

Sensor Noise Model Development of a Longitudinal Positioning System for AVCS

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ABSTRACT

Advanced Vehicle Control Systems (AVCS) as envisioned by the California Partners for Advanced Transit and Highways (PATH) program. System simulation is crucial to ensure that every portion of the whole system we have designed will perform adequately together. For automated highway systems, simulation is essential for controller design. To create a more realistic simulation environment, we need to model sensor output instead of assuming that we can measure the vehicle states exactly. That is the primary reason for the development of sensor models. Three positioning sensors are investigated in this project. Their models are developed based on real test data. In addition, the sensor models are evaluated by comparing their autocorrelation function estimates and histograms with those of real test data.

1. Introduction

While reliability and safety are of paramount concern in AVCS, accurate sensor information is crucial to achieve high performance of control system in IVHS. All sensor readings are corrupted by noise to some degree. Sensor redundancy is essential to achieve high sensor data fidelity. In this work, a positioning sensor system which includes the Global Positioning System (GPS) receivers, a RADAR sensor and a linear transducer is investigated. The GPS system is potentially powerful for IVHS because of its high accuracy achievable by Differential GPS (DGPS) technique 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 the linear transducer are developed based on the test data.

Platoon model is utilized to increase highway capacity in IVHS. Platoons are groups of two to ten vehicles following one another with a very small intervehicle spacing at highway speeds. Two types of cars are concerned in controller design of a platoon according to their positions in the platoon: the leader and the followers. For the followers in steady state motion, the goal of the control system is to keep a constant distance from the vehicle ahead. All the three sensors we are studying here are used to measure the intervehicle spacing to provide accurate position information needed for the follower controller.

For time series analysis, the histogram of the sample data was used to estimate the probabilistic density function (pdf). An autocorrelation function describes the second order statistics of a random process. These two important statistical properties are utilized to develop and evaluate sensor noise models in this work.

The Berkeley Expert System Technology (BEST) Laboratory of UC Berkeley has performed a number of studies on multiple sensors. These sensors include RADAR, SONAR, optical and others. In this paper, GPS sensors are integrated into the sensor suite and the performance of the fusion schemes for this new sensor is studied in Wang (1998).

The purpose of this paper is to: 1). investigate GPS system noise characteristics; 2). introduce a sensor model development method; 3). develop GPS sensor noise model and other sensor models involved.

2. Test Setup

Test data used in this work were collected in a field experiment on October, 30th, 1997 at Golden Gate Fields, Richmann, California. The experiment was performed in cooperation with SRI International with the assistance of PATH researchers using two PATH cars.

Three types of position sensors were used in the tests: GPS receivers, a RADAR, and a Rayelco transducer. Two GPS receivers were installed on the two cars respectively and a third one was used as a reference GPS station for the DGPS scheme. All three sensors were used to measure the intervehicle spacing. Several static and dynamic tests were performed at a distance of around 40 meters from the reference point. The RADAR and transducer data were synchronized while 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, and the GPS position data were collected at 4Hz. A synchronization method was introduced in Wang (1998) for use in sensor fusion.

3. Noise Characteristics Analysis Methods

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

Histogram (Estimate of Probability Density Function)

For time series analysis, a histogram of sample data was used to estimate the probabilistic density function (pdf). For example, a histogram of a pseudo zero mean Gaussian white process with 1000 samples generated in Matlab and the pdf of the corresponding ideal random process are shown in Figure 1.

The shape of the histogram more closely approximates the shape of the pdf when more samples are used. Similarly, in the development of sensor models, due to limited test data, we were only able to arrive at a rough data distribution, not the exact pdf. However, this is still useful since it does show important properties of the data and it is easy to use with no complex calculations involved. In reality, no exact solution to this kind of problem exists because for a probabilistic model, limited test samples are insufficient to 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 a typical random process for this scenario. Since techniques relating AWGN is well-developed, analysis would be simplified if the sensor noise of interest is AWGN or can be approximated as such. By contrast, if the characteristics exhibited by the data are too complex to be modeled easily and model accuracy is less important, use of a typical random process or combinations of several of them are justifiable for rough approximation.

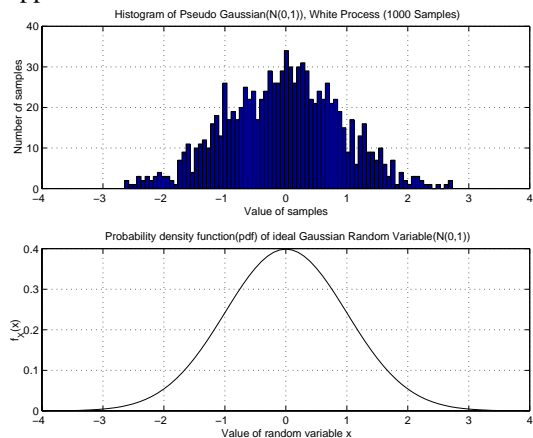


Figure 1 Histogram of Pseudo /Ideal AWGN

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 are dependent upon 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 could be defined as following:

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

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

$$\text{where } \bar{x} = \frac{1}{N} \sum_{i=1}^N x_i.$$

Estimates of the autocorrelation function (ACF), also called sample ACF, are obtainable 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 shows the sample ACF of a pseudo-white Gaussian process.

ACF can be considered to be a measure of the whiteness of a random process. If the sample ACF of a set of test data is quite similar to that of white noise, then it can be modeled as white noise. Note that different data could have the same sample ACF. Many types of ideal white noise share the same ACF. And many types of pseudo white noise have very similar ACF's. Sometimes it is difficult to interpret the data according to sample ACF especially when it shows that the data are highly correlated (Jenkins 1968). But sample ACF is still useful in the modeling.

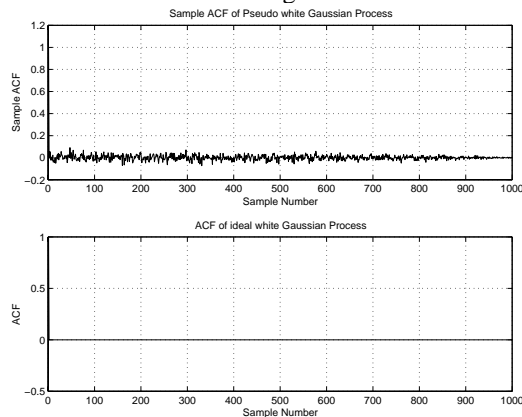


Figure 2 ACF of Pseudo/Ideal AWGN

In the following sections, we compare the histograms and sample ACF's of our test data with the pseudo white Gaussian process to determine 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 closely our models resemble the real sensor systems.

4. Noise Characteristics and Noise Models of three sensors

4.1 GPS sensor Noise Characteristics and Model

The major error sources 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 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 can be 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 know location, we can use it to figure out exactly what errors the satellite data contains, through use the receiver as 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	24.0m
Ionosphere	7.0m
Clock and Ephemeris	3.6m
Troposphere	0.7m
Non-common Mode Errors	
Receiver Noise	
Multipath	

Table 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 will output range and phase measurement for each carrier frequency. These four outputs and resulting combinations provide very useful signals needed for accurately calculating the distance measured. Table 1 (Farrell, et. al., 1997) summarizes the main error sources and their standard deviation in a GPS system for a single receiver. The common mode errors are common to every receiver in a local region. The non-common mode errors depend on specific receivers. They vary significantly for different types of receivers, so we do not assign a range to them here. 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 two practical problems with the GPS system used in AVCS. One is that the signals from the satellites can be blocked by high buildings, tunnels, overpasses, etc. If this occurs, the GPS receiver may be unable to get enough information for a calculation. The other is that GPS data arrive at a relatively low frequency. We have to synchronize GPS outputs with other sensors. And the low data update rate is undesirable for highly dynamic systems.

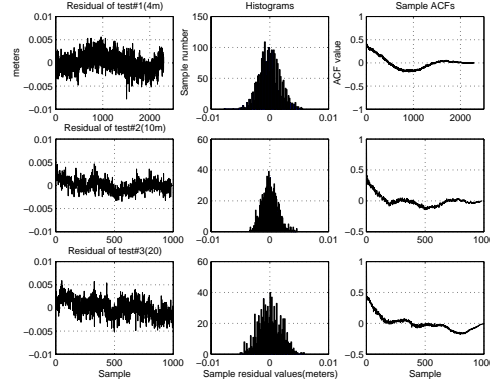


Figure 3 Residual of static test GPS data

A noise model of GPS data can be developed by observing all the static test residuals in Figure 3. 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.

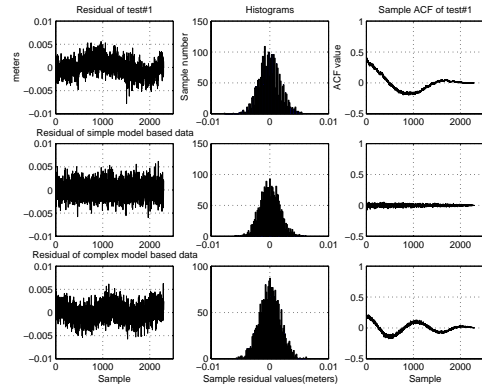


Figure 4 Comparison of GPS test/model based data

Based on these observations, the model is developed as $y(n) = x(n) + a(0.0015r_g(n) + 0.0012 \cos(2\pi n / r_u + \phi_0))$

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

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

$r_g(n)$ is white Gaussian, $\sim N(0,1)$

$a = 1.0$ 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

The first row of Figure 4 corresponds to one set of test data, the second row shows white noise model based data, and the third row shows the model based data we developed here. From Figure 4, it can be seen that this model is still not quite accurate since its sample ACF still differs from the test data. The goal for the sensor model is not to regenerate the exact test data, but to generate model sensor readings statistically similar with the real test data to serve for the

simulation of control system. Therefore, we do not need to arrive at an exact match between true test and model based data. From the three sets of test data it can be seen that their ACF's can differ as well.

4.2 RADAR Sensor Noise Model

The RADAR model we have developed here is based on test data under the calibration of scale: 13942.410 m/v 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, $\sim N(0,1)$

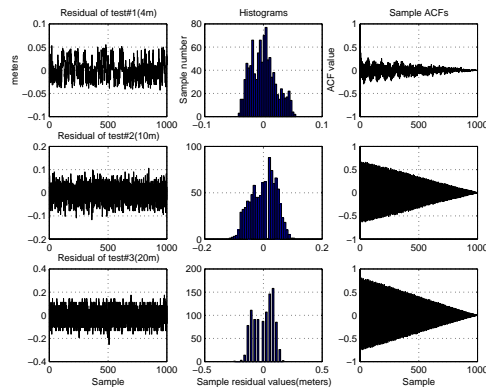


Figure 5 Residual of static test RADAR data

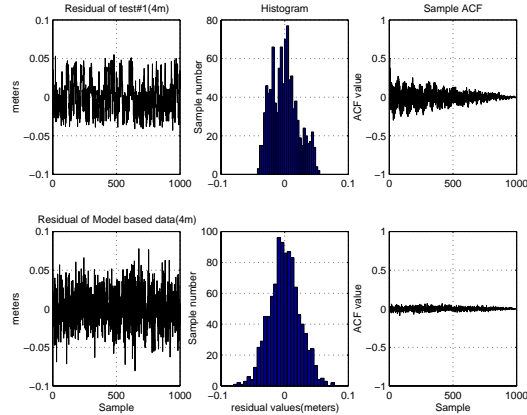


Figure 6 Comparison of RADAR test/model based data

From Figure 6, the sample ACF's of RADAR test data and model based data are appear to differ. A model with ACF similar to that of the RADAR test data is difficult to find and it would be very complex. Here a white Gaussian process with a variance changing with the distance measured is used to roughly model the RADAR outputs.

4.3 Linear Transducer and Noise Model

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 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 attached with the other car physically, this sensor would not be used in a real world automatic highway system. However, since it is quite simple and accurate, it can be used in tests as a reference positioning sensor. The transducer used in our experiments can measure distance up to approximately 15 m and has an accuracy of about 0.1%. The output data were available at 50Hz; however, to minimize the storage required, we sampled them at 10Hz.

The following model of Rayelco transducer is under the calibration of scale: 1.229 m/v 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,

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

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 7). The set $\{r_i, i=1, \dots, 10\}$ 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, so that samples at different times have almost the same probability distributions of being at the ten different layers.

Hence a uniformly distributed random process can be used for $r_u(n)$.

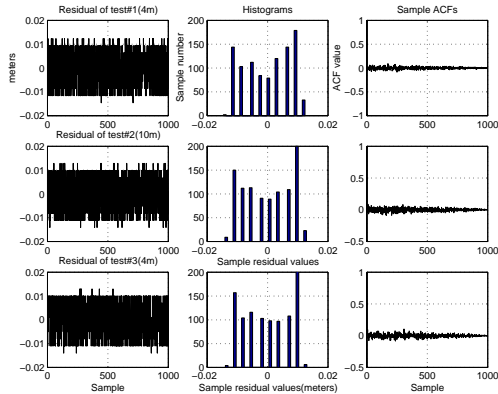


Figure 7 Residual of static test transducer data

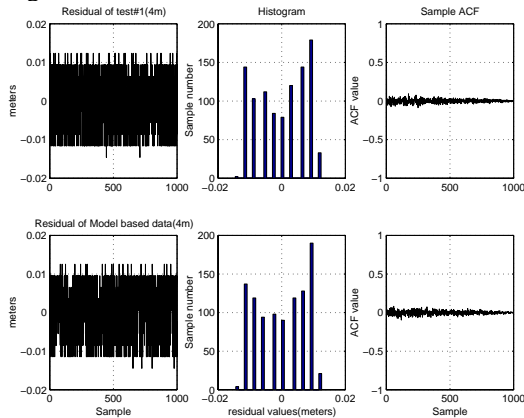


Figure 8 Comparison of transducer test/model based data

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

5. Conclusions and future work

According to the test data, when signals from at least five satellites are receivable, with effective use of the advanced GPS techniques under favorite environmental conditions, GPS readings can be quite accurate (error could be within 1cm). Therefore, GPS is potentially a 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.

As discussed above in order to keep the system working reliably, it is crucial that we study the GPS failure modes in future work. A simple closed loop simulation using these sensor models developed in this work has been done in Wang (1998). They need to be implemented in more complicated and realistic simulation environments.

Acknowledgments

The work was supported by a grant from Caltrans through PATH (Partners in Advanced Transit Highways), grant number MOU 322. The author would also thank SRI researchers and the PATH technical staff at the Richmond Field Station who helped to collect all the data on which this research is based.

This paper is prepared in cooperation with the State of California, Business, Transportation and Housing Agency, Department of Transportation and the U.S. Department of Transportation Federal Highway Administration.

The contents of this paper reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the State of California. This paper does not constitute a standard, specification, or regulation.

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