fusion, Data Synchronization, Supervisory Control, VDL, Management of Uncertainty, Reliability

111. Abstract

Advanced Vehicle Control Systems (AVCS) require large numbers of sensors for different levels within the control hierarchy. Whereas all sensors contain uncertainty to some degree, different sensors are particularly useful for specific environmental conditions. Therefore, sensor redundancy is essential to achieving high sensor data fidelity for use in real-world, non-ideal, unpredictable environments. In this work, a positioning sensor system, which includes Global Positioning System (GPS) receivers, a radar sensor, and a linear transducer is investigated. Positioning sensors provide information about the absolute or relative position of vehicles, a crucial component of the control system. GPS is potentially powerful for AVCS because of its high accuracy achievable by Differential GPS (DGPS) **and** other advanced GPS techniques. Field tests using these three sensors have been performed in cooperation with SRI International. Sensor noise models of GPS, radar, and linear Transducer sensors are developed based on the test data. **A** synchronization method is suggested for the scenario in which sensors output data at different frequencies and time delays. Two types of validation and fusion algorithms, PDAF and FUSVAF, are implemented for the open loop test data and the results are compared. A closed loop simulation has been performed using a simple PID controller as the follower control law within a platoon. The sensor models developed here are applied in the simulation, and the two fusion algorithms are implemented and the results are compared. Finally, additional simulations incorporate results into VDL.

IV. Summary

Sensors are always uncertain to some degree. They are also prone to a wide range of failure modes, each with varying degree of predictability. If these sensors are part of a system that relates to the safety of a system, noise and failure are unwelcome. Positioning sensors that give information about the absolute or relative position of vehicles within AVCS fall into the category of safety relevant sensors. The accuracy of single sensors is increased by improving the hardware and software or to use backup information to fuse information from several sources. This results in systems that perform acceptably in certain situations governed by internal sensor characteristics and environmental conditions.

This report describes our efforts to develop a methodology for the aggregation of sensors. This includes the incorporation of information that is only partially redundant, has time lags to other sensor information, and accommodates both synchronized and unsynchronized data. Reduced visibility, obstacles (e.g. debris, bridges, or tall vehicles) blocking sensor signals, degrading sensor performance due to aging, inclement weather render any one sensor useless in some situations. Therefore, sensor redundancy is essential to achieve high sensor data fidelity. Two types of redundancy are involved for a sensor system: functional redundancy and physical redundancy. Physical redundancy is obtained by using multiple sensors to measure a single quantity. Functional redundancy is obtained through a functional and logical relationship among the parameter values measured by different sensors. Whereas both redundancy types are used in AVCS, in this work we focus on physical redundancy. Noise characteristics of three different sensors are investigated.

Positioning systems give information about the absolute or relative position of vehicles. In the design of AVCS, the platoon model is utilized to increase highway capacity. Platoons consist of groups of anywhere from two to ten vehicles in a following pattern with an inter-vehicle spacing of approximately one meter at highway speeds. Vehicles within one platoon can be divided into two types: the leader (the first vehicle in the platoon) and the followers (all of the following vehicles). For the followers in a steady state motion, the goal of the control system is simply to follow the vehicle ahead and keep a relative distance of one meter. Because the entire platoon is moving at a very high speed, it is crucial that the inter-vehicle spacing is controlled accurately. Accurate measurement of the inter-vehicle spacing becomes significant since all follower control laws are based on it. Thus the motivation of this research is to increase the accuracy of the positioning sensor system.

The purpose of this project is to: investigate GPS system noise characteristics, develop GPS and other sensor noise models, integrate the GPS sensor with other sensors to perform sensor validation and fusion, use the sensor models to perform close loop simulation of tracking within a platoon, and perform simulation in the VDL framework. The sensor aggregation produced by this research results in improved accuracy of the measurements provided for the machine level controller, a smoother ride, and improved safety of the system as a whole.

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Chapter 1 Introduction

One of the main motivations within the AVCS program lies in providing a safe ride. AVCS must reduce uncertainty and increase safety relative to the human counterpart to be successful. In reality, however, sensors fail for a variety of reasons that often cannot be entirely predicted. The validity of a sensor reading is never guaranteed. Therefore it is mandatory to have a system that deals with these uncertain readings, and, after validation, makes the optimal decision about which action to take (Goebel, 1996, Alag, 1996).

The source of the sensor readings is manifold. Currently, there are numerous efforts under way within PATH to develop sensor systems for positioning tasks. These encompass radar, sonar, tachometer, gyros, GPS, vision, magnetic markers, laser, etc. Each sensor system has its unique advantages and disadvantages that makes one particular sensor more suitable in a given situation. What is missing is a comprehensive aggregation of all the sensor information to overcome shortcomings of any single sensor source. Attempts have been made (Agogino et al., 1995, 1997, Alag, 1995, Goebel, 1996, Goebel et al, 1996) but with limited scope due to the non-availability of more sensors. It is feasible to assume that costs of sensors will drop sufficiently to assume that vehicles will be equipped with a variety of sensors.

Therefore, PATH must allow aggregation of this sensor information. We envision this control scheme to work within the hierarchical structure of AVCS. Figure 1-1 shows the outline of the complex hierarchical structure of the AVCS control architecture that in addition to the link, planning, regulation, and physical layer consists of the network layer at the top. The task of the network layer controller is to assign a route to each vehicle entering the system. Below this is the link layer controller, one for a long segment of each highway. Its task is to assign a path to each vehicle entering the highway and target for the aggregate traffic. The remaining tasks are distributed among individual vehicles (Varaiya and Kurzhanski, 1988).

The platoon layer in each vehicle is responsible for planning its path as a sequence of three elementary maneuvers, and for coordinating with neighboring vehicles the implementation of each maneuver. The regulation layer below it is responsible for executing a pre-computed feedback control in response to a command from the platoon layer as well as performing lower-level control tasks (Varaiya, 1991; Varaiya and Shladover, 1991; Sachs and Varaiya, 1993). Currently there is no element that acts as a supervisor in the sense that the information of redundant sensors (both hardware and analytical) is coordinated and sifted for inconsistencies. This need (Hsu et al. 1991; Patwardhan et al. 1992) between the vehicle sensors and the platoon layer must be filled to ensure proper operation of the system. Many parts of the system still assume that the communication systems and sensors work perfectly. This assumption is not realistic. Although uncertainty is taken into account in some cases, (Hedrick and Garg, 1993; Patwardhan et al. 1992), there exists no element that looks at the sensor readings from all relevant sensors at the physical level as well as information from the communication. We consider a multi-tier monitoring and diagnosis system that considers the uncertainties in sensor readings to form a link between the platoon level controller and the regulation level controller and to rectify aberrant sensor readings by taking into account the information of several partly redundant sources. **As** shown in Figure 1-1, sensor aggregation is being carried out on the Regulation layer and has partly been completed in the previous two **PATH** projects. Based on these results and as a next step, validation algorithms (shaded box in the platoon layer) check whether the data are compatible with global measurements. Information about malfunctions is passed to the link and network layer as warnings.

Some of the reasons for uncertainty in sensory information is measuring device error, environmental noise, and flaws or limitations in the data acquisition and processing systems. Extracting information from raw data is often difficult because of noise, missing data or occlusions. Phenomena may show up at disparate locations and can have **a** variety of time scales, from low frequency signals to high frequency vibrations. If the **AVCS** is to function safely and reliably it is important to account for all these sources of uncertainties, identify them through their characteristic signature, and propagate them to the final diagnosis of the system state.

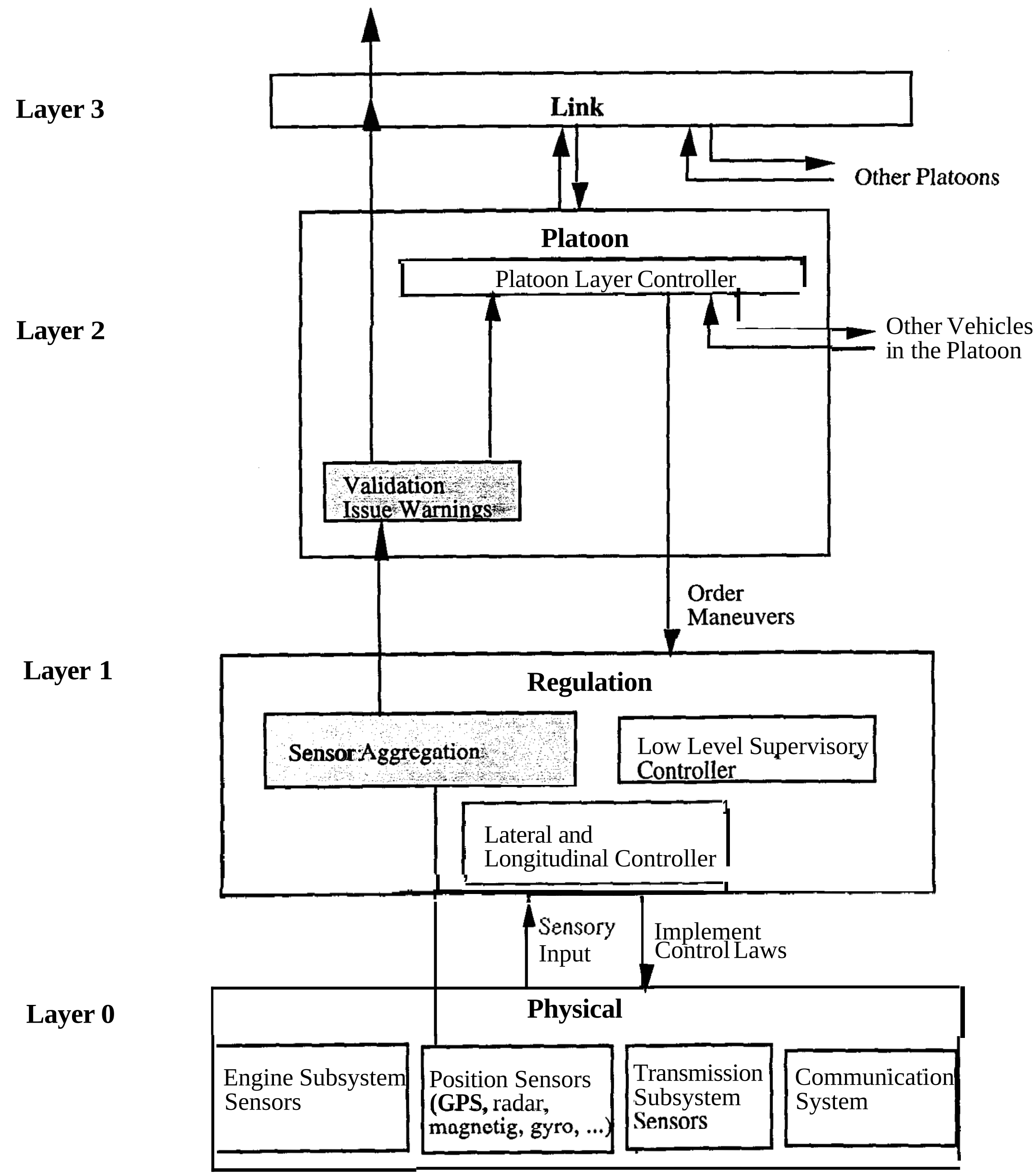

Figure 1-1: Position of Intelligent Sensor Validation and Sensor Fusion and Intelligent Decision Advisor in the AVCS Control Hierarchy

This report covers our results from MOU 322. Sensor model development is described in Chapter *2***.** Chapter 3 discusses first data synchronization and then fusion of GPS results with other data. Chapter **4** describes the VDL simulation of our fusion algorithms. Finally, conclusions and future directions are discussed in Chapter 5.

Chapter 2 Sensor Model Development Based on Test Data

For a complicated system like AVCS, we need to first simulate it to ensure that each component of the designed system will independently perform adequately as a system. For automatic highway systems, simulation is essential for controller design. To create a more realistic simulation environment, we need to simulate sensor output instead of assuming exact vehicle state measurement. This is the primary reason for the development of sensor models. Three position sensors are investigated in this chapter. Their models are developed based on real test data. In addition, the sensor models are evaluated by comparing their autocorrelation function estimations and histograms with those of the real test data.

Test Setup

All the real test data used in this work were collected during a field experiment on October 30th, 1997 at Golden Gate Fields, California. The experiment was performed in cooperation with SRI International with the help of several PATH researchers from Richmond Field Station using two PATH cars. The test setup is shown in Figure 2-1.

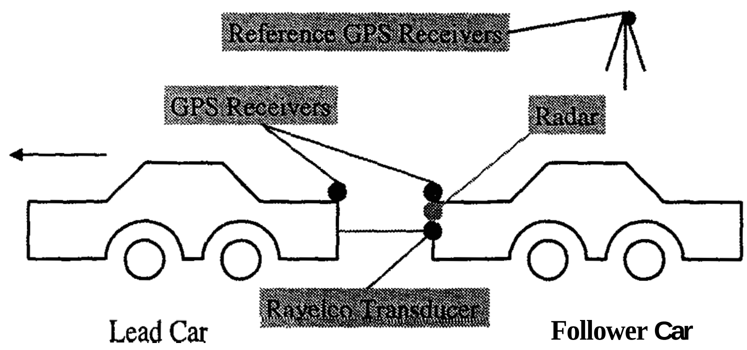

Figure 2-1: Test Setup

Three types of position sensors were used in the tests: GPS receivers, radar, and a Rayelco transducer. Three GPS receivers were used in the experiment. Two were installed on the two cars respectively and the third was used as a reference GPS station for the DGPS scheme. All three sensors were used to measure the inter-vehicle spacing.

In the tests, we first fixed the reference GPS receiver. Then several static tests were performed at a distance of about 40 meters from the reference point. Dynamic tests were performed by driving the two cars around the reference point. Three sets of static test data and one set of dynamic data are used in this work. The radar and transducer data were synchronized when they were collected. Their outputs are at a frequency of 50 Hz. The data were recorded at frequency of 10 Hz. GPS test data were processed by **SRI.**

Since GPS position data were at 4Hz, the GPS receiver readings needed to be synchronized with the other two sensor readings.

Noise Characteristics Analysis Methods

In this project, two major statistical methods are studied to analyze noise characteristics and evaluate the noise models: histogram and autocorrelation function (Jenkins, 1968).

Histogram --- Estimation of Probability Density Function (pdf)

In the category of time series analysis, the probabilistic density function (pdf) is estimated by forming the histogram of the sample data. For example, a histogram of a pseudo zero mean Gaussian white process with 1000 samples generated in Matlab and the pdf of corresponding ideal random process are shown in Figure 2-2.

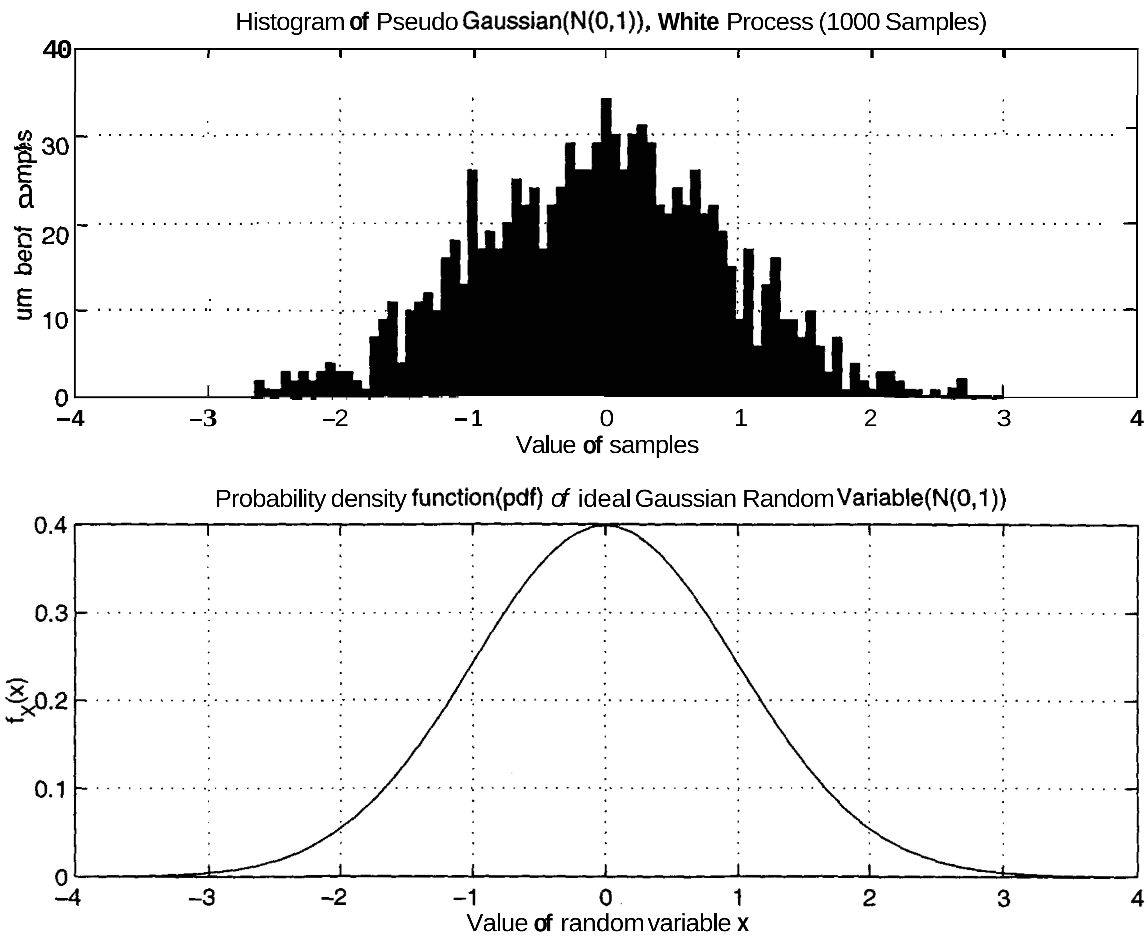

Figure 2-2: Histogram of Pseudo and ideal white

Gaussian Process

The shape of the histogram more closely emulates the shape of the pdf when more samples are used. Similarly, in the development of sensor models with limited test data, we are able to derive only a rough distribution of the data, not the exact pdf. However, this visual measurement is still useful since it shows important properties of the data and is easy to use without involving complex calculations. In reality, however, an exact solution to this kind of problem does not exist because for a probabilistic model, limited test samples could never cover the whole probability space.

Our goal of modeling a sensor system is to construct a probabilistic model using some commonly used random variables or processes. Additive White Gaussian Noise (AWGN) is one of the most typical random processes in this scenario. Since techniques relating AWGN are well-developed, computation would be greatly simplified if the sensor noise of interest is AWGN or could be approximated **as** AWGN. Furthermore, if the characteristics exhibited by the data are too complex to be modeled easily and model accuracy is not of crucial concern, we can implement the most typical random processes or combinations thereof for rough approximations.

Sample Autocorrelation Function (ACF)

An autocorrelation function describes the second order statistics of a random process. It is used here because it gives a visual picture of the degree to which samples in the process dependent on each other as a function of the separation between points in the data series.

From Jenkins, ***1968,*** the autocovariance function (ACVF) estimates of a discrete time series can be defined as the following:

If the observations $x_1, x_2, \ldots, x_N$ come from a discrete time series, the discrete autocovariance estimate is:

$$c_{xx}(k) = \frac{1}{N}\sum_{i=1}^{N-k}(x_i - \bar{x})(x_{i+k} - \bar{x}), \qquad k = 0, 1, \ldots, N-1$$

where $\mathrm{X} = \frac{1}{N}\sum_{i=1}^{N} x_i$.

Estimates of the ACF, also called the sample ACF, are obtained by dividing the above ACVF estimates by the estimate of the variance, which is

$$r_{xx}(k) = \frac{c_{xx}(k)}{c_{xx}(0)}.$$

Figure 2-3 shows the sample ACF of a pseudo white Gaussian process.

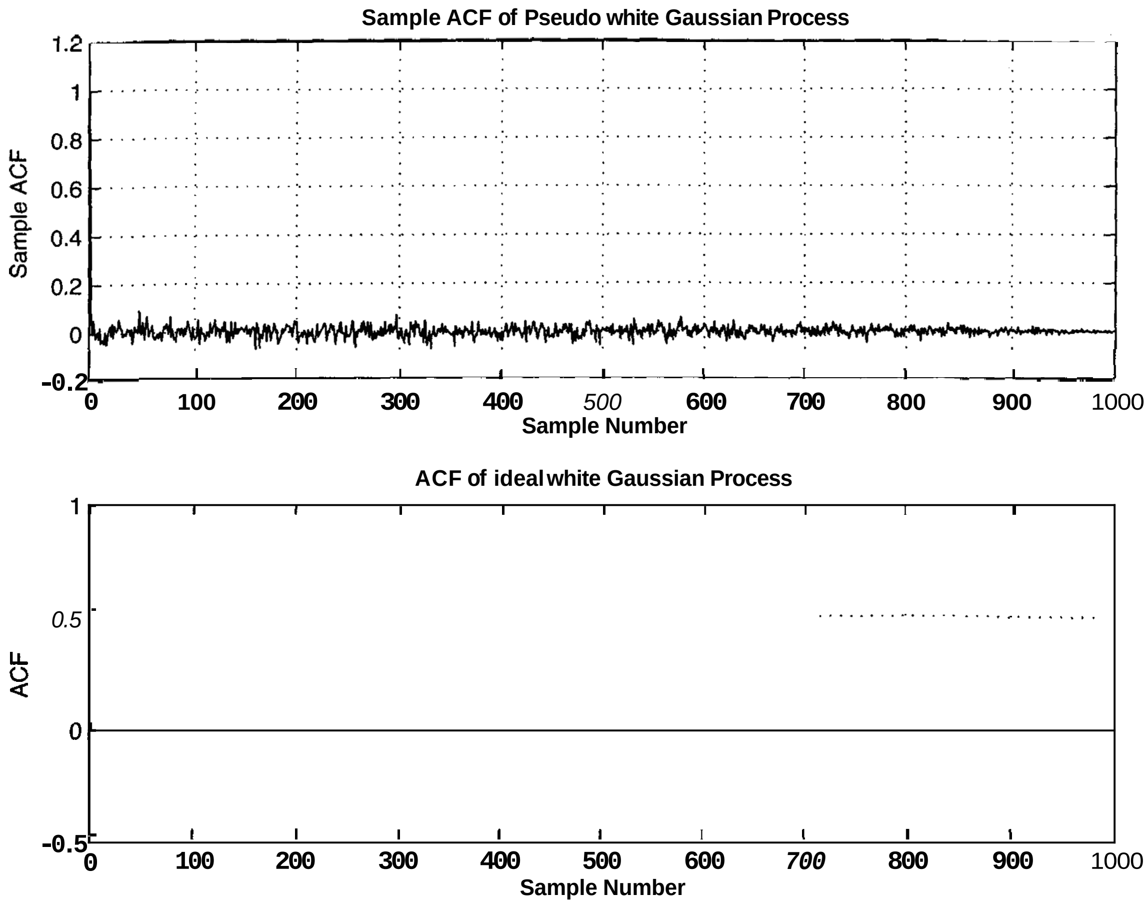

Figure 2-3: ACF of Pseudo and ideal white Gaussian Process

The ACF can be considered to be a measure of whiteness of a random process. If the sample ACF of a set of test data is quite similar to those in Figure **2-3,** then it can be modeled as white noise. Note that different data can have identical sample ACF. Many types of ideal white noise have exactly the same ACF as shown in the second plot of Figure **2-3.** And several forms of pseudo white noise have sample ACF's that are very similar. Furthermore, it is difficult to interpolate the data according sample ACF especially when it shows that the data are highly correlated (Jenkins, 1968). By visually observing the data and looking at the histogram, sample ACF can still be useful in modeling.

In the following sections, we will compare histograms and sample ACF's of our test data with the pseudo white Gaussian process in order to estimate how close our sensor outputs are to a white Gaussian process. **By** comparing the histograms and sample ACF's of the test data and model based data, we will show how close our models to the real sensor systems.

GPS Noise Characteristics and Noise Models

GPS Noise Characteristics (Bennett, 1996; Farrell, 1996; Christie, 1996; Grewall, et al, 1996; Kobayashi, et al, 1994,1995; Phillips, et al, 1996; Schonberg, et al, 1996)

The predominant sources of error in GPS measurements are: satellite clock error, ephemeris error, receiver errors, and atmospheric/ionospheric delay. In addition, the accuracy of GPS can purposefully be degraded by the **U.S.** Department of Defense (DoD) using an operational mode called "Selective Availability" or "S/A". S/A is designed to deny hostile forces the tactical advantage of GPS positioning. When, and if, it is implemented it will be the largest component of GPS error. Differential GPS measurements are potentially much more accurate than standard GPS measurement. The main idea of DGPS is the following. If we put a GPS receiver on the ground in a known location, we can use it to figure out exactly the errors the satellite data contains. Acting like a static reference point, it can then transmit an error correction message to any other GPS receivers that are in the local area, and they can use that error message to correct their position solutions. The correction can eliminate virtually all error in their measurements.

Common Mode Errors	Standard Deviation
Selective Availability Ionosphere Clock and Ephemeris Troposphere	24.0m 7.0m 3.6m 0.7m
Non-common Mode Errors	
Receiver Noise Multipath	

Table 2-1: GPS System Error due to Noise Sources

The two basic outputs of a GPS receiver are pseudo-range and carrier phase data. **A** dual frequency receiver outputs range and phase measurement for each carrier frequency. These four outputs and combinations thereof then provide useful signals needed for accurately calculation of the measured distance. Table **2-1** summarizes the main error sources and their standard deviation in a GPS system for a single receiver. The common mode errors are errors that are common to every receiver in a local region. The non-common mode errors are errors depending on specific receivers. Because they vary significantly for different types of receivers, ranges were not assigned. By combining several advanced GPS techniques, e.g., DGPS, narrow correlator technology, carrier phase tracking and carrier smoothing, and carrier cycle ambiguity resolution, the total error and noise can be reduced to a few centimeters or even less. In our experiment, two dual-frequency GPS receivers were installed on the two cars respectively.

Besides the error sources summarized above, there are also three practical problems with a GPS system used in AVCS. The first is that the signals from the satellites could be blocked by tall buildings, tunnels, overpasses, etc. If this occurs, the GPS receiver may not be able to receive enough information to enable a calculation. Another problem is that

GPS data arrive at a relatively low frequency. We have to synchronize GPS outputs with other sensors. Finally, the low data update rate is undesirable for highly dynamic systems.

A Simple Model of GPS Data

The residual of the three sets of static test data, their histograms, and their sample ACF's are shown in Figure **2-4.** A simple noise model of GPS data is obtained **as** following by considering the residual of the data as zero mean, white Gaussian noise.

$$y(n) = x(n) + 0.002a r_g(n);$$

where

$x(n)$ is the true distance we are measuring,

$y(n)$ is the **GPS** sensor output,

$r_g(n)$ is white Gaussian random process, $r_g(n) \sim N(0,1)$ at each time n,

$a = 1.0$ if five or more than five satellites are available,

$a = 2.5$ if four satellites are available.

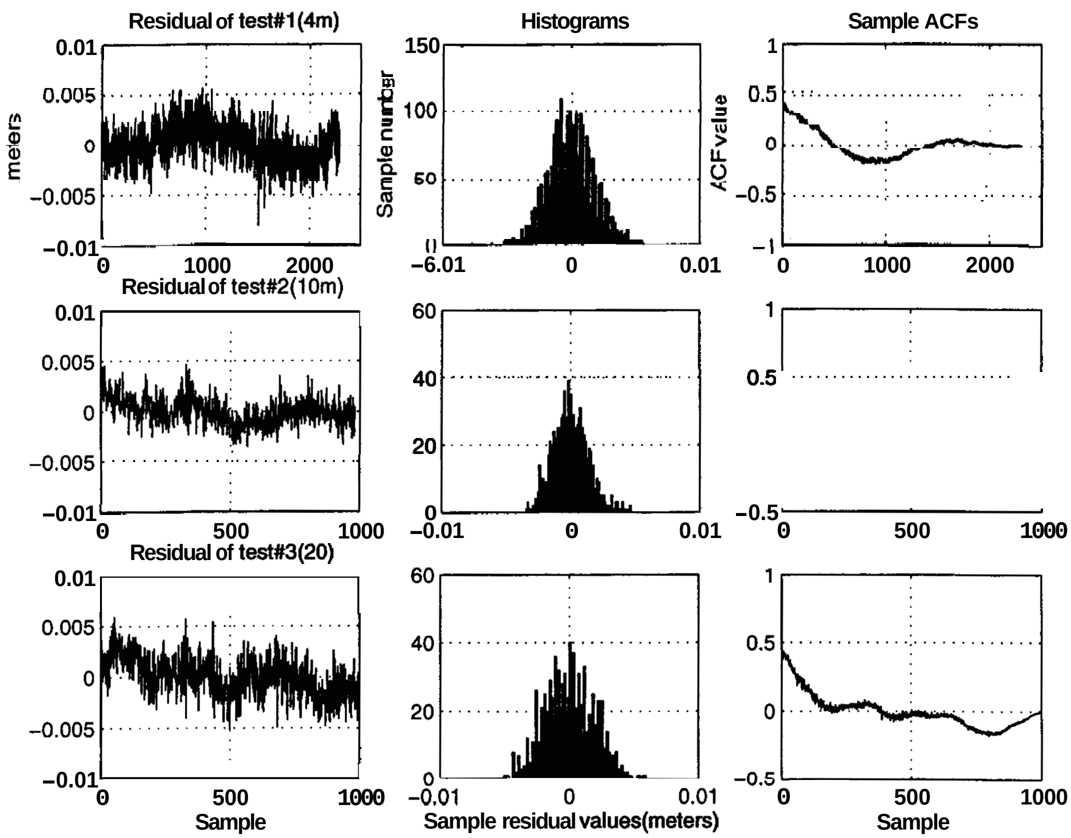

Figure 2-4: Residual of three sets of static test GPS data

From the sample ACF plots shown in Figure 2-3, it can be seen that the ACF of this simple model does not approximate the test data very closely. However, because the residual is quite small, using this simple model would not seriously detract most of the time. To increase accuracy, a more complex model is developed in the following.

A Complex Model of GPS Data

A relatively complex noise model of GPS data can be developed by observing all of the static test residuals in Figure **2-4.** From the residuals, one notices that besides the high frequency noise, there are also some low frequency variations occurring in a random manner. The high frequency noise is modeled as zero mean, white Gaussian noise. The low frequency variation is modeled as a cosine wave with a random period and a random initial phase.

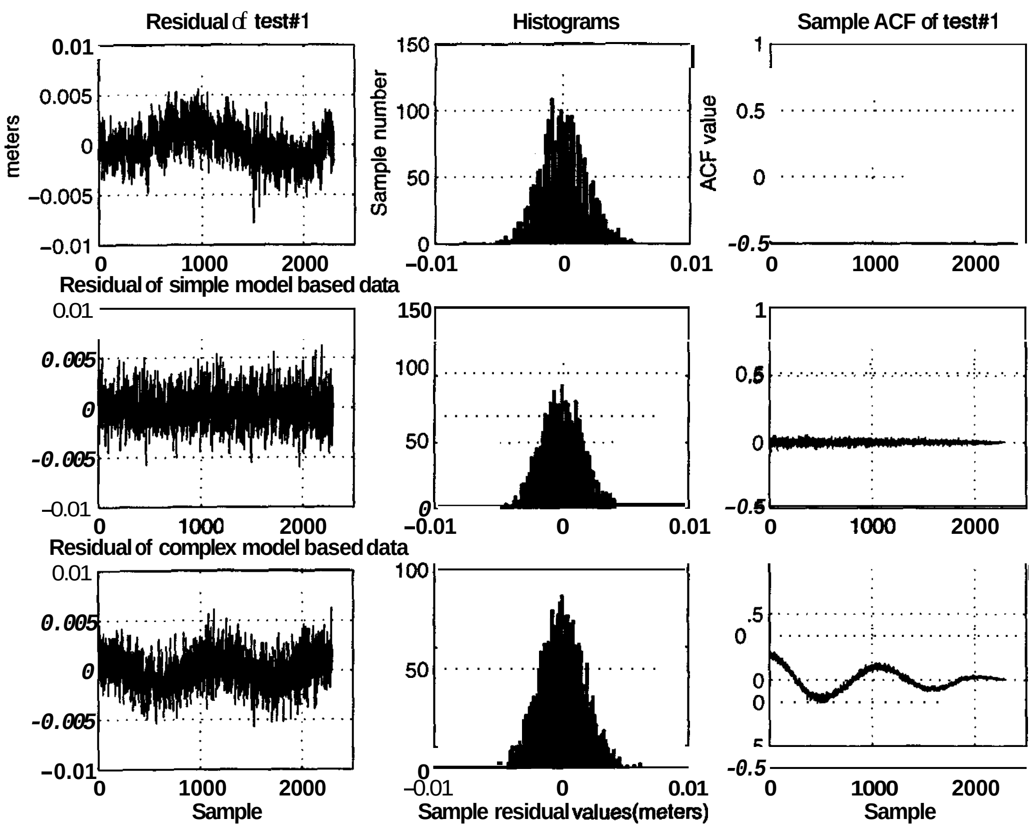

Figure 2-5: Comparison of GPS test data and model based data

Based on these observations, the model is developed as

$$y(n) = x(n) + a(0.0015 r_g(n) + 0.0012\cos(2\pi n / r_u + \phi_0))$$

where

$x(n)$ is the true distance we are measuring,

$y(n)$ is the GPS sensor output,

$r_g(n)$ is the white Gaussian random process,

r_g(n) $r_g(n)$- N(0,1) at each time n,

$a = 1.0$ if five or more than five satellites are available,
$a = 2.5$ if four satellites are available,
$r_u \sim U(1200,2000)$ is the random period of the low frequency variation,
$\phi_0 \sim U(0,2\pi)$ is the initial phase,
and U denotes a uniform distribution.

From Figure 2-5, although it can be seen that this model is not exact since its sample ACF still differs from those of the test data, it is similar. The goal for the sensor model is not to regenerate the exact test data, but to generate model sensor readings statistically similar to the real test data to serve for the control system simulation. Therefore, we do not restrict ourselves to an exact match between test and model based data, Actually, from the three sets of test data it can be seen that their ACF's differ as well.

Radar Sensor and Noise Model

Radar Sensor

Radar (Microwave Radio Detection and Ranging) sensors measure the signal reflected back from an object. In AVCS, the radar sensor is used to measure distance and movement of vehicles via the Doppler effect. It transmits electromagnetic energy toward a target and studies the time arrival and the Doppler frequency shift of the reflections in order to calculate the distance from the target. The measurement signal is the round trip time, which depends on the distance of the object and the strength of the echo. One benefit of the radar sensor is that it can detect targets under all weather conditions. The range accuracy of a simple pulse radar depends on the width of the pulse it transmits, which has a trade-off with the bandwidth requirement of the receiver and transmitter. The radar used in the experiment has a range of 30 meters and operates at a frequency of 24GHz. The output data is 50Hz and the records were taken at 10Hz in the test.

Noise Model of Radar Sensor

The radar model we developed and show here is based on the test data under the calibration of scale: 13942.410 meters/voltage and offset: 0.1168 meters.

$$y(n) = x(n) + (0.0048 + 0.004x(n))r_g(n);$$

where

$x(n)$ is the true distance we are measuring,
$y(n)$ is the radar sensor output,
$r_g(n)$ is white Gaussian random process, $r_g(n) \sim N(0,1)$ at each time n.

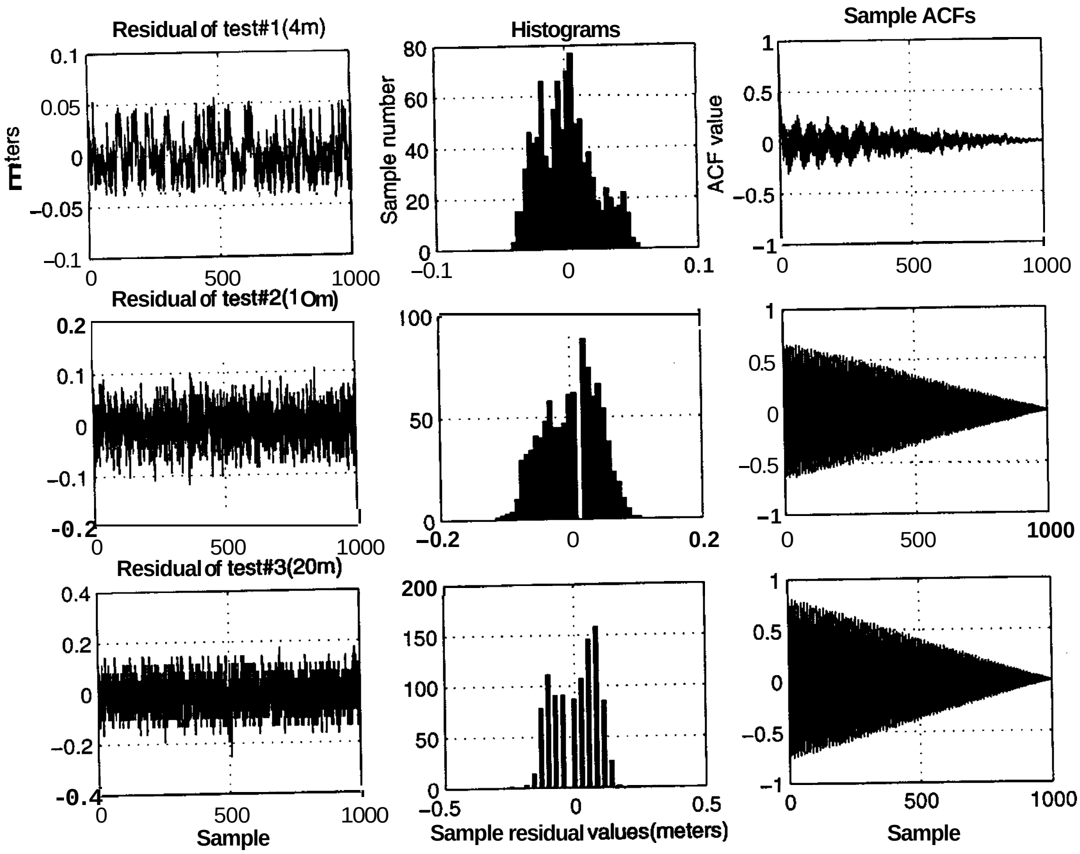

Figure 2-6: Residual of three sets of static test Radar data

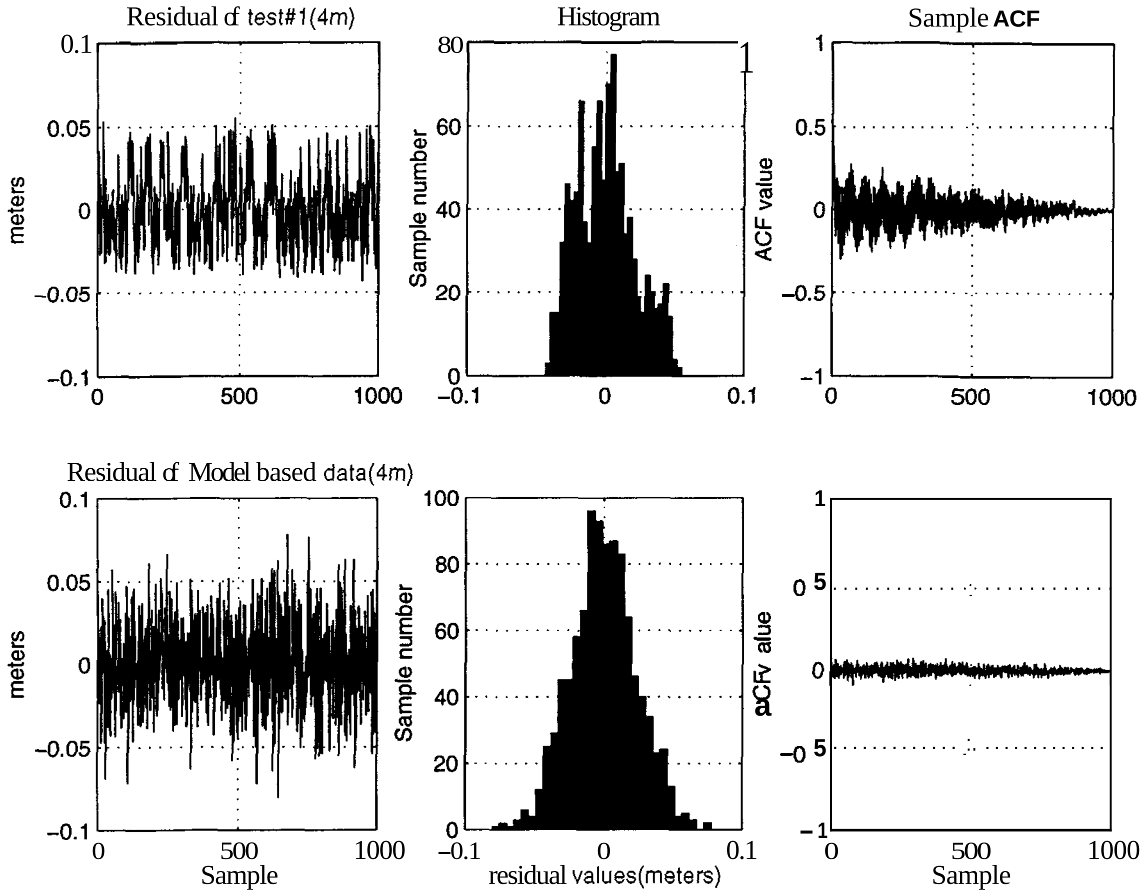

Figure 2-7: Comparison of radar test data and model based data

From Figure 2.7, it can be seen that the sample ACF's of radar test data and model based data are not quite similar. A model which has an ACF similar to that of the radar test data is difficult to obtain and would be very complex. Here a white Gaussian process with a variance changing with the measured distance is used to roughly model the radar outputs.

Linear Transducer and Noise Model

Rayelco Linear Transducer

A Rayelco transducer is a linear motion transducer used to measure movement by means of a stainless steel cable which extends from the transducer and attaches to the object to be measured. At the transducer, the cable is wound around a spring loaded drum, which rotates a sensor within the transducer when the cable is extended. The transducer provides an electronic signal consistent with the cable's movement which is exactly the object's movement. Since the transducer is installed in one car and one end of the cable is physically attached to the other car, this sensor would not be used in a real world automatic highway system. However, because it is quite simple and accurate, it can be used in tests as **a** reference positioning sensor. The transducer we used in the experiment can measure distance **up** to approximately 15 meters and has an accuracy of about 0.1%.

The output data were available at 50Hz, and to minimize the storage required, we sampled them at 10Hz.

Noise Model of Rayelco Transducer

The following model of Rayelco transducer is under the calibration of scale: 1.229 meters/voltage and offset: -0.0151 meters.

$$y(n) = x(n) + 0.003k(n);$$

where

$x(n)$ is the true distance we are measuring,

$y(n)$ is the radar sensor output,

$$k(n) = \begin{cases} -5 & \textbf{\textit{when}} \quad 0 \le r_u(n) < l_1; \\ -4 & \textbf{\textit{when}} \quad l_1 \le r_u(n) < l_2; \\ -3 & \textbf{\textit{when}} \quad l_2 \le r_u(n) < l_3; \\ -2 & \textbf{\textit{when}} \quad l_3 \le r_u(n) < l_4; \\ -1 & \textbf{\textit{when}} \quad l_4 \le r_u(n) < l_5; \\ 0 & \textbf{\textit{when}} \quad l_5 \le r_u(n) < l_6; \\ 1 & \textbf{\textit{when}} \quad l_6 \le r_u(n) < l_7; \\ 2 & \textbf{\textit{when}} \quad l_7 \le r_u(n) < l_8; \\ 3 & \textbf{\textit{when}} \quad l_8 \le r_u(n) < l_9; \\ 4 & \textbf{\textit{when}} \quad l_9 \le r_u(n) < 1. \end{cases}$$

where

r_u is a random variable uniformly distributed on [0,1] and l_i's are got as following:

$$r_1 = 0.0055; r_2 = 0.1425; r_3 = 0.1121;$$
$$r_4 = 0.0975; r_5 = 0.0985; r_6 = 0.1015;$$
$$r_7 = 0.1067; r_8 = 0.1249; r_9 = 0.1828;$$
$$r_{10} = 0.0280.$$

and

$$l_1 = r_1; l_2 = l_1 + r_2; l_3 = l_2 + r_3;$$
$$l_4 = l_3 + r_4; l_5 = l_4 + r_5; l_6 = l_5 + r_6;$$
$$l_7 = l_6 + r_7; l_8 = l_7 + r_8; l_9 = l_8 + r_9.$$

By observing the residual of the three sets of static test data, it can be seen that the output of the transducer was quantized uniformly into 10 different layers (shown in the histogram plots of Figure 2-8). The set $\{r_i, i = 1,\ldots,10\}$ was obtained by calculating the average percentages of the sample number distributed in every layer of the three sets of static test data. The sample ACF shows that the noise is quite close to white, meaning that samples at different times have almost the same probability distributions of being at the ten different layers. For this reason, a uniformly distributed random process can be used for $r_u(n)$.

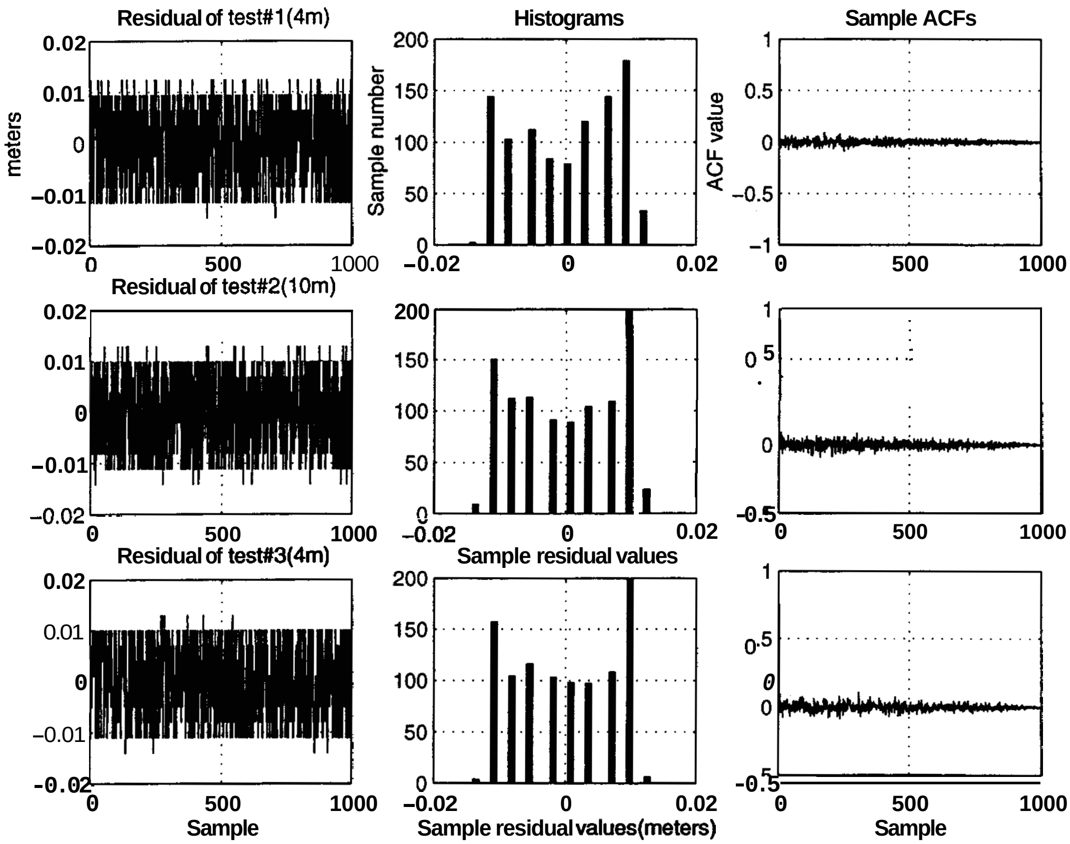

Figure 2-8: Residual of three sets of static test linear transducer data

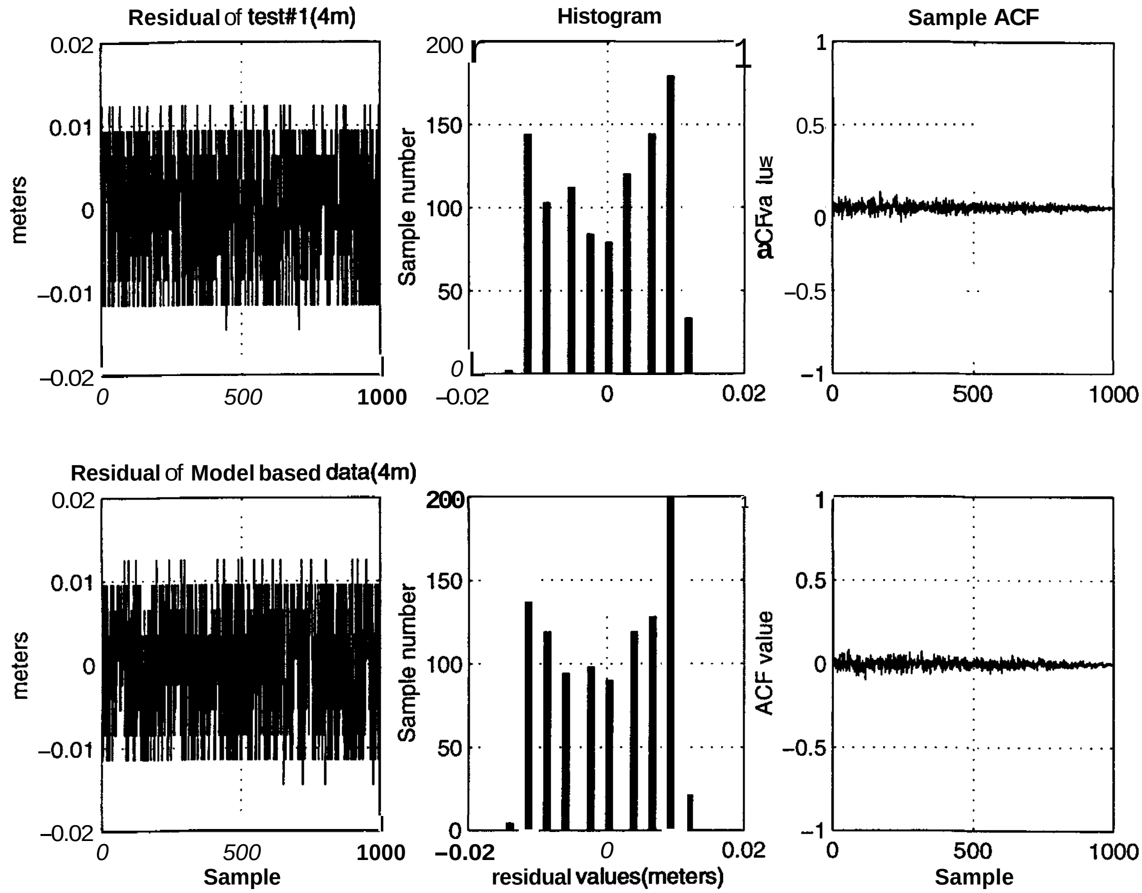

Figure 2-9: Comparison of linear transducer test data and model based data

Comparing the test data and the model based data, this model is quite accurate in the sense that the model based data have histograms and sample **ACF** which are very similar to those of the test data.

Chapter 3 Fusion of GPS with Radar and Linear Transducer Data

In this chapter, two types of sensor validation and fusion algorithms are applied to portions of the test data of the three sensors discussed in Chapter **2.** This sensor validation and fusion is conducted in order to evaluate performance of the fusion schemes when the GPS sensor is integrated. **A** closed loop simulation is also performed using the sensor models from Chapter **2.** 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).

Sensor outputs synchronization

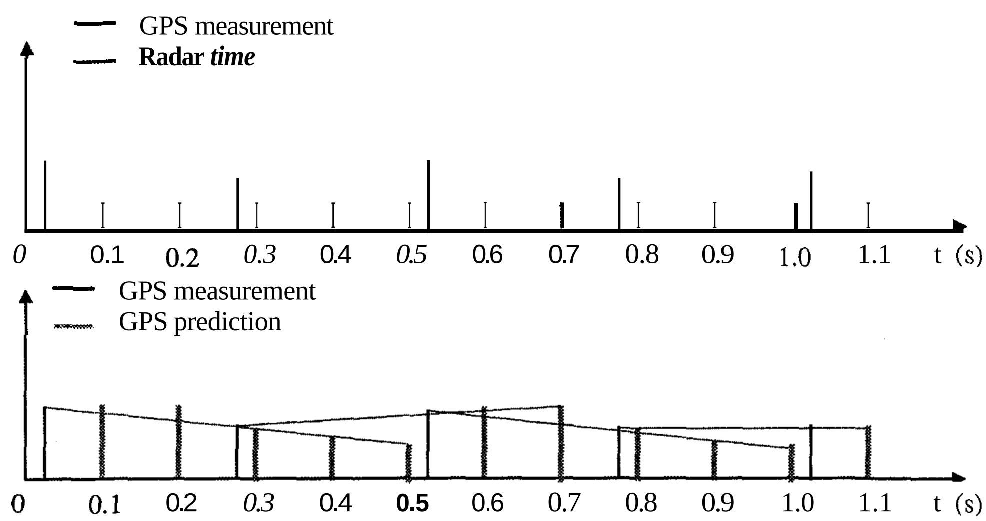

Figure 3-1: Sensor Output Synchronization Scheme

In this project, 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 time reference and tried to interpolate GPS data at 4 **Hz** into these time stamps. The simplest synchronization would occur at each time stamp, taking the closest value of the GPS data as the predicted GPS output at that time stamp. Because we need to do the synchronization online, we have access to only the past data, so the most recent GPS output could be used as the current GPS output prediction. However, the delay introduced by this manner of synchronization is undesirable for most dynamic cases. Therefore in order to accommodate dynamic cases, a linear predictor is used 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 most recent two measurements we have from GPS system. Then the predicted value of the GPS output at time t is just:

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

The geometry of the synchronization scheme is shown in Figure **3-1.** Although this method may be suboptimal, its strengths are evidenced by its easy and straightforward application. It will be used in following sections.

An adaptive method

The difficulty with the above simple method is its noise amplification, especially when the vehicle decelerates. Notice that there are two terms in the equation for the simple method. When the vehicles are at high velocity, ideally the second term would be large since the dynamic part is derived mainly from the speed. On the other hand, when the vehicles run slowly, we want the second term to be small since the dynamic part mainly comes from the noise. Based on the simple method presented above, an adaptive method is created by adding a parameter K on the second term of the equation. It becomes

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

For the GPS data, since the variance of the noise is quite small, we can just set a threshold for K at $|(x(n) - x(n-1))/(t, -t_{n-1})| = 0.05$ meters. If $|(x(n) - x(n-1))/(t, -t_{n-1})| > 0.05$, we set $K = 1.0$. Otherwise, $K = 0.2$.

However, to for generalization, we need to design different curves of K for different sensors. A general curve of K could be designed by a window function with an exponential function on each side. **An** exponential function would also be used on the right side due to the possibility that some sensor readings might have undesirable outliers.

Overview of two kinds of fusion algorithms--- PDAF and FUSVAF

Two types of validation and fusion schemes were developed by BEST laboratory members, Satnam Alag and Kai Goebel, for their Ph.D projects (Alag, 1996; Goebel, 1996). A common flow chart of the two methods is shown in Figure **3-2.**

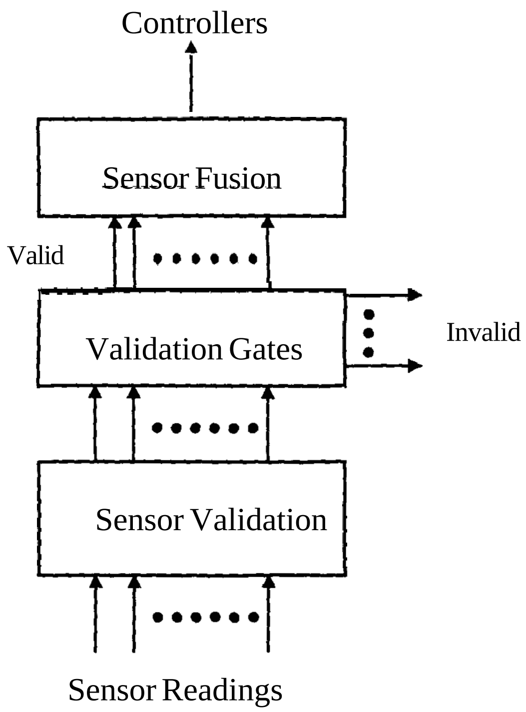

Figure 3-2: Sensor Validation and Fusion Scheme

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 discard most of the noise from the sensor readings and ***make*** the sensor system robust 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 out of the gates are considered to be invalid sensor measurements and would be rejected. Each valid sensor measurement is then assigned a confidence value (or a probability value) indicating to what degree they could be believed according how far they are from the predicted value. In the fusion block, we calculate the fused value by taking 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 is valid at a time, the predicted value could be taken as current fused value.

In PDAF, a rule-based system is used first to find out 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 sensors. Probabilities are assigned to each sensor based on a Gaussian validation curve. **PDAF** works well for zero mean, white, Gaussian noise because it is based on Kalman filtering. However, it is not as ideal when other types of noise are present (Bar-Shalom, 1993).

In FUSVAF (Goebel, 1996), 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 could 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 (Khedkar, 1992), a prerequisite for PDAF. In addition, it has great flexibility in the choice of validation gates.

Comparison of the fusion results by the two algorithms

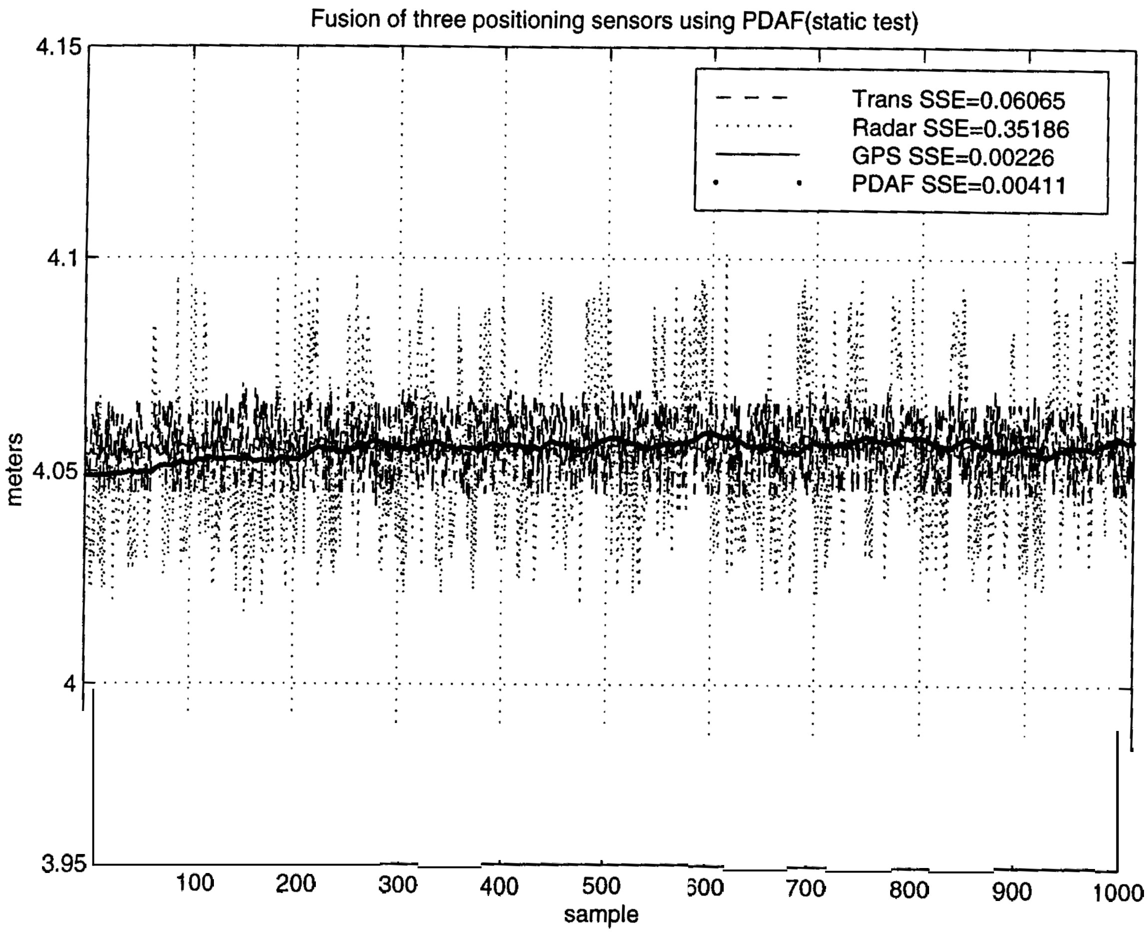

Figure 3-3: Fusion of three positioning sensors using PDAF(static test)

Figure 3.3 shows the fusion of the three sensors using one set of the static test data (4m test). The true distance between the centers of the two GPS receivers measured by a tape is about 4.06 meters. Millimeter level accuracy could not be achieved by a tape. Because the mean values of the GPS and the transducer data are both about 4.057meters, we took 4.057 as the true distance. Sum of square errors **(SSE)** of 1000 data samples are calculated for each sensor and the PDAF fused output. According to the **SSE** values, the radar is the most noisy sensor among those tested. The linear transducer has noise with magnitude within 1 cm, which is quite accurate as expected. The GPS data are quite accurate, with an **SSE** value is even less than that of the fused output.

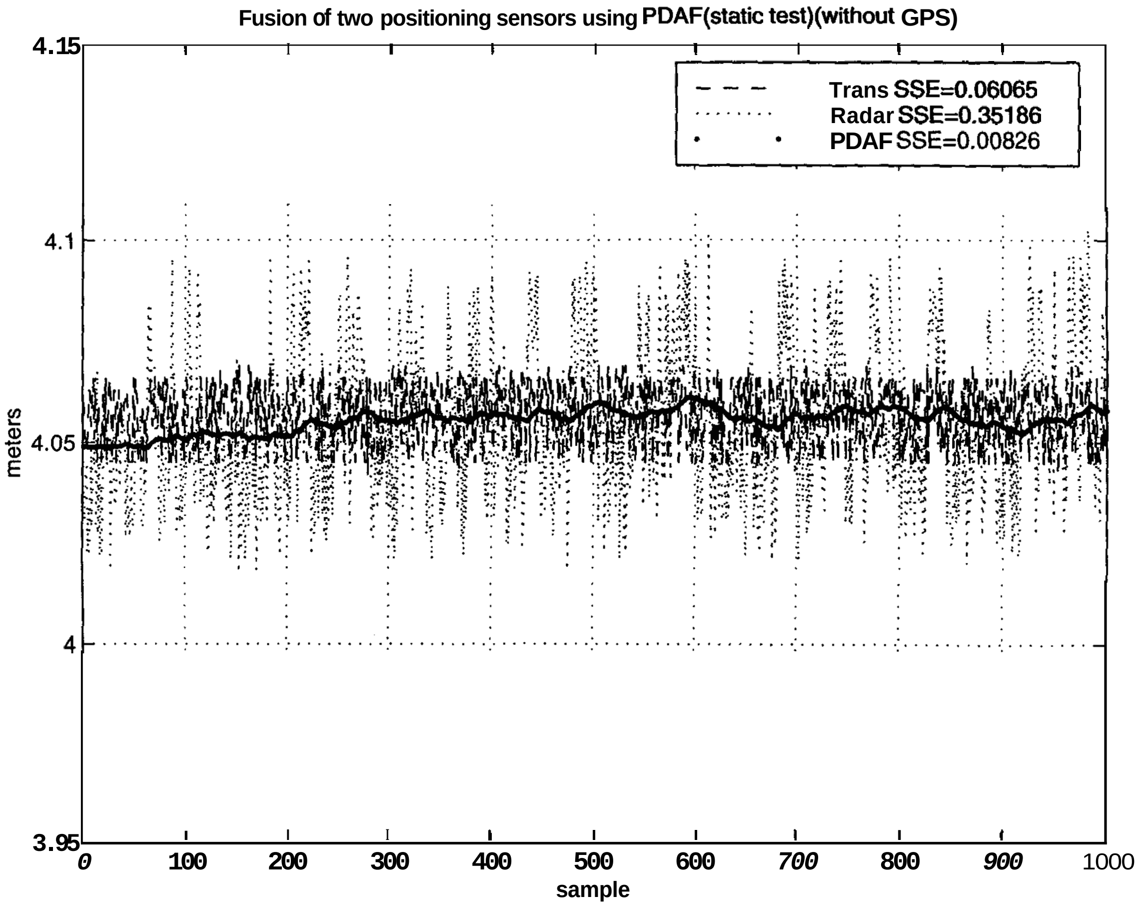

Figure 3-4: Fusion of two positioning sensors using PDAF(static test)(without GPS)

Figure **3.4** shows the fusion **of** two sensors using exactly the same radar and transducer data as in Figure 3-3. Comparing Figures 3-3 and 3-4, it can be seen that without GPS outputs, the fusion results slightly worsen. The PDAF fusion **SSE** value increases from 0.00411 to 0.00826 m^2. From this, we conclude that fusion of radar and transducer data using PDAF results in decent accuracy, and the integration of GPS outputs would enhance that accuracy.

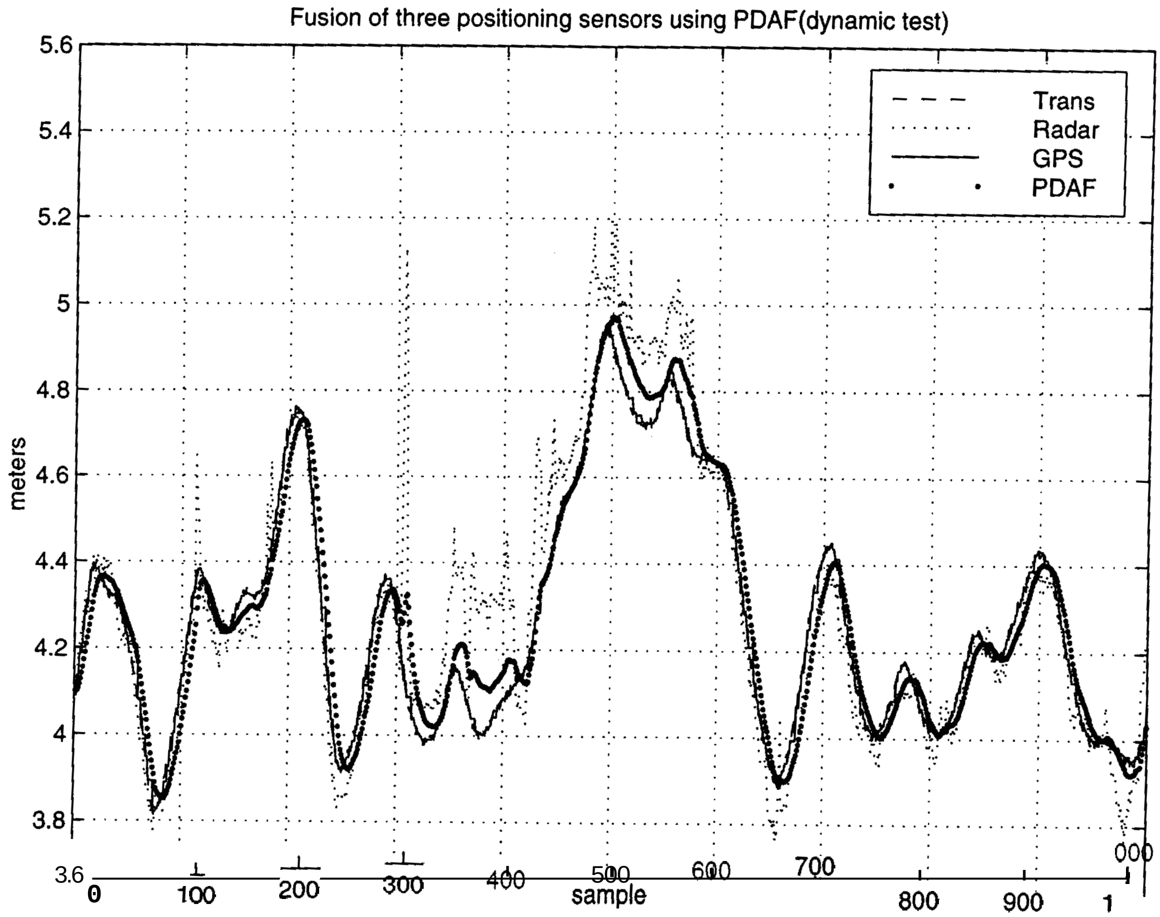

Figure 3-5: Fusion of three positioning sensors using PDAF(dynamic open loop test)

Figure 3.5 shows the fusion of three sensors using one set of dynamic test data. Here, we avoid the use of values like **SSE** to evaluate the performances of sensors and the fused outputs since we do not know the true distance for the dynamic case. But as expected, GPS and transducer data are reasonably similar. Radar readings contain more noise. The fused output is quite close to GPS and transducer outputs. At times, the fused output appears to be corrupted slightly by noisy radar outputs.

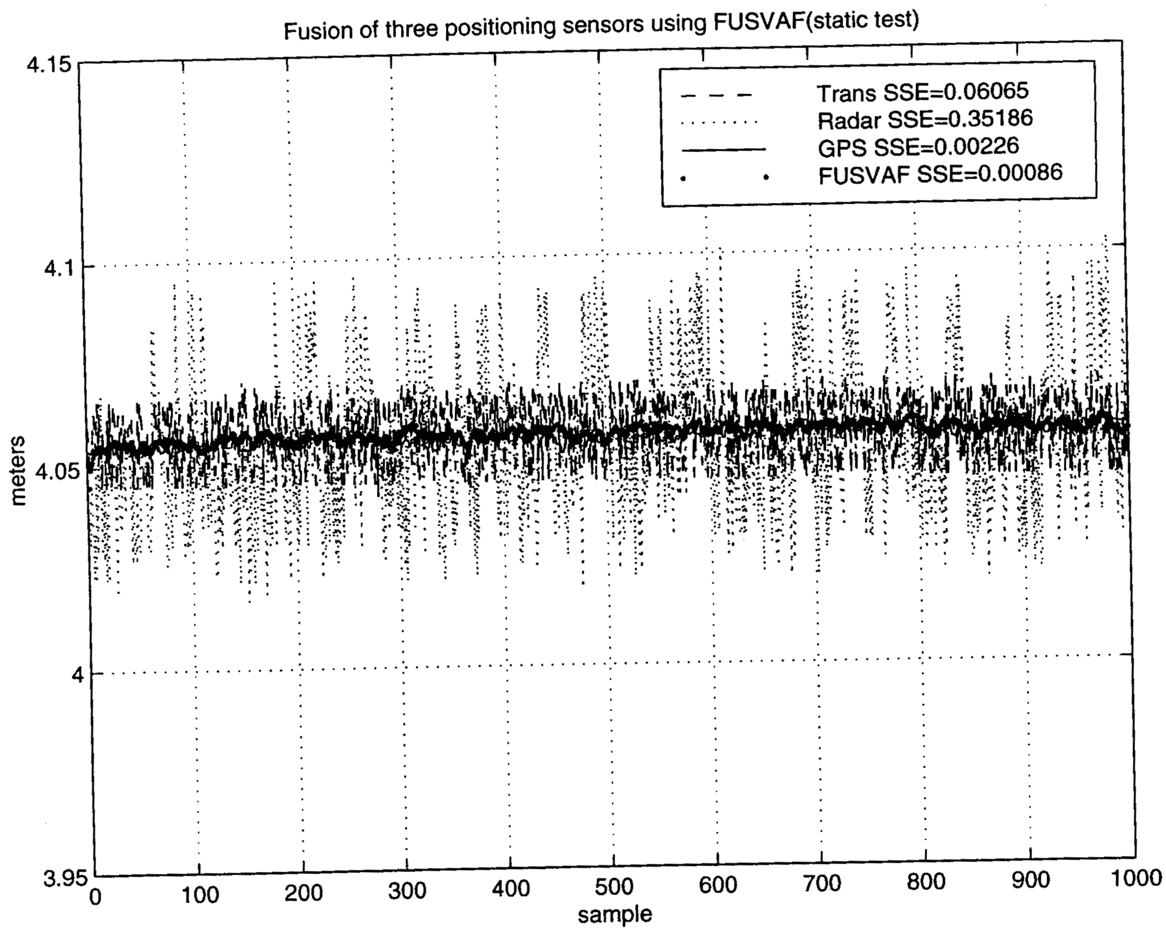

Figure 3-6: Fusion of three positioning sensors using FUSVAF(static test)

Figure *3.6* shows the fusion of three sensors using FUSVAF. The data used here are exactly the same as those in Figure 3-3. FUSVAF appears to be slightly more accurate than PDAF in the sense of **SSE.**

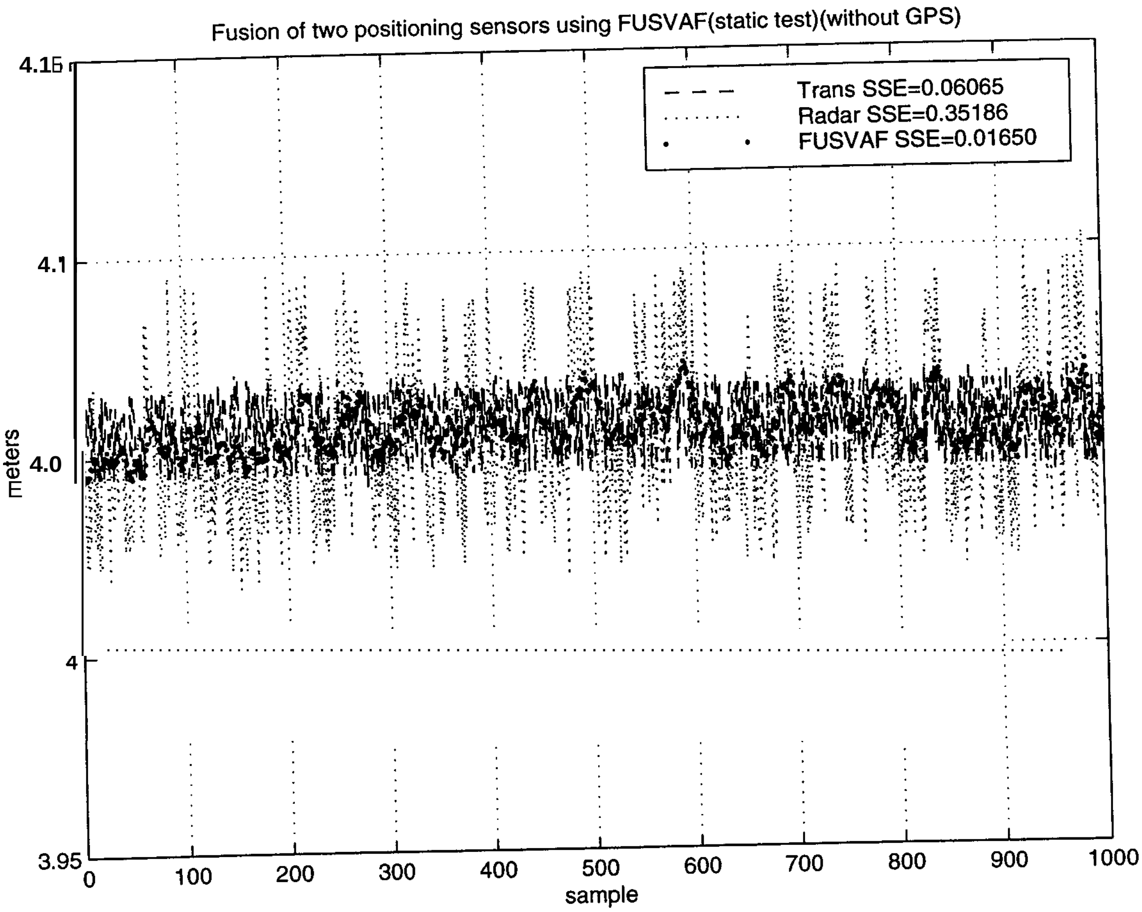

Figure 3-7: Fusion of two positioning sensors using FUSVAF (static test)(without GPS)

Figure 3-7 shows how FUSVAF behaves without GPS readings. Compared with Figure 3-4, whose results use the same sensor test data, the performance of **FUSVAF** in this case appears to be worse than that of PDAF.

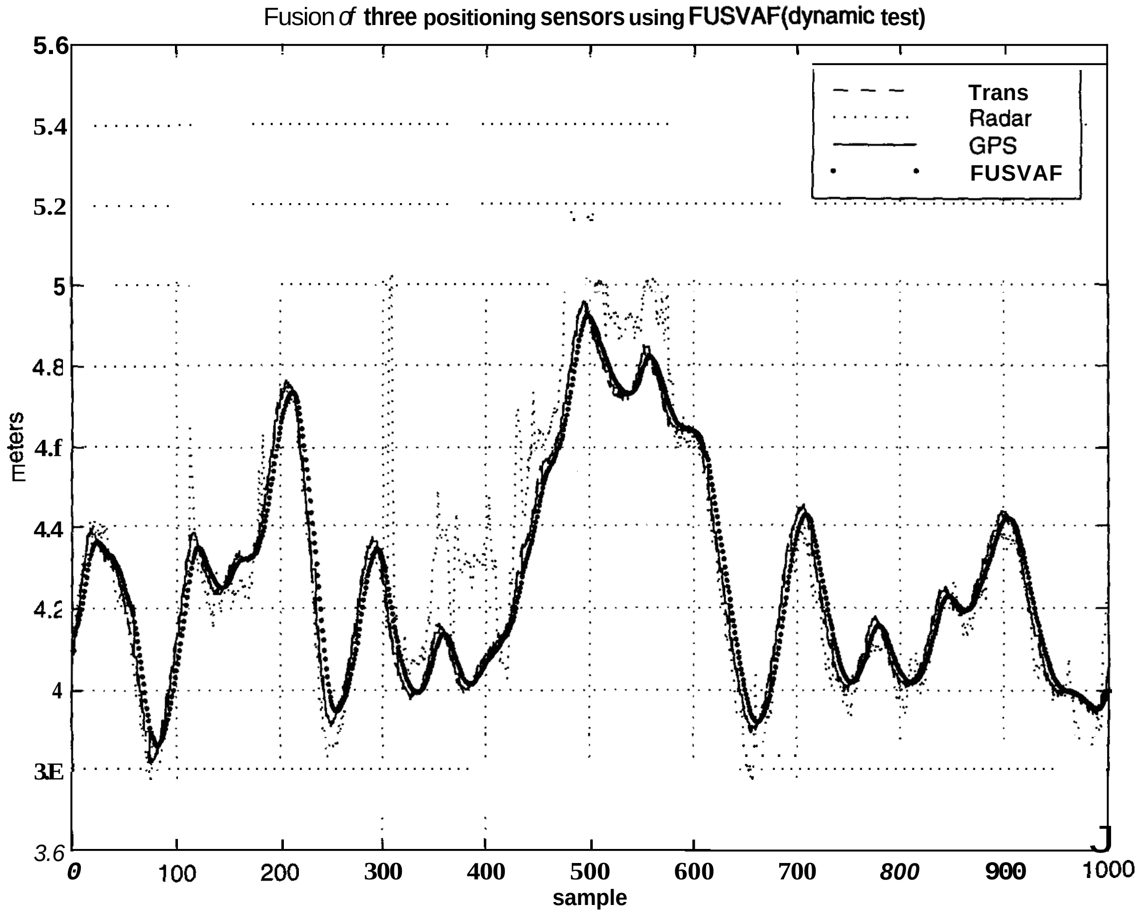

Figure 3-8: Fusion of three positioning sensors using FUSVAF(dynamic open loop test)

Looking at Figures **3-8** and 3-5, the fused outputs of FUSVAF are closer to the **GPS** and transducer outputs than PDAF. This evidences higher FUSVAF accuracy since **GPS** and transducer sensors are supposed to be more accurate than the radar.

Closed Loop Simulation

To this point we have developed the sensor models and implemented the two fusion algorithms using our open loop test data. Next we show how the fusion schemes work for the closed loop case when **GPS** sensors are integrated. Since we only consider steady-state, straight following motion of two cars, a simple PID can be used here for the follower control law. The control goal is to track the lead car to maintain the desired inter-vehicle spacing **of** D = **2** meters. 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. Quantity $d(i)$ is the distance between car $i-1$ and car i, which is precisely the quantity being measured with 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 $D=2$ meters. All units in the above equation are meters.

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

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

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

The controller parameters, c_p, c_v, c_a should be chosen (Godbole and Lygeros, 1993) such that

The transfer function H(s) is stable.
The impulse response h(t) is greater than zero for all t, to ensure no overshoots.
$\|H(j\varpi)\| < 1$, to any ϖ.

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

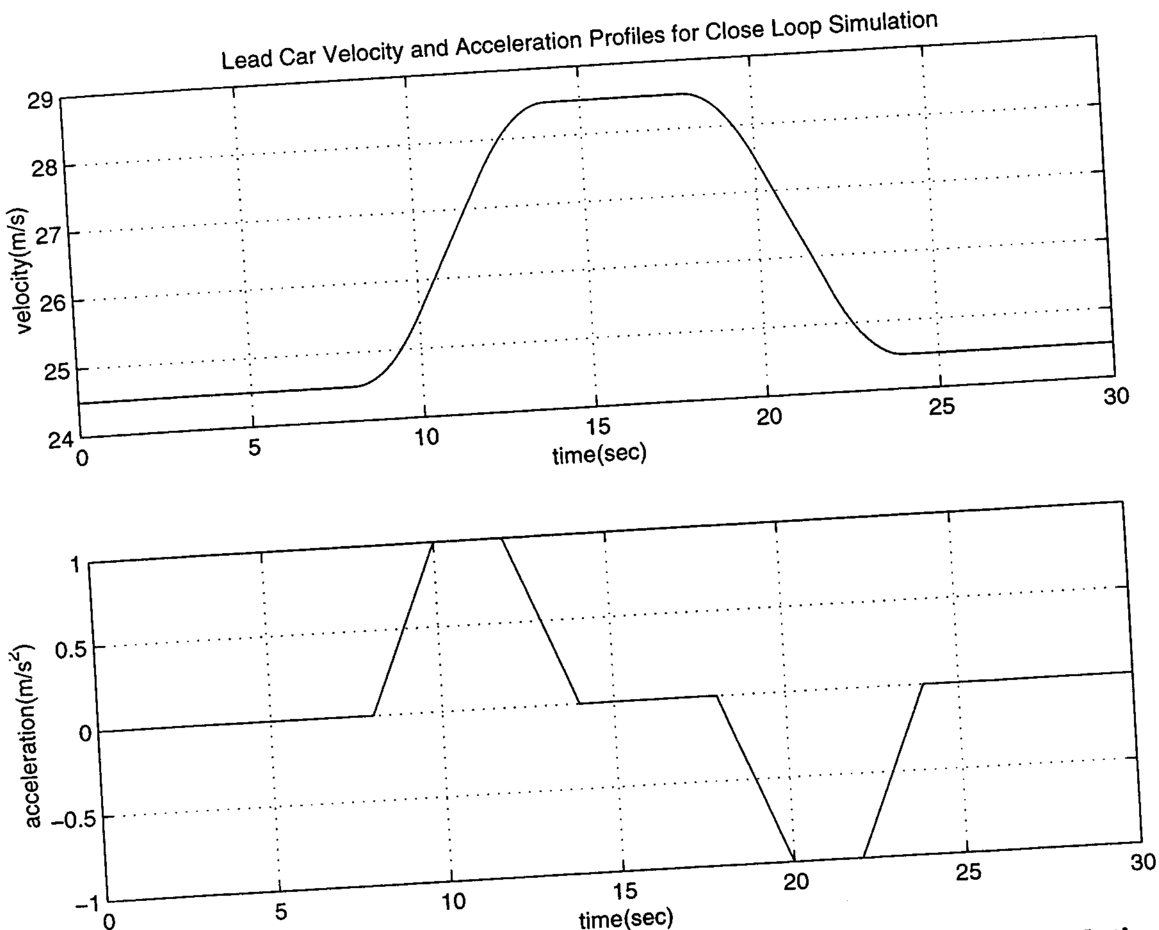

Figure 3-9: Lead car Velocity and Acceleration Profiles for Close Loop Simulation

Figure 3-9 shows the velocity and acceleration profiles of the lead car in the simulation.

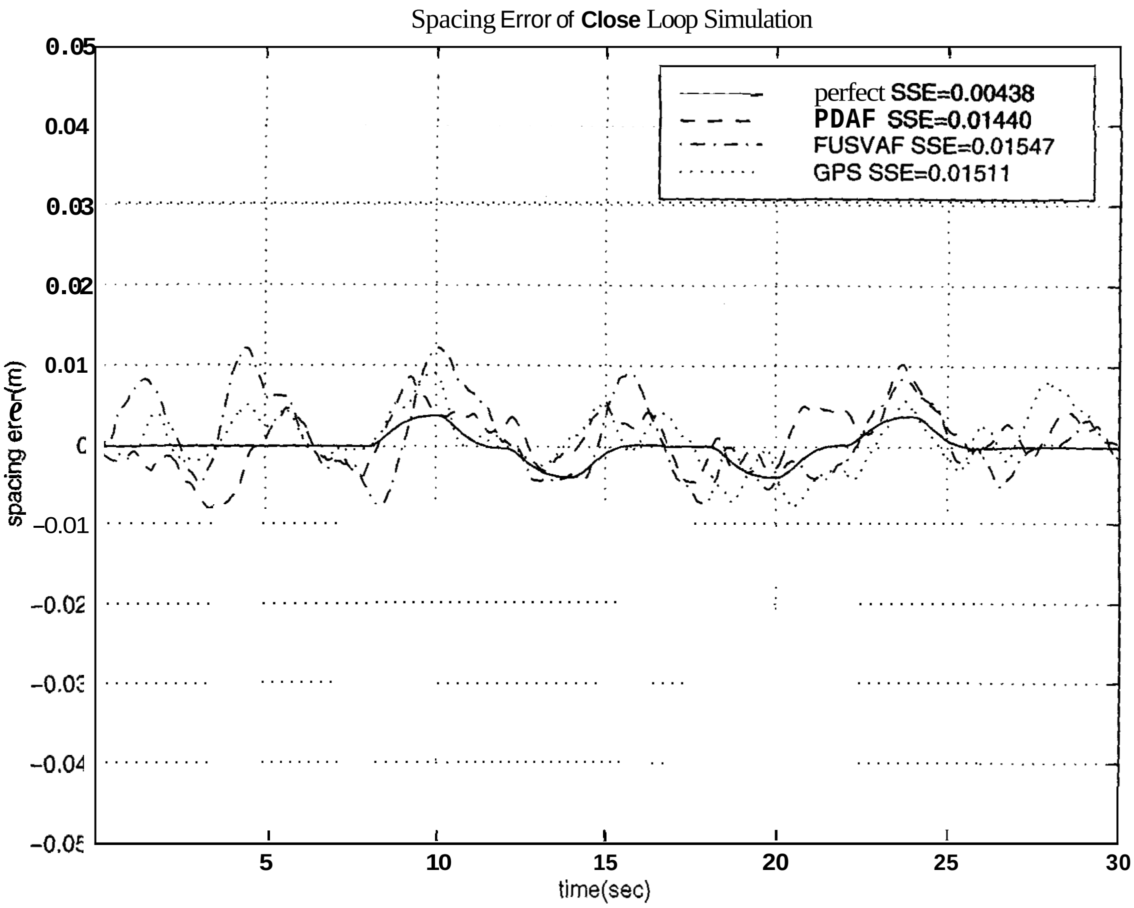

Figure 3-10: Simulated Spacing Error using different sensor fusion schemes

Figure 3-10 shows the simulated spacing error using different sensor fusion schemes. Note that the perfect curve refers to the case in which no noise is added, assuming an ideal case in which we have perfect sensors. Both PDAF and FUSVAF use the three sensor models (for GPS, the complex model is used) which we developed in Chapter **2.** 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 before it goes through the fusion algorithms. The GPS plot includes the **GPS** model based noise, with no sensor fusion schemes involved. Quantity **SSE** is the sum of squared spacing error of a 30 second simulation. Figure 3.10 shows the **SSE** values of one run. The **SSE** values might change slightly for every iteration of the simulation. For the perfect case, the **SSE** is 0.00438 m^2. For PDAF, **SSE** varies from 0.0120 to 0.0155 m^2. For FUSVAF, **SSE** varies from 0.013 to 0.017 m^2. And for **GPS** only, **SSE** changes from 0.013 to 0.0165 m^2. Generally speaking, in the sense of **SSE,** PDAF performs a little bit better than the FUSVAF and the GPS only case. FUSVAF and the GPS only case perform almost identically.

Chapter 4 VDL Simulation of Sensor Fusion Algorithms

Introduction

The VDL (Vehicle Dynamics and Longitudinal Control) software package (Yip, 1993) is a platoon simulation program which models inter-vehicle longitudinal spacing and was developed by the Vehicle Dynamics and Control Laboratory at UC Berkeley (Swaroop, 1994). Up to 9 cars in a platoon are modeled with adjacent spacing of 2 meters. The control objective is to maintain the desired spacing between adjacent cars in the platoon. The main file long_sim.c sets up the overall structure of the simulation and the time integration loop to update the state variables. After performing some initializations, it calls up the "controller" routine to update the controls. It then calls up the "rk4" routine to perform a fourth-order Runge-Kutta time integration to update the state variables. This time integration loop continues until the specified simulation end time is exceeded. For our case, we consider only the first car following the lead car, as shown in Figure 4-1.

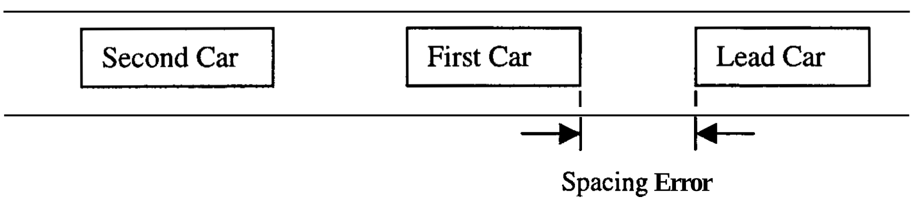

Figure 4-1: Platoon Longitudinal Control

Lead Car Profile

The lead car's position, velocity and acceleration profiles are given in Figures 4-2, 4-3, and 4-4. We can see that the lead car transitions from uniform velocity to acceleration and then decelerates back to uniform velocity.

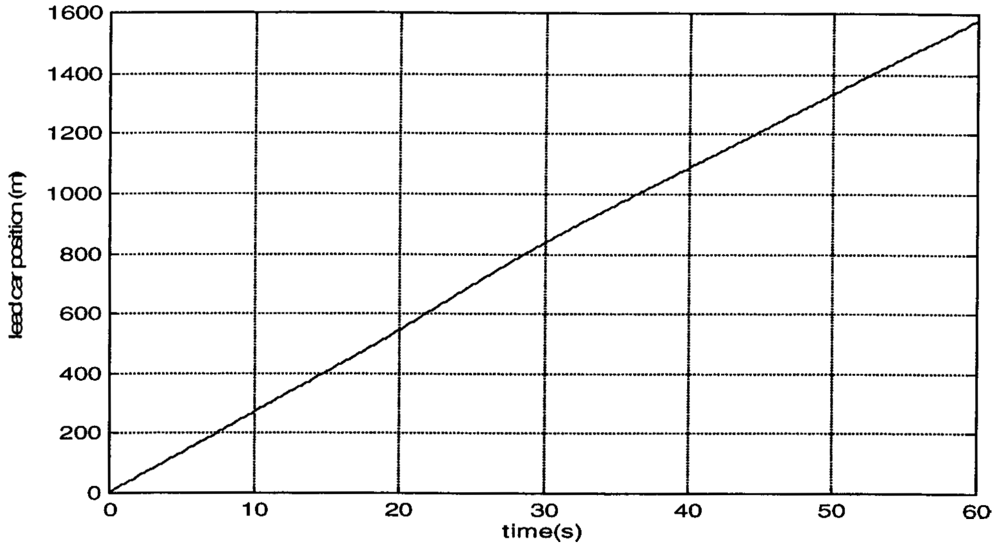

Figure 4-2: Lead car position profile

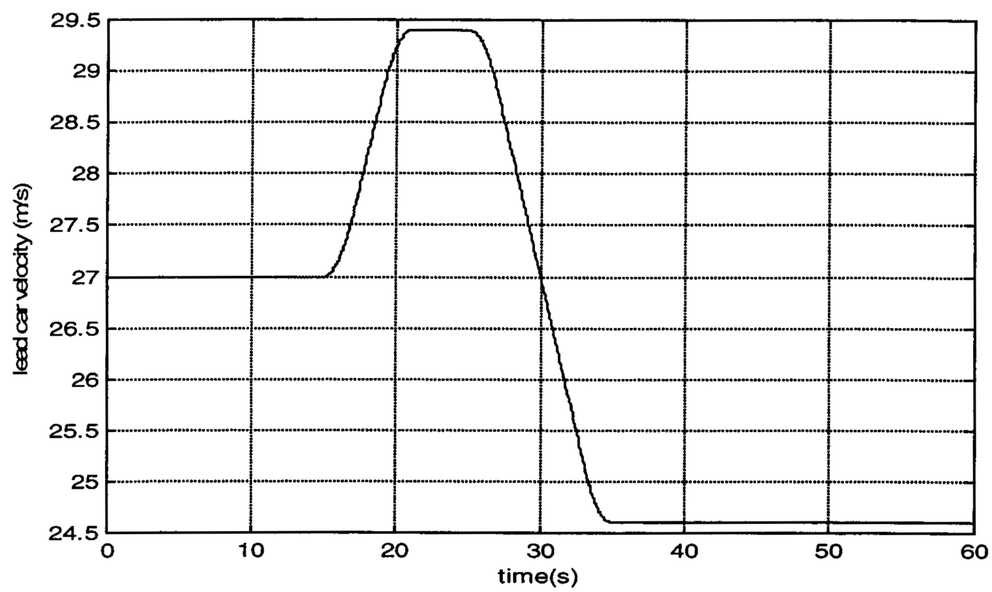

Figure 4-3: Lead car velocity profile

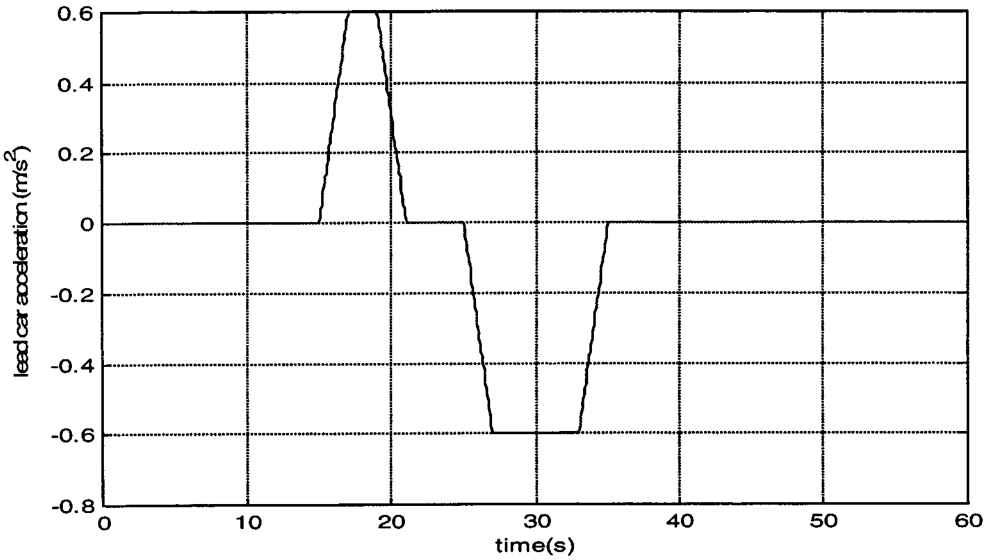

Figure 4-4: Lead car acceleration profile

Program Flow Chart

The program flow chart is depicted in Figure 4-5.

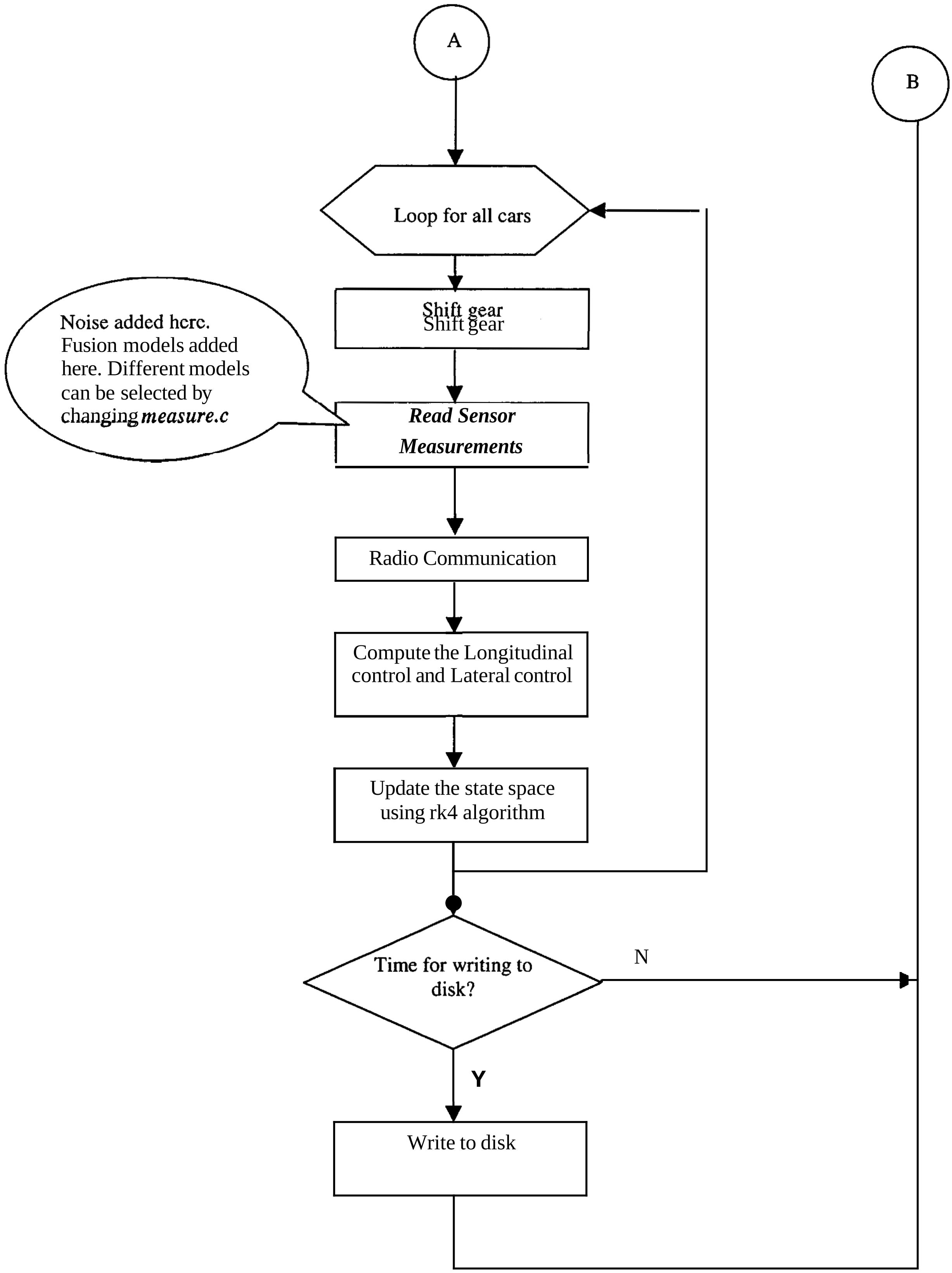

Figure 4-5: Program Flow Chart

Simulation Results

First we ran the simulation program with no sensor model but with sensor noise added to the position measurement. The spacing error is depicted in Figure 4-6.

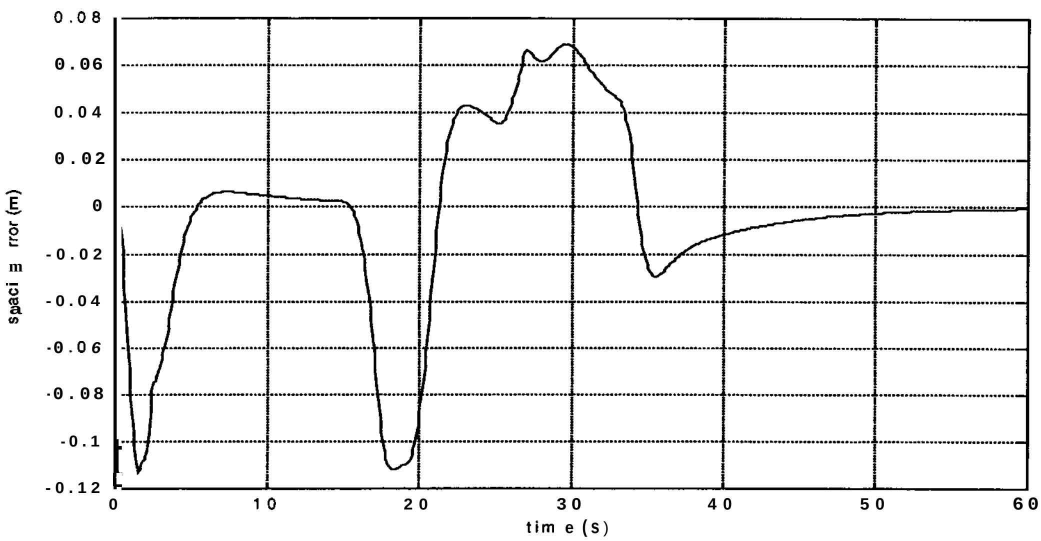

Figure 4-6: Spacing error without sensor noise

We can see that when the lead car is at constant speed, the spacing error is close to zero, when the lead car accelerates the spacing error decreases, and as the lead car decelerates the spacing error increases. Finally, spacing error converges to zero when the lead car returns to a constant speed.

When we integrate our sensor models into the program, the noise is added directly after the Runge-Kutta integration but prior to the controller. Three sensor models are added to the program named AddMeasureNoise.c. The **GPS,** radar, and Rayelco sensor noise effects on spacing error are illustrated in Figures 4-7, 4-8, and 4-9. We can see that noise was introduced into the spacing error measurement with similar magnitude for all three sensors. The average mean square errors for the three sensors are 2.4514e-4, 8.6954e-5, and 3.3520e-4, respectively. Note that the Rayelco sensor has the largest measurement noise while radar has the smallest.

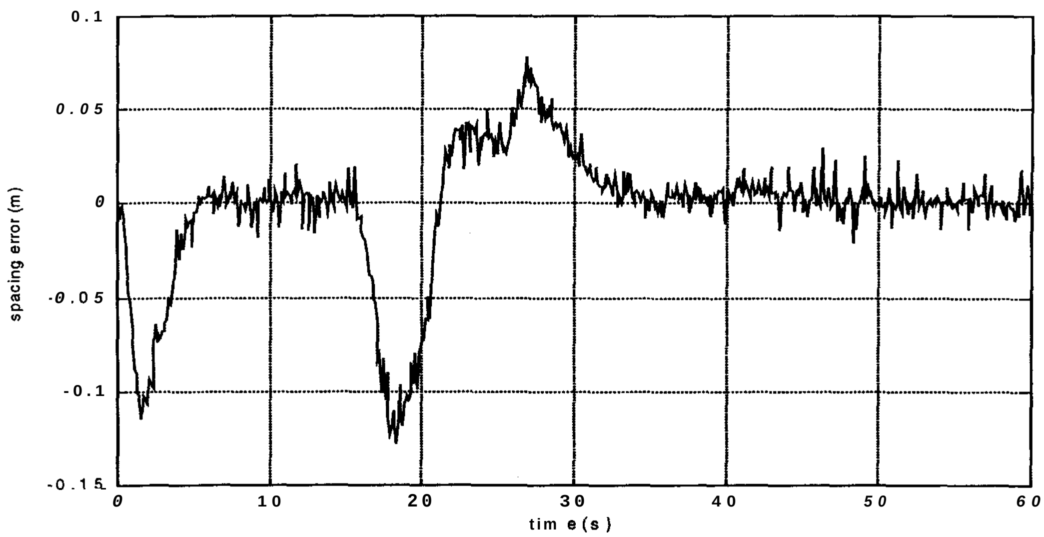

Figure 4-7: Spacing error with GPS noise

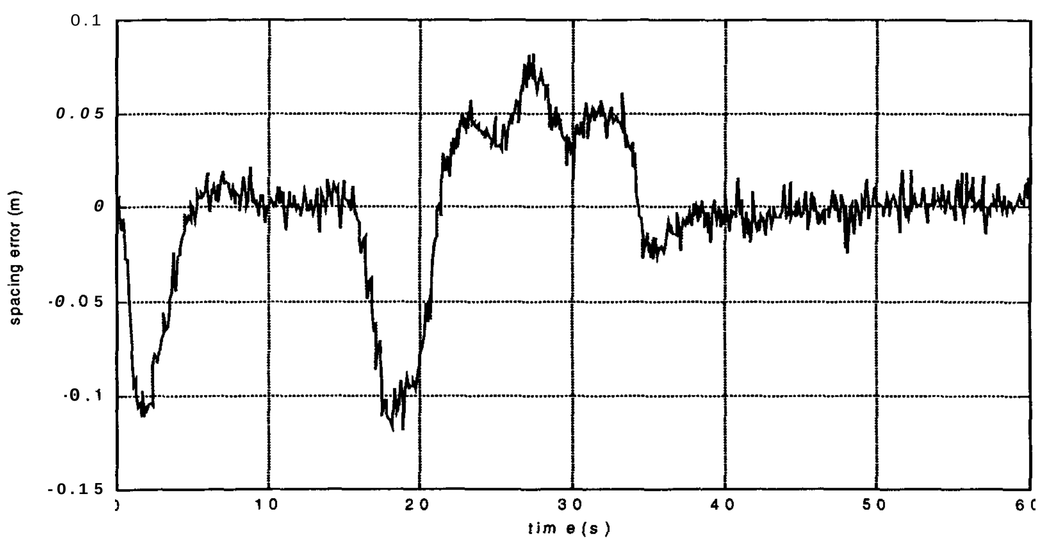

Figure 4-8: Spacing error of with radar noise

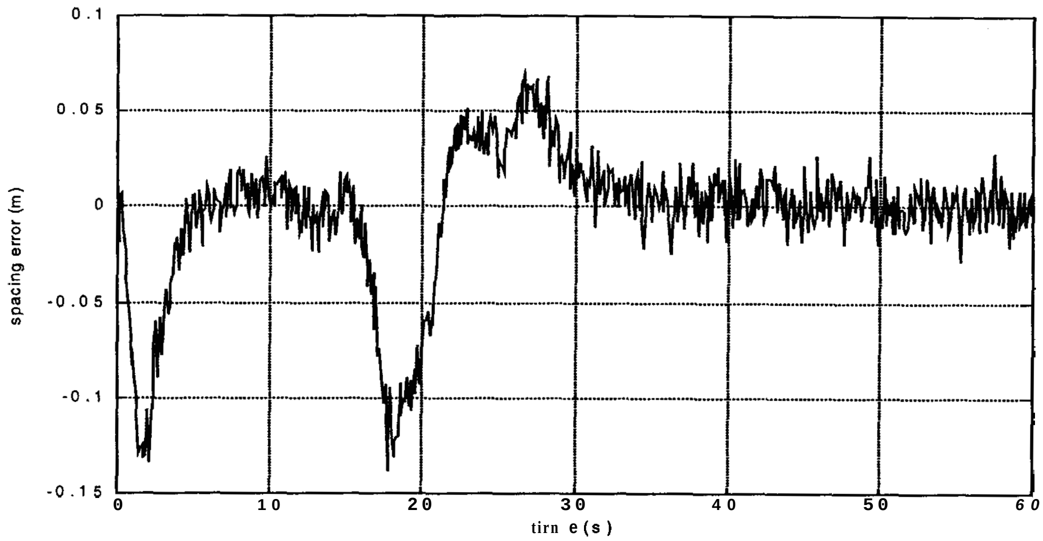

Figure 4-9: Spacing error of with rayelco noise

In order to extract useful information with sensor measurement, we use two methods to smooth out the noise. One method uses the Probabilistic Data Association Filter (PDAF), as developed by Satnam Alag (Alag, 1996), which results in the fused sensor measurement in Figure 4-10. The other method used is the Fuzzy Sensor Validation and Fusion Algorithm (FUSVAF) as developed by Kai Goebel (Goebel, 1996) and its result is depicted in Figure 4-11. We can see that both fusion algorithms achieve excellent extraction of the real spacing error from the sensor measurement. Compared to the spacing error without sensor noise, the noise magnitude is very small. Compared to additional analysis by Jiangxin Wang using MATLAB (Wang, 1999) as described in Chapter **3,** similar conclusions can be reached.

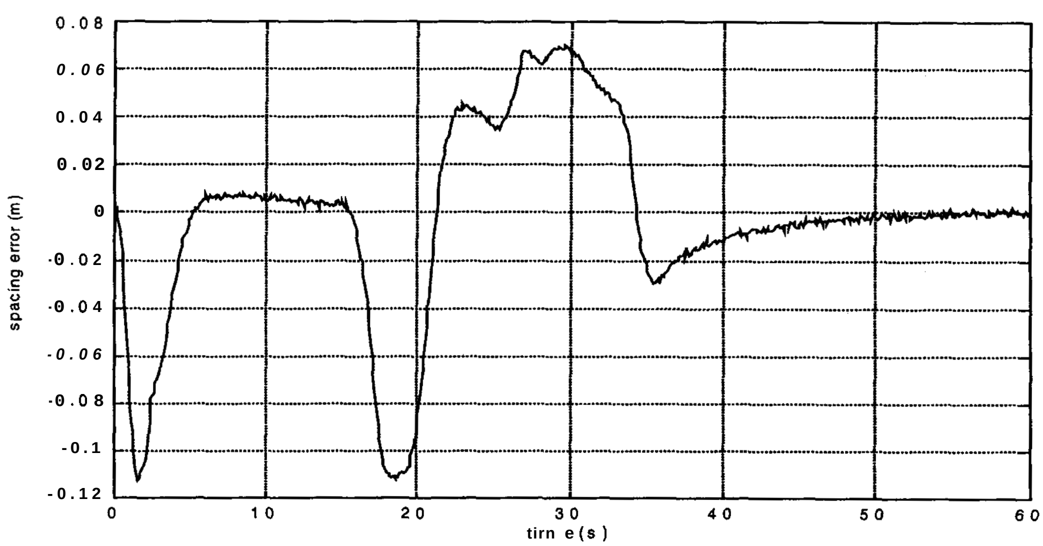

Figure 4-10: Spacing error of car 1 with PDAF fusion algorithm

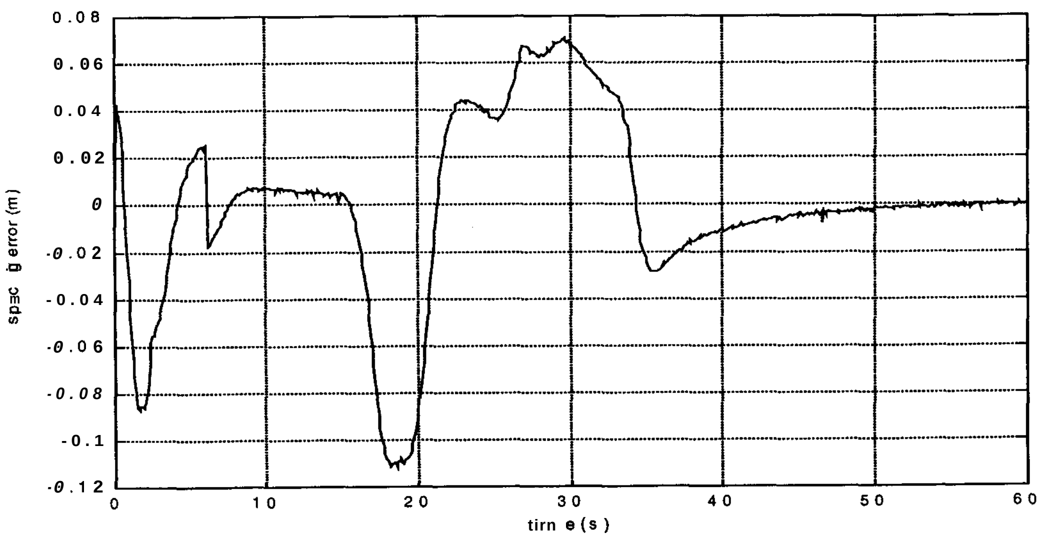

Figure 4-11: Spacing error of car 1 with FUSVAF fusion algorithm

We note that during the first 10 seconds of the experiment the fuzzy algorithm performed poorly thus resulting in a significant overall average mean square error of 7.2518e-5. Compare this to the overall mean square error of the PDAF algorithm, which was only 1.3697e-6. However, recalculation after the first 10 seconds shows the Fuzzy algorithm to have a smaller average mean square error of 1.3872e-6, as compared to that of the PDAF algorithm, 1.4138e-6.

Conclusions

From the simulation results in the VDL environment, we can see that (1) individual sensors exhibit not insignificant noise. However, through the combination of several sensors' information, coupled with the use of appropriate sensor fusion algorithms to smooth out the noise, we can achieve nearly accurate measurement. (2) Both the PDAF and FUSVAF algorithms achieve excellent extraction of the real spacing error from the sensor measurements. It must be noted that the error for the FUSVAF algorithm decreases significantly after a short period of time.

Chapter 5 Conclusions and Further Directions

Conclusions

The results of the open loop fusion and close loop simulation show that both PDAF and FUSVAF fusion schemes behave as expected and are consistent with previous research (Agogino et al., 1995, 1997). In the presence of GPS, radar and linear transducer noise (noise models for simulation), the two fusion schemes filter out noise to varying degrees and fuse multiple sensor readings. Furthermore, GPS provides a potentially powerful positioning sensor for vehicle control. The word 'potentially' is used here because we have not yet been able to make the system work reliably enough to be implemented directly. In addition, PDAF and FUSVAF are both effective fusion schemes for different combinations of positioning sensor systems that include the GPS sensor.

From the simulation results in the VDL environment, we can see that individual sensors exhibit not insignificant noise. However, through the combination of several sensors' information, coupled with the use of appropriate sensor fusion algorithms to smooth out the noise, we can achieve nearly accurate measurement. Both the PDAF and FUSVAF algorithms achieve excellent extraction of the real spacing error from the sensor measurements. It must be noted that the error for the FUSVAF algorithm decreases significantly after a short period of time.

Future Directions

It is shown in this research that GPS can achieve very high accuracy when it works well. As discussed above in order to keep the system working reliably, it becomes crucial to study the failure modes of GPS.

Closed loop simulation has been done in this research using a simple PID controller and VDL. Additional simulation in other environments such as SmartAHS would be beneficial for further analysis of performance of the integrated sensor system.

A simple linear predictor is used in this project to synchronize the sensor outputs. More situations need to be considered, e.g., if the sensor output is too noisy, which means that two neighboring points might have big difference, then the prediction of the current sensor reading only based on the most recent two sensor outputs would result in noise with large magnitude. Adaptive or fuzzy methods or their combination could be considered here to solve the problem.

PDAF and FUSVAF have their own advantages and disadvantages. An interesting and potentially very powerful endeavor would be to develop a combined validation and fusion scheme, exploiting the desirable properties of both and rejecting their shortcomings.

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